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Abstract: This paper investigates whether proximity to universities matters for corporate patenting in Chinese provinces. The investigation is based on estimating regional knowledge production functions using a Chinese provincial dataset for the years from 2000 to 2008. Geographic proximity of companies to universities is taken as a key element to measure firms' accessibility to university research. In addition, quality-adjusted accessibility measures are considered in extended models to take into account quality difference in university research. The results suggest the existence of spatial academic effects on corporate patenting activities in China as found in the previous literature for Western economies. In China, however, these effects are especially strong for realising technologically less demanding non-invention corporate patents than for invention corporate patents. Moreover, companies' geographic proximity to universities dominates over university research quality difference for determining the relevance of universities as knowledge sources for companies. Extended models are estimated for robustness checks which ascertain the main results.

Keywords: spatial proximity, logsum accessibility, university, corporate patenting, China

JEL classification: O31, O53, R11

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1 Introduction

Innovation is key for sustaining long-term economic growth (NSF, 1972). Companies with long-term profit maximisation as their goal undertake innovation activities to introduce new products and to develop new technologies to enhance their market competitiveness. In terms of input, they invest considerable amounts of financial resources and human capital in their own R&D activities to explore new knowledge as a base for novel products. In addition, they may acquire externally available new knowledge and build their R&D activities on existing knowledge to develop their products. In the latter case learning from others enables them to focus limited resources on key innovation activities, thereby increasing their efficiency in producing innovation outcomes given the same amount of innovation inputs invested (e.g. Mansfield, 1991).

Academic institutions like universities are considered to be one of the major knowledge sources to spur companies' patenting activities (e.g. Criscuolo et al., 2005; Wagner, 2006; Liu, 2009). Traditionally, publically funded universities focus on basic research to explore new knowledge in order to expand the public knowledge stock to the benefit of society as a whole. In basic research, research outcomes and related pay-offs are often difficult to be adequately appropriated by innovators. In line with their objective to expand the public knowledge stock, universities are expected to share their research findings with others through publications, presentations, conferences and workshops to which external innovators may have easier access at relatively low cost. The latitude of universities to share their knowledge with external innovators has been further expanded by the Bayh-Dole Act of 1980 in the US and by similar policies in the other industrialised countries (Mowery et al., 2004). Universities have been then given the right to file patents for their publicly financed inventions. This is expected to encourage universities to make their research findings more concrete in order to be more easily applied by industries (Cohen et al., 2002). Nevertheless, despite some convergence in the wake of these policy changes, there remains a gap between universities and companies in research focus, commercial will and the modus operandi. Therefore, companies which are in need of academic knowledge for new projects and/or for solving problems confronted with during their innovation processes have to communicate and interact with academic researchers to ensure a more efficient use and transformation of academic knowledge.

The efficiency of these knowledge transfer processes may thus have an essential spatial element: it is more advantageous for developing corporate innovation outcomes if companies are located closer to their (potential) academic knowledge sources. The clustering of industrial innovators close to UC Berkeley and Stanford University (Silicon Valley) and to MIT and Harvard University (Route 128) in the US was often alluded to as support for this hypothesis (Dorfman, 1983). The seminal work of Jaffe (1989) on estimating regional knowledge production functions led to a series of studies focusing on this topic. Most of them found evidence supporting the hypothesis that academic research has a positive impact on corporate innovation outcomes and that such positive effects decrease over distance.

However, most of the studies until now strongly focused on industrialised countries such as the US but not on emerging economies like China, though China has played an increasingly important role in global knowledge production processes (WIPO, 2010). This is especially true since the turn of the century. In the case of China, such spatial effects of academic research on corporate innovation outcomes can be even more strongly expected. The traditional division of labour in China which required companies to focus on production activities and universities on research makes it more crucial for companies which lack innovation experience but are now encouraged and/or forced to engage in innovation activities to interact with universities and to make use of academic research results more efficiently to develop new products and/or technologies.

Focusing on the case of China, this paper aims to analyse the spatial effects of academic research on corporate innovation performance based on a Chinese provincial panel dataset from 2000 to 2008. To measure the potential accessibility of companies to academic knowledge, taking distance between companies and universities into account, the logsum accessibility indicator is calculated. The logsum accessibility indicator, different from the indicators considered in Jaffe (1989) and Anselin et al. (1997), captures the individuals' utility maximising goal which implies that the individuals/companies will seek to access a maximal relevant amount of appropriable academic knowledge available to them.[1] Applying the knowledge production framework, this paper regresses corporate innovation outcomes on companies' own R&D efforts and their accessibility to academic knowledge, controlling for other firm- and industry-related as well as region-specific influential factors based on the literature. It investigates whether spatial academic effects on corporate innovation outcomes

[1] See Section 3.2 and Ben-Akiva and Lerman (1985) for more information.

differ across academic knowledge embodied in different forms and across different corporate innovation outcomes considered.

The structure of the paper is organised as follows. Section 2 briefly summarises the related literature on spatial academic effects on corporate innovation outcomes. Section 3 introduces the dataset for our analysis and some key statistics to provide a broad picture about the development of corporate innovation activities and of academic knowledge production processes over the past decade in China. After that the logsum accessibility indicator and the estimation models for further analysis are described in some detail. Section 4 presents the estimation results of both baseline models and extended models for robustness checks, dealing with issues such as endogeneity problem and serial and spatial autocorrelations. Section 5 concludes.

2 Related Literature

Academic research carried out by universities is to great extent financed by governments. Depending on governments' policy focus, universities may restrict their research on research areas where market failure exists and companies lack R&D interests or they may extend their research to more applied research areas in order to explore and develop new knowledge for industrial usage (Bozeman, 2000). The amount of financial resources and human capital invested in the academic research processes does not guarantee per se that the academic findings can be fully realised. University researchers may well present key academic findings in publications such as journal articles, and/or in patent-related documents. They may not document as comprehensively the less crucial part of academic findings; but this part of their knowledge may still be relevant as context information advantageous for understanding the documented/codified key academic findings. The non-codified findings remains as tacit information which represents another component of academic knowledge accumulated over time and which can only be transmitted to others via direct communications and interactions. Tacit information may also include knowledge and the experience about dead-end research.

The borderline and the relationship between codified knowledge and tacit information are not without controversy. While Dasgupta and David argue that codified knowledge and tacit information can be "two substitutable inputs (at the margin) in production of further knowledge" (Dasgupta and David, 1994: 494), factor analyses of Cohen et al. (2002) suggest that personal interactions, which are the major ways to transmit tacit information, tend to complement, in particular, publically available codified knowledge such as publications. In the latter case, in which (at least a great part of) codified academic knowledge can be understood better by companies via personal interactions and communications with university researchers, distance between companies and universities may affect how efficiently the 'theoretically boundary-unrestricted' codified academic knowledge can be used as additional inputs to improve companies' innovation productivity. Distance, as such, even plays a more important role in the event that companies are only keen on obtaining academic researchers' tacit information but not their documented knowledge for innovation support. Indeed Storper and Venables (2004) argue, although they do not focus solely on interactions between companies and universities, that proximity may promote knowledge transfers and spillovers because it eases face to face contact. They argue, based on self-developed theoretical models, that "face to face contact is particularly important in environments where information is imperfect, rapidly changing, and not easily codified" (Storper and Venables, 2004: 351).

That proximity between companies and universities may be advantageous for spurring industrial innovations, is illustrated by conspicuous cases in point in both industrialised countries as well as in emerging economies. The most well known and well investigated cases are Silicon Valley and Route 128 in the US (e.g. Dorfman, 1983). Comparable examples can also be found in Asia such as Hsinchu Science Park in Taiwan (National Chiao Tung University and National Tsing Hua University) (Chen and Choi, 2004) and Zhongguancun in Beijing in China (Peking University and Tsinghua University) (Zhou, 2005).

While case study literature provided more detailed context about the institutional framework, economic background and industrial trajectories of some selected real world examples of high-tech clusters with academic centres of excellence, the seminal work of Jaffe (1989) led to a series of econometric studies focusing on investigating the role of proximity to universities and university research for corporate innovation performance. Under a modified Griliches knowledge production function framework (Griliches, 1979) Jaffe (1989) analysed US state-level data for various years[2] to examine the spatial spillover effect of university research on companies' knowledge production activity where companies' new knowledge was proxied by the number of corporate patents. He considered two proximity-related variables in his regression model. Firstly, he considered university R&D expenditure in the same state as the corporate patents filed, implying that university research carried out beyond

[2] The dataset analysed was for 29 states and the following years: 1972-1977, 1979 and 1981.

the state boundary was assumed to be too far away for the potential industrial knowledge receivers to adequately profit from the academic knowledge.[3] Secondly, to consider the proximity issue within states as well, he constructed a geographic coincidence index (GCI) which measured how concentrated university research and industrial labs were located across cities within states. Multiplying GCI by the variable of state-level university R&D, he built an interaction term for his regression model. Here the GCI was expected to reflect the role of university-industry concentration for intensifying the spillover effect of university research within states. His analysis found some support for the relevance of spatial spillover effects from university R&D for corporate patenting activity, but such effect was still much smaller than the contribution of industrial R&D to corporate patent outputs. Regarding the role of GCI as an intensifier of the spillover effect, Jaffe (1989) only found weak evidence. Based on a slightly different cross-sectional dataset for 29 states, Acs et al. (1992) reestimated the regional knowledge function with the two proximity-related variables developed by Jaffe (1989) but using the number of innovations[4] to directly proxy the industrial innovation performance. Their analysis basically strengthened the findings of Jaffe (1989).

Further improvements in the dataset and methodology were made by Anselin et al. (1997; 2000). Anselin et al. (1997) analysed an extended state-level dataset and they considered four alternatives – three of them derived from the spatial interaction theory – for the original GCI (-based interaction term) developed by Jaffe (1989) to proxy the within-state concentration between university and industrial research. Parallel to the state-level analysis, they, for the first time for an analysis of this kind, examined the proximity issue at a more disaggregated level – metropolitan statistical areas (MSA). Due to the more disaggregated spatial unit considered they used spatial lag variables to measure the extent of university research in the MSA itself and in neighbouring counties. Moreover, when necessary, they applied spatial econometrics techniques to cope with potential spatial dependence problems of the cross-sectional dataset. All the improvements made by these two studies again provided support for the previous findings. Such positive academic effects declined over distance but were not restricted to the boundaries of counties.

[3] Since Jaffe (1989) did not explicitly consider university R&D beyond the own state boundary, he emphasised that "(his) results do not relate directly to the question of the social rate of return to university research. They underestimate that return, to the extent that spillovers flow beyond state boundaries" (Jaffe, 1989: 968).

[4] Knowledge per se is an intangible good which is difficult to be measured adequately. Using patent data to proxy knowledge produced is a convenient way but not without drawbacks. For example, not all innovations are patented and the 'value' of patented innovations can be significantly different across innovations. Some patented innovations are worth being further transformed into new products for markets but others may remain in shelves for long. See Pakes and Griliches (1980) and Griliches (1990) for more information.

Research on the spatial academic effect on corporate innovative performance has also been carried out using data for some selected European industrialised countries (Piergiovanni et al., 1997; Blind and Grupp, 1999; Piergiovanni and Santarelli, 2001; Fischer and Varga, 2003; Barrio-Castro and Garcia-Quevedo, 2005). Although their analyses focused on different European countries and there were some technical differences, their findings generally provided further support for the existence of positive academic spillover on corporate performance.

That companies' own R&D efforts strongly matter for their innovation outcomes (Jaffe, 1989) was also confirmed by the abovementioned regional studies for the US and Europe. Moreover, Feldman and Florida (1994) found that networks of companies from related industries and specialised business services, together with industrial R&D and university R&D comprised a technological infrastructure which was advantageous for stimulating companies' product innovations. Last but not least, the population size of regions was generally considered in the regression models to proxy the size effect of regions.

Compared to the research carried out for the US and Europe, econometric analysis on the same topic using Chinese data is scarce, though spatial academic research effects on corporate innovation performance should be expected to be pronounced for China as well. The traditional division of labour – universities and firms responsible for research and production respectively – and increasingly strong governmental support for intensifying university-industry linkages and for encouraging indigenous industrial innovation mean that it is increasingly advantageous for companies to engage in searching formal and informal academic support for their innovation activities (Eun, 2009; Gu and Lundvall, 2006). Li et al. (2010) analysed a provincial panel dataset from China to investigate the transfer of innovation capability from universities to companies. Two focus variables which they used to proxy the cooperation between universities and companies were the number of companies cooperating with universities and the amount of university R&D expenditure financed by companies. The former variable was found to affect corporate patenting performance positively at the 1% significance level, while the latter variable was ultimately omitted from the final model due to a problem with multicollinearity. Furthermore, the paper did not explicitly consider the geographic aspects of academic research. Thus, the finding provided only some implicit support that proximity to academic research may matter for corporate innovation performance in case of China. [5] As additional caveat of the paper was that it did not take into account the time lag between innovation inputs invested and patents as innovation outputs created, nor did it deal with issues such as firm-level and provincial heterogeneity.

There are some studies investigating innovation activities of companies and/or total factor productivity in China using more sophisticated econometric methods (e.g. Hu et al., 2005; Hu and Jefferson, 2009; Jefferson et al., 2006). Their regression models were derived from the knowledge production function framework as well. However, their analysis was carried out at the firm level instead of at the regional level and the authors did not explicitly consider universities as potential knowledge sources for supporting companies' innovation activities. Rather, the focus was put on companies' own R&D efforts, external knowledge inputs either purchased (domestically and internationally) or transmitted through companies' exporting or FDI activities and different firm characteristics such as ownership structure. Their findings indicate that firms' own R&D is highly significant for innovation as evidenced for Western economies. However, the omission of potentially important regional spillovers from universities to firms in these papers remains a shortcoming. Nevertheless, the positive effect of the firms' global engagement and organisational characteristics makes it clear that comparable variables (but at the regional level) need to be considered in a regression model for our research purpose.

3 Data and Estimation Issues

3.1 Data

This paper aims to analyse whether there exist significant spatial academic research effects on corporate innovation performance also for China. In other words, it does not investigate the direct effects of academic knowledge transferred from universities to companies on their innovation performance, but it investigates whether proximity of companies to universities may support them to better understand and learn the academic knowledge that they may also obtain over distance and thus may be advantageous for enhancing their own innovation productivity. To do this, we apply the regional knowledge production function framework as applied in the related literature for the US and Europe (s. Section 2). For this purpose, our econometric analysis is based on a provincial panel dataset for 30 provinces from 2000 to

[5] Li et al. (2010) found that the more companies were cooperating with universities, the more patents were created by companies in the same province. Assuming that effective cooperation requires fruitful communication and interactions between innovators from universities and companies, the positive finding in the paper may suggest the existence of a positive role of proximity for determining the potential academic spillover effect on corporate innovation performance.

2008. While Tibet is excluded from the econometric analysis due to limited data availability, basic data of Tibet is considered as far as possible for the descriptive analysis below if nothing else is mentioned. Data inputs for the panel dataset for both the descriptive and econometric analysis were collected from different official statistical sources for various years that are summarised in Table B1 in Appendix.

With intensified global competition and the policy change of the Chinese government towards promoting product upgrading and higher value-added activities, companies in China are increasingly encouraged and/or forced to engage in more innovation activities. As a result, the number of patent applications filed by companies at the China's State Intellectual Property Office (SIPO) increased by about 27% annually from 2000 to 2008.[6] Almost half of these corporate patent applications, especially the invention ones, were filed by large and medium-sized industrial enterprises, although they just represented a small proportion of all companies in China.[7] The high innovativeness of the large and medium-sized industrial enterprises and the availability of R&D data for these companies at the provincial level cause us to focus our further analysis on the large- and medium-sized industrial enterprises only. For the sake of simplicity we use the words 'companies' and 'corporate' patenting performance as synonyms for large and medium-sized enterprises and their patenting activities.

In 2008, these companies filed more than 122,000 patent applications.[8] This was ten times higher than the number of patent applications they filed in 2000. Classifying the 31 Chinese provinces into three geographic regions, most of the corporate patents were filed in the eastern region[9] of China (77% in 2000) which consists of 11 provinces and accounts for roughly 11%

[6] There are three types of patents in China: invention patents, utility model patents, and external design patents. These three patents are different from each other in terms of how radical and novel is the commercial knowledge generated, the application requirements, the length of application processing time, and the length of protection term. According to the SIPO (2008), the application requirements for invention patents are most demanding and complicated compared to the requirements for the other two types of patents. Accordingly, the examination process for granting invention patents is more time-consuming but the protection term of such patents is longer than other two types of patents. More (intensive) research inputs in innovation activities are expected to be needed for realising invention creations suitable for being patented as invention patents than the inputs needed for other two technologically less demanding patent types. See Hanley et al. (2011) for more information.

[7] In 2008, 41% (46%) of all corporate patent applications (corporate invention patent applications) were filed by large and medium-sized industrial enterprises, which accounted for just 9% of all industrial enterprises above designated size in China. Industrial enterprises above designated size are those with annual revenue from principal business over 5 million RMB (NBSC-CNSYST, 2009; NBSC-CNSY, 2009).

[8] Total numbers of corporate invention and non-invention patents as well as their R&D expenditure over the research period (2000-2008) are presented in Figure B1 in the Appendix.

[9] The eastern region comprises 11 provinces: Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin and Zhejiang. The western region comprises 12 provinces (Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Tibet, Xinjiang and Yunnan), the Central region 8 provinces (Anhui, Heilongjiang, Henan, Hubei, Hunan, Jiangxi, Jilin and Shanxi).

of the total geographic area of the mainland China. The eastern region is the geographically smallest region but it is the one with the highest economic development and with the greatest share of population (39% in 2000; 40% in 2008). The corresponding shares of patent applications in the central region and in the least developed western region were just 14% and 9% in the same year. The western region with the least number of corporate patents is the largest region in China, accounting for 12 provinces and 72% of the total geographic area in the mainland China but only 28% of the total population lives there (in 2000 and in 2008). Over the research period, the distribution of the corporate patent applications across these three regions hardly changed, amounting to 78%, 12%, and 10% in eastern, central and western region in 2008, respectively. In contrast, the distribution of corporate patent applications at the provincial level in 2008 differed quite markedly from the corresponding proportion in 2000. For example, Guangdong – the pioneer province of China's economic reform still ranked first as the province with the highest number of corporate patent applications in China, but its share in 2008 (27%) was much higher than that in 2000 (19%). Shandong – the province with the second highest number of corporate patent applications in 2000 – accounted for 18% in 2000 but only for 10% in 2008. Both provinces ranked top in their population size (both roughly 7% in 2008) as well but not so in the geographic size (about 1.9% for Guangdong (15^{th} in ranking) and 1.6% for Shandong (20^{th} in ranking)). As suggested in the literature (s. Section 2), different amounts of innovation inputs proxied by, for example, R&D expenditure, are expected to be one of the major determinants for the diverging patenting performance. Guangdong indeed also ranked first among all non-Tibet provinces with respect to the industrial R&D expenditure in both years. Shandong which ranked second in this regard in 2000 was outperformed by other provinces in 2008, which was consistent with the development of corporate patenting activities over time.

Companies' patenting performance is additionally expected to be affected by how easily firms can interact with university researchers thereby making use of academic knowledge created by universities. For a long time, university research represented the only official research sector for the Chinese economy. Though nowadays official research is no longer restricted to universities, universities are characterised by an impressive record of patenting: universities applied for more than 30,000 invention patents in 2008, compared to less than 2,000 patents in 2000.[10] In addition, the number of scientific articles universities published and had

[10] Universities in China file more invention patent applications than the other two types of patents. In 2008, the number of utility model patent applications (external design patent applications) filed by universities amounted

registered in well-known foreign referencing systems in 2008 (more than 240,000) was also much higher than the number for 2000 (roughly 42,000).[11] Similar to the distribution change of corporate patent applications across provinces, the distribution of university research results in 2008 markedly changed compared to 2000. Beijing and Shanghai ranked outstanding among all provinces with respect to both university research results over the research period despite their extremely small size in population and in geographic area. Their relative weights in 2008 were lower than in 2000, however.[12] When considering both the increase in the number of universities and the more equal distribution of universities across provinces in China over the research period (Bickenbach and Liu, 2011a), companies in 2008 had a larger scope to reach and interact with universities and gain an easier access to academic knowledge from universities than it was the case in the past. As a result, companies were in a position to profit more from considerably more accessible academic knowledge in 2008 than in 2000. This should entice a high propensity of firms for filing patents. Zhejiang, for example, ranked fourth with respect to the number of corporate patent applications filed in 2000, became the province with the second highest record of corporate patent applications in 2008. While companies invested relatively more in R&D activities over the period (7% of total industrial R&D expenditure from all non-Tibet provinces in 2008 compared to 4% in 2000), they may also have profited strongly from the rapid increase in invention patent applications filed by universities in Zhejiang (9% of all university invention patents in 2008 compared to 3% in 2000).

3.2 Estimation Issues

3.2.1 Baseline Estimation Model and the Accessibility Measure

This paper, in line with previous literature, derives its estimation model from the Griliches-Jaffe knowledge production function framework. The baseline model is as follows:

$$\log P_{rt} = \alpha + \beta_1 \log(RD_{rt} C_{rt}^{\mu}) + \sum_{l=2}^{L} \beta_l \log X_{lrt} + \eta_r + \varepsilon_{rt}$$

$$= \alpha + \beta_1 \log RD_{rt} + \beta_1 \mu \log C_{rt} + \sum_{l=2}^{L} \beta_l \log X_{lrt} + \eta_r + \varepsilon_{rt} \tag{1}$$

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to less than 1/3 (1/6) of the number of academic invention patent applications. The development of the three academic patents over the research period (2000-2008) is presented in Figure B2 in Appendix.

[11] Foreign referencing systems considered are SCI (Science Citation Index), EI (Engineering Index) and ISTP (Index to Scientific & Technical Proceedings). Total number of academic journal publications as well as universities' R&D expenditure over the research period (2000-2008) are presented in Figure B3 in Appendix.

[12] Universities in Shanghai (Beijing) filed about 16% (16%) of all academic invention patent applications in 2008, compared to 25% (19%) in 2000. Regarding the publication records, Beijing (Shanghai) accounted for 'only' 20% (10%) of all registered scientific papers in 2008, compared to 30% (12%) in 2000.

where r represents our regional observation unit – Chinese province. [13] The number of patent applications filed by companies (P) in province r in year t is expected to be positively determined by the size of the firms' R&D expenditure (RD). Assuming the existence of a positive academic research effect on corporate patenting, companies in one province with easier access (C) to universities than companies in the other province are expected to be capable of transforming their R&D inputs into positive patenting results more productively than their counterparts. X_{lrt} are control variables derived from the previous literature.[14] Since companies may rely on innovation inputs to different degrees to carry out various innovation outputs, we consider, in addition to the number of total patent applications filed by companies in a province, two more disaggregated categories as additional dependent variables: invention patents and non-invention patents (utility model and external design patents). To cope with the potential problem of unobserved regional heterogeneity, η_r is considered as a provincial fixed effect in the regression model. ε_{rt} is the error term.

$$\log P_{rt} = \alpha + \beta_1 \log RD_{rt} + \tilde{\mu} ACCE_{rt-1} + \sum_{l=2}^{L} \beta_l \log X_{lrt} + \eta_r + \varepsilon_{rt} \qquad (2)$$

The variable C in Equation (Eq.) (1) is a general term used to represent companies' accessibility to university research. In contrast, the variable $ACCE$ in Eq. (2) is a measure we construct based on the logsum indicator to measure the average university accessibility for companies in the province r at the time t. Since the variable is an interval variable, we consider the constructed variable instead of its log transformation in our estimation model. The corresponding coefficient should thus be interpreted as the percentage change of corporate patenting results with respect to a one unit improvement in companies' accessibility to universities (semi-elasticity). In contrast, the other coefficients (βs) can be, if not otherwise mentioned, directly interpreted as elasticities of corporate patenting results to a 1% increase in R&D expenditure and other covariates. A summary of the basic statistics for variables used in the estimation models is provided in Table B1 in Appendix.

The accessibility measure at the provincial level, $ACCE$, is constructed based on city-level statistics as follows:

$$\bar{d}_{it} = -(1/\gamma)\log[\sum_{j=1}^{J} NO_{jt}^{uni} \exp(-\gamma DIS_{ij})] \qquad (3a)$$

[13] In this paper the abbreviation 'log' is synonym for the abbreviation 'ln'. Both mean the natural logarithm.
[14] One control variable is considered directly instead of its log format in the regression model due to its statistical nature. More information about the control variables considered is provided in the next paragraphs.

$$\bar{d}_{rt} = \sum_{i \in r} \bar{d}_{it} (NO_{it}^{ind} \Big/ \sum_{i \in r} NO_{it}^{ind}) \tag{3b}$$

$$ACCE_{rt} = -\bar{d}_{rt} \tag{3c}$$

As the first step (Eq. (3a)), we calculate the average distance to university in kilometres ($\bar{d}_{it}$) from a representative company's point of view in city *i*. Theoretically, this company can access knowledge from universities not only in its own city but also in all other cities in China. Here we use the variable DIS_{ij} to measure the great-circle distance in kilometre between the company in city *i* and the universities in city *j*. Under a strong but practical assumption that universities are indifferent from each other with respect to their research quality, companies able to access a higher number of universities (NO_{jt}^{uni}) are expected to be able to access a higher number of university research outcomes. This variable is assumed to be exogenous, i.e. it cannot be determined by companies' innovation engagement. The private sector has been officially allowed to found universities since 1999. In 2008, still about three-fourths of universities in China are public universities. The location decision of these universities has been made by the central government and local governments following their own policy. Bickenbach and Liu (2011a) found, for example, that the concentration of the universities decreased over time that is consistent with the focus of the regional development policy emphasised by the Chinese governments since the new century. Universities located in cities farther away from the company (city *i*) would, however, contribute less to the overall potential academic knowledge for the company.[15] The scale of the distance decay effect would accordingly depend on the size of the distance decay parameter considered (γ). Assuming γ equal to 0.05 km^{-1} as our base value, this means that the potential contribution of a university located one more kilometre away from the company would decrease by 5%. Different values of the distance decay parameter are considered later for robustness check.

In this way, we calculate the average distance to university for companies in all existing cities in China.[16] A representative company in city *i* with a smaller average distance is interpreted to have a larger scope to access to universities. As the second step (Eq. (3b)), we calculate the

[15] See Schulz and Bröcker (2007) for a short summary of different accessibility measures. See Ben-Akiva and Lerman (1985) for more information about the underlying concept of the logsum accessibility measure, namely the utility maximising behaviour of individuals through making their multidimensional choices among alternative goods.

[16] The number of cities (prefectural level cities) was different in some years due to upgrading of some county-level cities to prefectural level cities. In total there were 286 cities in the years from 2004 to 2008, while there were only 284, 278, 267, 262, and 236 in the years back from 2003 to 1999, respectively.

province-level average distance to universities ($\bar{d}_{rt}$) as a weighted average of city-level average distances using city-level share of companies as weights. NO_{it}^{ind} is the number of industrial companies located in city i at the time t.[17] The reason for using the weighted average is the unequal distribution of companies across cities with different levels of access to universities. We expect that the average province-level distance to universities to be lower, i.e., higher accessibility, if relatively more companies are located in cities with higher accessibility to universities but not in cities with lower accessibility to universities. Similar to its city-level counterpart, the province-level average distance to universities is measured as an interval-scaled variable. The distance between two such values but not the value itself is meaningful for interpretation. As the final step to derive our accessibility measure (Eq. (3c)), we multiply the province-level average distance by (-1). In this way the provincial university accessibility is no longer inversely ranked. Instead, if companies have higher accessibility to university in the province *r*, the corresponding *ACCE* would be also higher in value than that in the provinces where companies have lower accessibility to university. Assuming a potential time lag between the foundation of universities and the potential positive effects on corporate patenting performance, the *ACCE* is represented in Eq. (2) by its one-year lag. Assumed the existence of positive university effects on corporate patenting, the corresponding coefficient $\tilde{\mu}$ is expected to be significantly positive.

The accessibility measure constructed here (*ACCE*) differs from the GCI proposed by Jaffe (1989) and the other alternatives used by Anselin et al. (1997) especially in the following aspects. Firstly, we only assume that universities located outside Chinese mainland are not accessible by companies and thus they are not considered in the accessibility measure constructed. In other words, we assume that companies theoretically have access to all universities in China, even if they are located outside the city in which companies are located. Companies may still have a high accessibility to university research if in their neighbouring

[17] Due to limited availability of data on the number of large and medium-sized industrial companies across cities over time, we use the number of industrial enterprises as proxy which was the best statistics we could obtain for our purpose here. At the provincial level, both variables are significantly and highly correlated over the research period (0.94 at the 1% sig. level). Before 2007 industrial statistics provided data of state-owned enterprises and non-stated-owned enterprises with annual revenue from principal business over 5 million RMB. Since 2007 such statistics provided data of industrial enterprises with annual revenue from principal business over 5 million RMB. Comparing the definition of industrial enterprises covered before and after 2007, the only difference was the explicit indication of the inclusion of state-owned enterprises in the related statistics. But since state-owned enterprises are mostly large in size and are characterised by high revenue compared to non-stated-owned companies in China, industrial statistics since 2007 still covered most of these state-owned enterprises. Thus, the simplification in the definition of industrial enterprises in statistics is not expected to be a severe problem for our analysis.

cities but not in their own cities a lot of universities are available as knowledge sources for them. Secondly, we consider company distribution across cities more explicitly when we calculate the average accessibility of companies at the provincial level. Thirdly, we do not predetermine any critical covering distance beyond which universities are assumed to be no relevance. Instead, we consider the geographic distance between companies and universities directly in our variable construction. Last but not least, we can easily take into account additional aspects, such as university quality difference (see below), in our case for analysis. In spite of the advantages listed above, the possibility that the value of the variable after the first two steps can be negative is rather unusual at the first glance. But as explained above, the value itself cannot be interpreted directly. Due to the interval-scaled feature of the variable, reference values are always needed to come out with final *ACCE* variable for analysis.

In addition to companies' R&D efforts and their accessibility to universities, different firm characteristics are expected to influence companies' willingness for and their performance in patenting activities. We consider four variables to control for firm heterogeneity at the regional level. First, we consider the industrial concentration of companies (*INDCON*) within the province based on the number of companies in 38 industrial sectors, using the concept of the GINI index. We expect a significantly relevant Marshall externality (Marshall, 1920) where the concentration of companies in few industries in a province facilitates knowledge transfer and knowledge diffusion among companies. This, in turn, further spurs the knowledge creation and patenting activities of companies in that province (e.g. Feldman and Florida, 1994). The second variable is also an industry-related variable (*ICT*), which is measured as the share of companies from the ICT industry (information and communication technologies). The ICT industry refers to an industry producing communication equipment, computers and other electronic equipment. This variable attempts to capture the high preference and tendency of ICT firms for patenting activities (Eberhardt et al., 2011). The other two firm covariates deal with companies' potential advantage in more easily obtaining knowledge and technologies for innovation from foreign market and investors through either their engagement in foreign trade activities and/or through their on-site confrontation with more foreign companies (e.g. Criscuolo et al. 2005; Hu and Jefferson, 2009; Wagner, 2006). The former one is embodied in a variable called *OPEN* which is measured as the ratio of trade volume to GDP, while the latter one *FOR* is based on the share of foreign companies of a province. [18]

Last but not least, since our analysis is based on regional data and uses provinces as the observation unit, we consider two more variables to control for observable regional characteristics. The first variable – population size of the province (*POP*) – was considered in most of the related literature introduced above (e.g. Jaffe, 1989; Feldman and Florida, 1994) to control for size differences between provinces. Region size is expected to positively affect the number of patent applications filed. A positive effect is also expected with respect to the second variable – the relative size of high-educated population of the province (*HEDU*) – which was also considered by Bottazzi and Peri (2003). Highly educated people support a rapid transmission of knowledge among individuals. The greater the relative size of the regional population of highly educated individuals, the higher the expected volume of regional corporate patenting. The remaining unobserved regional heterogeneity is dealt with by considering a provincial fixed effect variable in our regression model. All control variables apart from the industrial concentration measure are presented in logs in the regression models.

3.2.2 Further Estimation Issues

For all regression models estimated we separately consider three different variables to proxy regional industrial innovation performance, i.e., corporate knowledge produced at the regional level: total number of corporate patents (*P_all*), total number of corporate invention patents (*P_inv*) and total number of corporate non-invention patents (*P_ninv*). The differentiation of invention patents from non-invention patents enables us to investigate, in particular, whether academic research effects on industrial innovation performance are different when the industrial knowledge produced is characterised by different levels of novelty and technical requirements. Variables which are considered to be potential determinants for regional industrial innovation performance in Eq. (2) enter the estimation model sequentially. We start by considering only the two key variables, namely companies' R&D expenditure (*RD*) and their accessibility to universities (*ACCE*). In the subsequent regressions, we also include the

[18] For the variables '*INDCON*', '*ICT*' and '*FOR*' data of industrial enterprises, but not just data of large and medium-sized companies, are used here. We expect that companies considered in the analysis (large and medium-sized companies) may not only profit from the concentration of large and medium-sized companies in few industries or from foreign large and medium-sized companies but from the corresponding concentration of industrial enterprises or from the presence of foreign companies in general.
In total 38 industrial sectors are considered in measuring '*INDCON*'. Taking into account the redefinition of the industrial classification in 2003, the sectors which were not continuously specified over time are reclassified to 'other sectors'. Companies from these reclassified sectors accounted for just a minority of the whole companies.

second group of determinants, namely the two industry-related variables (*INDCON* and *ICT*) and the two region-specific variables (*HEDU* and *POP*). We consider the first two variables to control for observed industry-related firm heterogeneity and the latter two for observed regional heterogeneity. Lastly, we consider the variables *OPEN* and *FOR* as well to control for companies' differing global engagement to take into account potential effects from the external world on industrial innovation performance. We estimate the regression models with both Within-estimator and Random Effect estimator (RE-estimator). After estimation we run statistical tests to investigate whether the Within-estimator or RE-estimator is more preferred. In case of significant within-panel correlation, we estimate our models using the cluster-robust VCE estimators (e.g. STATA, 2007).

We apply two methods to deal with potential endogeneity problems with respect to companies' R&D engagement, since one may expect that companies' willingness to invest more in R&D depends on their success in producing new knowledge and new patents in the past. Firstly, we deal with endogeneity problems by representing the variable (*RD*) in terms of its lagged value. Secondly, we re-estimate our full baseline models with instrumental variable estimation techniques. We use company size (measured as sales) and company's capital use relative to its production outputs – both at the provincial level – as instrumental variables for the RD variable (e.g. Bound et al., 1984) since they are expected to affect companies' success in patenting through their strong impact on firms' R&D engagement but not through other channels. More concretely, companies with higher sales revenue in the past are expected to be more capable in engaging in large-scale, long-term R&D activities with potential innovation success being worth to be patented. In 2008 companies' R&D expenditure amounted to, on average, 1.03% of their sales revenue of 2007. The correlation coefficient between companies' R&D expenditure in 2008 at the province level and their corresponding sales revenue in 2007 was as high as 0.985. This gives some support for our expectation that companies' R&D expenditure is strongly determined by the financial resources which companies have accumulated through positive sales outcomes in the past. Although one may expect that companies with higher sales revenue may also invest more in acquiring technologies from external sources such as universities and universities were found to be significantly relevant knowledge sources, in addition to firms' R&D activities, for their patenting activities (e.g. Liu, 2009), this expectation of a strong relation between firms' financial situation and their willingness for sourcing knowledge from universities is less supported by related statistics. Take again the year of 2008 as example. In this year companies spent on average only an extremely small share of their sales revenue of 2007 (0.06%) for acquiring technologies from all external but domestic sources, including universities. This share was only about one twentieth of the share of sales revenue which companies invested in their own R&D activities, showing a low direct relevance of external knowledge sources as a whole for the innovation activities of our focus companies. Moreover, the external sources considered in the statistics include not only universities but also non-university innovators and when it comes to acquiring innovation-related technologies and know-how from external sources, universities have been perceived by Chinese firms as least relevant sources compared to other knowledge sources (Liu, 2009). Against this background, firms' sales revenue in the past is expected to significantly affect their success in patenting through their strong influence on their own R&D engagement only but not on their increasing willingness for sourcing knowledge from universities.[19]

Differently, the reasoning why firms' capital-to-output ratio is supposed to be a valid instrument as well is more forward-looking. Companies in China have been responsible for labour-intensive and low value-added production activities for a long time. An increasing capital intensity for production gives some hints for companies' willingness to undertake a structural change to move up the value chains to take over more capital-intensive work to sustain their market competitiveness and thus some hints for their willingness to deal with new market challenges with a more risk-taking attitude. Such a risk-taking attitude is strongly required when companies are forced or encouraged to decide on investing in large-scale R&D activities, outcomes of which cannot be foreseen in advance. Risk-loving companies are expected to be more willing in engaging in such costly R&D activities with high outcome uncertainty. Instead, firms' risk-taking attitude is not expected to be significantly relevant for their decision for sourcing existing, thus less uncertain, innovation outcomes from others, especially from universities, which otherwise were found to be relevant innovation inputs for firms' patenting success as well. As a result, companies with an increasing capital intensity are expected to be more risk-loving in nature that can thus have positive influence on their patenting results through their stronger willingness to engage in large-scale long-term R&D

[19] Still one may expect that firms in provinces characterised with a strong increase in patenting activities can also profit a lot from their patenting success and thus are characterised with a strong growth in their overall sales revenue. This may challenge the exogeneity assumption of the sales variable. But this expectation cannot be supported statistically. The corresponding correlation coefficient for the research period (2000-2008) was as low as 0.113. Being measured by year the correlation coefficient can be even smaller in magnitude (close to zero) or be negative. This difference between firms' patenting success and their sales growth may be a result of firms' increasingly strong incentives for patenting in the past years that is to some extent driven by the improvement in patent law that favours patent holders and ownership reform (Hu and Jefferson, 2009).

activities bounded with high risks and outcome uncertainty. We carry out statistical tests to investigate the relevance and the exogeneity of the instrumental variables considered. We ultimately investigate whether endogeneity problems indeed restrict the use of the *RD* variable. We apply Moran's I test statistics on the calculated error terms following the instrumental variable estimation to investigate the presence of significant spatial autocorrelation problems.

Moving to our second focus variable, we alter some features of the original *ACCE* variable (Eq. (3)) and consider these alternative *ACCE* variables in our regression models to check the robustness of its effect on regional industrial innovation performance. First of all, we use alternative values of the distance decay parameter (γ) to calculate the *ACCE* variable: 0.01 km^{-1} and 0.1 km^{-1}. With γ set equal to 0.01 km^{-1} instead of our base value 0.05 km^{-1} the contribution of a university, located one more kilometre away from the company, to academic knowledge potential relevant for companies would decrease by only 1% rather than 5%. In contrast, with γ set equal to 0.1 km^{-1} this decrease doubles from 5% to 10%. Later we expand our *ACCE* variable by adding the quality aspect of university research into the construction of the variable, making our *ACCE* variable more appropriate for reflecting firms' access to the pool of 'relevant' academic knowledge.

We apply two quality concepts to calculate quality-adjusted *ACCE* variables for analysis. More technical details on the construction of the two types of quality-adjusted variable ($ACCE_{rt}^{a1}$ and $ACCE_{rt}^{a2}$) are summarised in Appendix A. The first quality concept is based on the provincial ranking of universities according to their research quality in terms of the number of invention patent applications filed by the universities. We consider a positive quality decay parameter (δ = 0.01 rank^{-1} as our base value) to discount the number of accessible universities by their quality ranking in addition to distance. To check robustness, we consider δ equal to 0.005 rank^{-1} and 0.05 rank^{-1}, respectively. The second quality concept takes the variation of provinces in the number of invention patent applications filed by universities into account more directly (instead of only considering their ranking) to measure the 'relevant' academic knowledge. To check robustness we consider the number of published academic journal articles and the amount of university R&D expenditure as alternative measures of university quality. These different variables to proxy academic knowledge additionally help us investigate whether proximity of companies to academic knowledge embodied in academic invention patents matters more for corporate patenting than the proximity to academic knowledge embodied in journal articles. The intuition here is that information disclosed in academic journal articles might be more complete and more comprehensively explained to readers. This would help reduce the need to intensively communicate with university researchers. Last but not least, the difference in the role of proximity to academic outputs for corporate patenting and the role of proximity to academic inputs can be better explored. In most studies reviewed above academic research was proxied by university R&D expenditure instead of university innovation outputs. However, university research outputs may be more relevant than university R&D inputs in this regard since the latter one is still bounded with high outcome uncertainty.[20]

4 Estimation Results

The estimation exercises described in Section 3.2 can be summarised in the following five subsequent steps. Firstly, we start with estimating the baseline models with different sets of explanatory variables using both Within- and RE-estimators. Secondly, we deal with the potential endogeneity with respect to the industrial R&D expenditure (*RD*) based on instrumental variable analysis. Thirdly, we use alternative values of the distance decay parameter to check the robustness of our main findings. Fourthly, we move from the base accessibility measure to quality-adjusted accessibility measures to take into account the quality difference in university research in the analysis. Finally, to check the robustness of the findings regarding the quality-adjusted accessibility measures we use alternative values of the quality decay parameter and three different variables to proxy the university quality. We present the results of the corresponding estimation exercises in sequence in this section.

Table 1 displays three groups of the baseline estimation results according to the three different types of companies' innovation outcomes at the provincial level. Due to significant within-panel (serial) correlation[21], we applied cluster-robust VCE estimators in estimating all regression models. We present estimation results based on the fixed effect regression models

[20] The element variables considered to proxy the university quality for building up the quality-adjusted *ACCE* variables are assumed to be exogenous as well. Bickenbach and Liu (2012) found that the concentrations of innovation activities (patenting activities, R&D expenditure and R&D personnel) of universities and companies have decreased since the new century. The co-agglomerations of the innovation activities of these two types of innovators based on the EG co-agglomeration indices (Ellison et al., 2010) have decreased as well, suggesting that the increase in innovation engagement of universities seems not to be determined by the corresponding increase in innovation activities of companies in the same provinces.

[21] We implement a Wooldridge (2002) test for serial correlation in the idiosyncratic errors in linear panel data models.

only, since random effect models are less preferred after running the statistical tests[22] to compare both models. Test results significantly reject the hypothesis of no systematic difference in estimation results from both models (at the 1% sig. level).

For all three groups of the results, the explanatory variables are introduced sequentially as explained in Section 3.2. Our first key variable – companies' own R&D expenditure (*RD*) – is found to play a significant and substantial role for companies' success in innovation across all estimation models. Total corporate patenting outcomes respond to a 1% increase in R&D expenditure by between 0.83% and 0.95%, depending on the sets of explanatory variables considered. Companies' own R&D expenditure is, as expected, much more relevant for companies' success in invention patenting which requires higher and more sophisticated technical and technological standards than for their success in non-invention patenting. A 1% increase in companies' R&D expenditure induces a roughly 1% increase in invention patent applications and a 0.8% increase in non-invention ones filed at the provincial level.

Table 1 – Baseline model estimation

	P_all			P_inv			P_ninv		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RD	0.946***	0.820***	0.833***	1.124***	0.978***	0.966***	0.922***	0.804***	0.819***
ACCE	0.013***	0.008***	0.008***	0.007*	0.002	0.001	0.010***	0.006*	0.006**
INDCON		0.043*	0.044*		0.029	0.029		0.049*	0.052**
ICT		0.300**	0.257**		0.261*	0.278**		0.295**	0.204**
HEDU		0.307**	0.240		0.457**	0.487**		0.241*	0.106
POP		1.139	0.901		1.664	1.789		0.721	0.276
OPEN			-0.099			0.073			-0.148
FOR			0.391*			-0.189			0.764***
Obs.	270	267	267	270	267	267	270	267	267
F	170.13***	80.28***	83.28***	203.07***	146.36***	150.38***	155.66***	65.92***	75.04***
R-sq	0.761	0.775	0.780	0.750	0.762	0.763	0.675	0.685	0.703

Note: All columns: fixed effect model using robust cluster VCE estimator. All variables except for *ACCE* and *INDCON* are in log in the estimation model. *ACCE* in one-year lag is considered in the regression models. All coefficients are expected to be positive. Hypotheses are tested based on one-tailed tests. ***/**/* refer to 1%/5%/10% sig. level. _cons is not shown here.

Compared to the strongly positive role of companies' own R&D expenditure for their patenting results, the relevance of companies' proximity to universities is found to be weaker and not always significant. A one kilometre reduction in their provincial average distance to a university, i.e., one unit increase in the ACCE indicator, leads to about a 0.8% to 1.3% increase in total corporate patent applications filed at the provincial level. Comparing the estimation results for invention patent applications versus non-invention patents, we find that companies' proximity to universities matters significantly only for their non-invention patenting results but not for the technologically more demanding invention patenting results.

[22] We run a test of overidentifying restrictions (Sargan-Hansen Test Statistic) instead of the Hausman test, since the former one is more suitable for cases using heteroskedasticity- and cluster-robust estimators. See Schaffer and Stillmann (2010) for a detailed discussion.

Remember: companies' own R&D expenditure is significantly important for all types of patenting results. Our finding that proximity matters particularly for non-invention patenting activities may be attributable to the research focus of universities in China that has emphasised applied and experimental research more strongly than the basic research. Corresponding statistics show that on average 76% of all university R&D expenditure goes to the applied (52.7%) and experimental (23.6%) research over the years from 2000 to 2008 and only 24% to basic research. Compared to the basic research results, applied and experimental research results of universities may be more easily integrated and transformed in companies' own innovation activities per se due to its closeness to practice. The integration and transformation of such research results is expected to be even more attractive for companies that lack innovation experiences and capabilities and just start to carry out innovation activities with lower-level technological requirements. Thus, companies located closer to universities may benefit more from such academic knowledge in terms of better non-invention patenting results. However, our findings may also suggest that, when it comes to technologically more demanding patenting, companies may search for advanced academic knowledge from higher quality universities, irrespective of the location of the universities. In this case, the proximity to universities in general does not need to play a significant role at all. Whether university quality indeed plays a role is investigated by later estimation models using quality-adjusted accessibility measures.

Regarding the set of control variables considered in the estimation models, we find in most cases some empirical support consistent with our expectation. A higher share of ICT companies in a province (*ICT*) drives the corporate patenting results of the province – both invention and non-invention patents – strongly upwards. We generally find a significantly positive role of industrial concentration (*INDCON*) for provincial patenting, in line with Marshall externality arguments. Disaggregating patents into invention and non-invention patents, we find that the industrial concentration index only leads to significantly higher number of non-invention patent applications but not for invention patent applications. A one unit increase in the industrial concentration index induces a significant 5% increase in non-invention patent applications and an insignificant increase in invention patent applications. The concentration of companies from the same industry may facilitate particularly the diffusion of less advanced knowledge. Such knowledge is probably less strictly concealed by companies within the firm boundary, thus spurring more non-invention patent applications than invention ones.

Companies' engagement in global affairs proxied by the ratio of international trade to GDP (*OPEN*) is not found to be positively associated with innovation success to any extent. In contrast, foreign companies' provincial presence (*FOR*) significantly matters for the provinces' corporate patenting results, especially the non-invention ones. Similar to the explanation above, this may be attributable to a relatively easier diffusion of less advanced and less strictly protected knowledge owned by co-located foreign enterprises to local companies. Moreover, local affiliates of foreign enterprises usually take over the low-tech but labour-intensive part of the overall operations.

Both variables aiming to capture observable regional heterogeneity – size of the province (*POP*) and the share of population (at least six years old) with at least university degree (*HEDU*) – are found to be positively relevant for provincial corporate patenting results. However, only the positive effect of higher education is found to be significant, especially for companies carrying out more sophisticated R&D activities for invention patenting.

Up until now our estimations have looked at contemporary corporate R&D expenditure and companies' province-level patenting activities. There exists a potential endogeneity problem with respect to companies' R&D expenditure, however. To deal with this, we firstly replace the contemporary R&D expenditure with its one- and two-year lags separately in the regression models. Our main results are in line with the findings reported earlier.[23] Secondly, we deal with the potential endogeneity of R&D expenditure by applying instrumental variable estimation techniques.[24] We use province-level company size (*SALES*) and companies' capital use with respect to their production outputs (*CAPOUT*) in log format and lagged for one year as instruments (see Section 3.2.2). The relevance of these instrumental variables is supported by the F test results after the first-stage estimation (much higher than 10) and their exogeneity cannot be rejected by the overidentification tests (Hansen J Test Statistic) at the usually considered significance levels. The endogeneity tests for the R&D variable (significant at least at the 5% sig. level) reveal that we were correct in suspecting endogeneity. These tests underline the substantial importance of applying instrumental variable estimation techniques in the analysis. Moran's I tests are carried out as post-estimation tests to investigate whether the error terms are spatially autocorrelated. As the baseline spatial weight matrix, we consider

[23] Estimation results are not presented in tables here due to space limitations. They can be obtained upon request.
[24] Here we use the STATA module 'xtivreg2' for analysis (Schaffer, 2010).

the binary contiguity weight matrix.[25] The Null hypothesis that there is no spatial autocorrelation cannot be significantly rejected (at least at the 5% sig. level).[26]

Table 2 – Panel OLS vs. Panel IV-Estimation

	P_all		P_inv		P_ninv	
	(1) Baseline	(2) IV	(3) Baseline	(4) IV	(5) Baseline	(6) IV
RD	0.833***	1.007***	0.966***	1.201***	0.819***	0.989***
ACCE	0.008***	0.009***	0.001	0.002	0.006**	0.007**
INDCON	0.044*	0.027*	0.029	0.007	0.052**	0.035*
ICT	0.257**	0.273**	0.278**	0.301**	0.204**	0.220**
HEDU	0.240	0.068	0.487**	0.255	0.106	-0.062
POP	0.901	0.656	1.789	1.459	0.276	0.037
OPEN	-0.099	-0.337	0.073	-0.249	-0.148	-0.381
FOR	0.391*	0.460**	-0.189	-0.096	0.764***	0.831***
Obs.	267	267	267	267	267	267
F	83.28***	88.61***	150.38***	134.67***	75.04***	70.90***
R-sq	0.780	0.773	0.763	0.754	0.703	0.697

Note: 1. Baseline estimation results from Table 1 are presented again in Col. (1), (3), and (5). 2. For Col. (2), (4), (6): fixed effect IV (2SLS) estimation using robust cluster VCE estimator. IV for *RD*: *SALES* and *CAPOUT*. Both IVs are in log format and in one-year lag. 3. All variables except for *ACCE* and *INDCON* are in log in the estimation model. *ACCE* in one-year lag is considered in the regression models. All coefficients are expected to be positive. Hypotheses are tested based on one-tailed tests. ***/**/* refer to 1%/5%/10% sig. level.

Table 2 shows the estimation results for the three types of patents using instrumental variables and the original findings based on panel OLS. Results are qualitatively unchanged when we move from the panel OLS to the instrumental variable analysis. However, the magnitudes of the significant coefficients differ slightly. Companies' R&D expenditure is still found to play the most substantial role for determining corporate patenting outcomes. A 1% increase in R&D expenditure induces an even higher increase in patenting results in the case of the instrumental variable analysis (1%) than in the case of the panel OLS (0.8%). The increase in R&D expenditure stimulates more invention patent applications than non-invention ones, similar to the result obtained without the application of the instrumental variables. Regarding the role of academic knowledge in supporting industrial innovation performance, companies' average proximity to universities is found to be, in general, significantly and positively relevant for province-level corporate patenting activities. Again, the instrumental variable analysis also shows that the proximity to universities matters more for non-invention patenting than for technically more demanding invention patenting applications.

[25] The baseline spatial weight matrix considered – with diagonal entries equal to zero – is 'binary contiguity matrix with 1 assigned to neighbour province sharing boundary with the province considered'. We apply two alternative spatial weight matrices: 'inverse exponential distance weight matrix with distance referring to geographic distance between capitals of provinces' and 'inverse exponential distance weight matrix with distance referring to geographic distance between the central points of provinces'. The latter two weight matrices are row-standardised and the distance decay parameter considered in these two matrices equal to 0.05 km^{-1}.

[26] Based on the binary contiguity matrix and the second alternative matrix, the Null hypothesis can not be significantly rejected in all cases (at least at the 5% significance level). Based on the first alternative spatial matrix, in which the geographic distance between capitals of provinces is used, the Null hypothesis can only be rejected in case of considering all patent applications or all non-invention patent applications as output variables for the year of 2004 (at the 5% significance level).

For the following estimation exercises we also apply instrumental variable techniques due to the problem with endogeneity which we earlier diagnosed in relation to the R&D variable.[27] As the next step, we re-estimate the models using alternative values of the distance decay parameter (γ) to check the robustness of the estimation results with respect to the role of companies' average proximity to universities for their patenting activities. Table 3 presents the corresponding estimation results. Explanatory variables, except for the accessibility indicator, which were found to be significantly relevant, remain significant. In contrast, the accessibility indicator which was found to be significantly relevant for corporate (non-invention) patenting (γ = 0.05 km^{-1}), remains significant with a similar magnitude if γ is set equal to 0.1 km^{-1} but it becomes insignificant if γ is set equal to 0.01 km^{-1}.

Table 3 – Panel IV-Estimation with different levels of distance decay parameter

	P_all			P_inv			P_ninv		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gamma =	0.01	0.05 (base)	0.1	0.01	0.05 (base)	0.1	0.01	0.05 (base)	0.1
RD	0.954***	1.007***	1.024***	1.153***	1.201***	1.211***	0.957***	0.989***	1.002***
ACCE	0.003	0.009***	0.008***	0.002	0.002	-0.001	0.002	0.007**	0.006***
INDCON	0.029*	0.027*	0.028*	0.006	0.007	0.008	0.037**	0.035*	0.036*
ICT	0.266**	0.273**	0.257**	0.304**	0.301**	0.297**	0.214**	0.220**	0.208**
HEDU	0.035	0.068	0.087	0.216	0.255	0.265	-0.080	-0.062	-0.048
POP	0.636	0.656	0.734	1.346	1.459	1.518	0.045	0.037	0.096
OPEN	-0.316	-0.337	-0.328	-0.251	-0.249	-0.241	-0.364	-0.381	-0.374
FOR	0.487**	0.460**	0.436**	-0.078	-0.096	-0.095	0.849***	0.831***	0.813***
Obs.	267	267	267	267	267	267	267	267	267
F	83.02***	88.61***	100.29***	127.52***	134.67***	123.34***	66.34***	70.90***	92.81***
R-sq	0.777	0.773	0.770	0.759	0.754	0.753	0.698	0.697	0.695

Note: 1. IV estimation results (with gamma [distance decay parameter] = 0.05 km^{-1}) from Table 2 are presented again in Col. (2), (5), and (8). 2. For the other columns: fixed effect IV estimation using robust cluster VCE estimator, considering different gammas. IV for *RD*: *SALES* and *CAPOUT*. Both IVs are in log format and in one-year lag. 3. All variables except for *ACCE* and *INDCON* are in log in the estimation model. *ACCE* in one-year lag is considered in the regression models. All coefficients are expected to be positive. Hypotheses are tested based on one-tailed tests. ***/**/* refer to 1%/5%/10% sig. level.

In the latter case with γ set equal to 0.01 km^{-1}, we actually assume that the contribution of universities located about 70 km[28] away from the company to the potential company-relevant academic knowledge is only half of the contribution of universities located in the same city of the company. Based on this assumption, we may overestimate the relevance of universities located far away from the company. This would lead us to assign too high a value for the accessibility indicator to companies in cities where companies there actually have lower

[27] We run again statistical tests to check the relevance (F-test), the exogeneity of the instrument variables, and the endogeneity of the RD variable after estimating the models. In all models estimated, we obtain F-test results much larger than 10 and the exogeneity of the instrumental variables can not be rejected at the usually considered significance levels. The endogeneity test significantly rejects the Null hypothesis that the RD variable is exogenous in all models except the one considering the quality-adjusted ACCE with academic knowledge being embodied in academic journal articles where the corresponding p-value is slightly higher than 10%.

[28] The half-value distance is calculated equal to 'ln(2) divided by the value of the distance decay parameter considered'.

accessibility to universities. As a result, the estimation shows that a reduction in the company's distance to universities, i.e., a further increase in one unit in the accessibility indicator does not really support companies in accessing more academic knowledge and producing more (non-invention) patents. In contrast, the similar finding regarding the role of university proximity for corporate patenting in cases with γ equal to 0.05 km^{-1} and 0.1 km^{-1} respectively suggests that only universities located really close to companies, i.e., in the same city are relevant as academic knowledge providers to support companies' (non-invention) patenting activities.

Results so far are based on a strong assumption that universities in China are the same in terms of research quality. The relevance of universities as potential academic knowledge providers for companies is solely determined by the geographical distance, i.e., how easily companies can interact with universities to obtain academic support. In fact, however, universities in China are considerably different from each other with respect to their research quality and capacity. In 2008 there were more than 2,200 universities in China. Only a small portion of these universities were officially selected by two central projects (985-Project and 211-Project) as priority universities and/or universities with the potential for performing internationally competitive research. In total there are currently 112 priority universities and 39 universities with top research capacity in China and more than 30% of these are located in two provincial level municipalities: Beijing and Shanghai (Bickenbach and Liu, 2011a; 2011b). In order to take the different research quality of universities in China into account in our analysis we replace the original accessibility measures by the quality-adjusted ones. Table 4 shows the instrumental variable regression results using the first type of quality-adjusted accessibility measure, based on the province ranking by its number of academic invention patent applications. In addition to the base value of the quality decay parameter (0.01 $rank^{-1}$), two alternative values (0.005 $rank^{-1}$ and 0.05 $rank^{-1}$) are considered for robustness check.

The regression results are not only consistent across models with different values of the quality decay parameter, but they hardly deviate from the baseline findings estimated without taking university quality into account in our accessibility measures (Table 3, Col. (2), (5) and (8)). [29] If university quality plays a role and face to face contact is crucial for determining the efficiency of tacit knowledge transfer from universities to companies, then the reduction by

[29] For robustness check, regression models as those in Table 4 are estimated using the same type of quality-adjusted *ACCE* indicators but based on two other quality ranking measures: the number of academic journals published and registered in major foreign referencing systems and the amount of university R&D expenditure. No significant difference in regression results can be observed. Results can be obtained upon request.

one kilometre in the distance between companies and the reference university with the best quality is expected to affect corporate patenting activities more strongly than a corresponding reduction in the distance between companies and universities where university quality is not considered. It implies generally higher semi-elasticities with respect to the university accessibility measure. The corresponding coefficients in the case of invention patents are expected to be more likely significant. The findings in Table 4 do not support our expectation, however. They rather suggest that companies' proximity to universities seems to play an equally relevant role for determining academic research effects on corporate innovation performance in China, irrespective of university quality difference being considered or not.

Table 4 – Considering quality-adjusted ACCE (Concept 1) with different levels of quality decay parameter

	P_all			P_inv			P_ninv		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Delta =	0.005	0.01 (base)	0.05	0.005	0.01 (base)	0.05	0.005	0.01 (base)	0.05
RD	1.007***	1.007***	1.010***	1.201***	1.200***	1.197***	0.990***	0.990***	0.993***
ACCE_a1	0.009***	0.009***	0.009***	0.002	0.002	0.003	0.007**	0.007**	0.007**
INDCON	0.027*	0.027*	0.028*	0.007	0.007	0.006	0.035*	0.035*	0.035*
ICT	0.273**	0.272**	0.267**	0.301**	0.301**	0.301**	0.220**	0.219**	0.215**
HEDU	0.068	0.067	0.067	0.255	0.254	0.249	-0.062	-0.062	-0.063
POP	0.659	0.663	0.704	1.456	1.453	1.442	0.040	0.042	0.074
OPEN	-0.340	-0.343	-0.366	-0.250	-0.251	-0.264	-0.383	-0.385	-0.403
FOR	0.462**	0.465**	0.486**	-0.095	-0.095	-0.086	0.833***	0.835***	0.851***
Obs.	267	267	267	267	267	267	267	267	267
F	88.70***	88.80***	90.36***	134.95***	135.07***	128.45***	70.76***	70.61***	69.38***
R-sq	0.773	0.773	0.774	0.754	0.754	0.755	0.697	0.697	0.697

Note: 1. *ACCE_a1* refers to quality-adjusted accessibility measure (Concept 1) and is in one year lag in the estimation models. The base variable used to assess university quality at the provincial level is the total amount of invention patents applied by universities located in the same province. Here quality concept 1 is applied and the base value for delta [quality distance decay parameter] = 0.01 rank^{-1}. 2. All columns: fixed effect IV estimation using robust cluster VCE estimator. IV for *RD*: *SALES* and *CAPOUT*. Both IVs are in log format and in one-year lag. 3. All variables except for *ACCE_a1* and *INDCON* are in log in the estimation model. All coefficients are expected to be positive. Hypotheses are tested based on one-tailed tests. ***/**/* refer to 1%/5%/10% sig. level.

In order to consider provincial differences in the relative ability of universities to produce invention patents more explicitly, we apply our second quality concept to calculate the quality-adjusted accessibility measures. Table 5 presents the corresponding estimation results. We additionally consider universities' journal publication records and their ability to engage in R&D investment to proxy academic knowledge potentially relevant for companies. Different capabilities of universities in producing invention patents and academic papers are expected to exert differing effects on corporate innovation activities. Academic invention patents are expected to be closer – in technical terms – to industrial demand for input technology than academic papers. But the latter may be more easily obtained and at lower cost than the former. Moreover, the relative ability of universities to produce innovation outputs is expected to affect corporate patenting more strongly than university R&D efforts, which are still tied to high risk and uncertainty over future outcomes.

Qualitatively our estimation results are consistent with our baseline findings. Proximity of companies to academic knowledge sources with more invention patents, journal articles and R&D inputs remains significantly and positively relevant for overall corporate patenting activities. In the quantitative terms, we observe some differences in the magnitudes of the proximity effects, depending on the different quality measures used. Specifically, a one unit increase in companies' accessibility to an academic invention patent application induces only a 0.05% increase in corporate patent applications filed. This effect is much smaller than the effect produced by a one unit improvement in companies' proximity to a university (0.9%). More commercially relevant academic knowledge is more easily accessible by a one unit improvement in companies' proximity to a university than the additional amount induced by a one unit increase in companies' accessibility to an academic invention patent. Moreover, the effect of a one unit increase in companies' access to academic invention patents on corporate patenting is additionally smaller than the corresponding effect with respect to academic journals and university R&D expenditure. The latter covariate is only marginally significant for corporate patenting activities in general, however. In fact, it even becomes insignificant for corporate non-invention patents. The finding of relatively low relevance of university R&D expenditure is consistent with our expectation that the highly uncertain outcomes involved in the university R&D processes makes companies unsure about the commercial benefits they could expect to get from interacting with universities.

Table 5 – Considering quality-adjusted ACCE (Concept 2) with different measures for university research quality

	P_all			P_inv			P_ninv		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
QL=	upinv	ujournal	urd	upinv	ujournal	urd	upinv	ujournal	urd
RD	1.026***	0.889***	0.984***	1.204***	1.208***	1.213***	0.996***	0.823***	0.991***
ACCE_a2	4.61e-04***	0.008***	0.004*	1.78e-04	1.75e-05	-3.23e-04	0.001***	0.010***	0.002
INDCON	0.032*	0.030*	0.030*	0.008	0.008	0.008	0.040**	0.036**	0.038*
ICT	0.255**	0.258**	0.256**	0.297**	0.297**	0.297**	0.206*	0.210**	0.207*
HEDU	0.084	0.120	0.083	0.252	0.264	0.266	-0.060	-0.019	-0.041
POP	0.878	0.843	0.796	1.499	1.506	1.515	0.200	0.153	0.173
OPEN	-0.295	-0.293	-0.305	-0.241	-0.242	-0.242	-0.345	-0.343	-0.355
FOR	0.409*	0.386**	0.409*	-0.114	-0.097	-0.093	0.773***	0.739***	0.808**
Obs.	267	267	267	267	267	267	267	267	267
F	112.45***	102.49***	88.37***	107.42***	94.84***	94.78***	85.99***	78.41***	91.46***
R-sq	0.769	0.784	0.772	0.754	0.753	0.753	0.696	0.716	0.694

Note: 1. *ACCE_a2* refers to quality-adjusted accessibility measure (Concept 2) and is in one year lag in the estimation models. 2. Three different base variables are used to assess the university quality: upinv (base), ujournal (academic articles published in refereed journals) and urd (uni R&D expenditure). 3. All columns: fixed effect IV estimation using robust cluster VCE estimator. IV for *RD*: *SALES* and *CAPOUT*. Both IVs are in log format and in one-year lag. 3. All variables except for *ACCE_a2* and *INDCON* are in log in the estimation model. All coefficients are expected to be positive. Hypotheses are tested based on one-tailed tests. ***/**/* refer to 1%/5%/10% sig. level.

In addition to university R&D expenditure we recall that academic knowledge is defined here as 1) university production of invention patents and 2) publication of academic journal articles. What is surprising is that the proximity effect of the first measure on corporate patenting is lower than the second effect. One would rather expect that need for communication and thus the need for overcoming long distance between companies and universities is relatively low for companies to access academic knowledge from academic publications than from university invention patents. On the one hand, university researchers may more comprehensively disclose their findings in journal articles than in patent application documents. On the other hand, journal articles are more easily accessible by companies at low cost. Our finding suggests that other influential factors may impede a free flow of academic knowledge via academic journal articles. For example, such potential factors might be the incomplete disclosure of information in journal articles thereby necessitating firms to get in touch with academics if they are to understand the 'full picture'. In this case, proximity to universities with journal publications helps the transfer of complementary tacit information to companies. In contrast, companies' proximity to academic invention patents does not matter much for their general corporate patenting activities. Such proximity is even found to be not significant for corporate invention patents at all. This may be attributable to the fact that acquiring the licenses to use academic invention patents is relatively costly. This high cost may reduce the willingness of companies to make use of such academic knowledge for their own innovation activities. Low willingness to access academic knowledge through acquiring university invention patents makes it irrelevant how far away companies are located from universities filing invention patents.

For corporate non-invention patent applications we observe results comparable to those observed for corporate patenting activities in general. A one unit increase in quality-adjusted accessibility of companies to academic journal articles results in a positive effect on corporate non-invention patent applications ten times as high as that induced by a one unit increase in corresponding accessibility to academic invention patents. A further contributing factor, other than those already mentioned, may help explain such difference. The low relevance of companies' proximity to academic knowledge proxied by academic invention patents could be attributable to the per se low rentability of sourcing academic knowledge from university invention patents for companies' less sophisticated non-invention patenting outcomes. Again the low relevance of advanced academic knowledge for corporate non-invention patents weakens the role of companies' proximity to universities to obtain that kind of knowledge to support their own innovation activities.

5 Conclusion

Previous literature identified universities to be important knowledge sources for companies (see Section 2). However, academic knowledge which has a high relevance for industrial innovation may not be fully disclosed as codified information for external use. Accordingly, face to face communication and interaction to obtain complementary but tacit information may be crucial for companies' success in transforming academic knowledge into commercial use. Hence, proximity of companies to universities may be a key determinant of academic research effects on corporate innovation success.

This paper investigated whether spatial academic research effects are influential in spurring corporate patenting in China. We documented effects on corporate innovation for the large and medium-sized industrial enterprises which contribute overwhelmingly to innovation in China. The investigation was based on a provincial dataset for 30 provinces in mainland China (2000 to 2008) to estimate regression models derived from the Griliches-Jaffe regional knowledge production function framework. To measure the proximity of companies to universities, we calculated a corresponding logsum indicator. We first focused on geographic aspects before taking quality differences in university research into account. Our results generally supported the existence of spatial academic research effects on corporate patenting activities in China. However, companies' proximity to universities was only found significantly positively relevant for the technologically less demanding non-invention patents but not for invention patents. Industrial R&D expenditure was found to be the most significant factor for companies filing invention patent applications. Although industrial R&D also matters for corporate non-invention patent applications, the magnitude of the effect here was found to be smaller.

To relax the initial assumption of homogenous university research quality, we replaced the original *ACCE* variables with the quality-adjusted ones. Against our expectation, the main results were hardly changed. This, however, does not mean that university research quality does not affect the academic research effect on corporate innovation performance at all. Instead, it suggests that in contemporaneous China, companies' geographic proximity to universities seems to play an equally important role for determining the relevance of universities as knowledge sources for companies, irrespective of universities' research quality differences. One potential explanation could be that what matters for the academic research effect on corporate innovation is not the amount of academic knowledge provided by universities in different cities only but their productivity in doing so. To obtain more insights into this issue, one may need to extend the quality-adjusted *ACCE* variable by integrating a university-based productivity term. However, such extension for analysis cannot be done at the current stage due to limited data availability.

Our main finding that companies' proximity to universities is significantly relevant for especially companies' non-invention patenting activities but not invention ones may be to some extent determined by the characteristics of academic knowledge provided by universities. Research activities of universities in China are not restricted to basic research only. About 76% of the university R&D expenditure on average was invested in applied and experimental university research over the research period, while only 24% was left for basic research. The substantial importance of applied and experimental university research may be driven partially by the traditional role of universities as the single research sector for supporting companies' production activities in China. Results of applied and experimental research are expected to be more easily further used by companies due to their closeness to practice. While companies lacking innovation experience and capabilities start to innovate, they may focus more strongly on non-invention innovation activities with lower technological requirements. As innovation inputs in addition to own R&D engagement, research results of universities – the traditional research sector – play a substantial role. To better understand the related academic research results for own innovation use, companies may need to interact with universities intensively. Thus, their proximity to universities plays a significant and relevant role for their own non-invention patenting results. However, when companies have accumulated innovation experience and improved their innovation capabilities over time, they may be more capable of carrying out more complicated innovation activities. Our results showing that companies' proximity to universities do not (yet) affect their invention patenting activities significantly may suggest that universities in China may also need to upgrade their research activities towards more basic and scientific research. In this way they may be more capable of providing advanced knowledge for supporting companies' more sophisticated innovation activities with frontier technologies and knowledge as outcomes.

Last but not least, our results showed that companies' proximity to academic knowledge, proxied by different academic research outputs and capacity, affects corporate patenting to varying degrees. Adjusting accessibility by using academic journal articles to proxy the quality of academic knowledge was found to give a much larger effect compared to using university invention patents as proxy. Academic journal articles usually are easily available for readers at a relatively low cost. In general, geographic constraints should not play a role for companies to access published academic knowledge. Our findings may suggest, however, that even in this case, face-to-face communication and interaction between companies and universities are important. Interfacing with publishing academics helps firms to gain the 'complete picture', since in such publications probably not all relevant academic knowledge is fully disclosed nor is fully understandable to readers.

To sum up, the analysis provided some evidence that, in addition to the predominant importance of the companies' own R&D expenditures, universities matter as a knowledge source for corporate innovation performance in China. Companies' proximity to universities plays a relatively more important role than university quality for companies to obtain and profit from academic knowledge for their own innovation activities. Differentiating companies' patenting results by technical requirements and novelty, their proximity to universities seems to play a significantly positive role for accessing academic knowledge efficiently for supporting their non-invention patenting activities only. The traditional work division between universities and companies on the one hand and companies' deficiency in innovation experience on the other hand may be two reasons relevant for this finding. Universities, however, can still play an important role for supporting companies' more complicated innovation activities, if more basic research can be carried out and more advanced knowledge can be provided for being learned and used for more complicated innovation activities of companies in the future. The trend with an increasing importance of invention patenting activities relative to non-invention ones for companies at least gives some support for suggesting the existence of such demand from firms in the future.

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Appendix A

The first concept applied to construct the quality-adjusted ACCE variable is as follows:

$$\bar{d}_{it}^{a1} = (-\tfrac{1}{\gamma})\log[\sum_{j=1}^{J}(NO_{jt}^{uni}\exp(-\delta QR_{rt}))\exp(-\gamma DIS_{ij})] \tag{4a}$$

$$\bar{d}_{rt}^{a1} = \sum_{i\in r}\bar{d}_{it}^{a1}(NO_{it}^{ind} \Big/ \sum_{i\in r} NO_{it}^{ind}) \tag{4b}$$

$$ACCE_{rt}^{a1} = -\bar{d}_{rt}^{a1} \tag{4c}$$

Compared to Eq. (3a) the exponential term '$\exp(-\delta QR_{rt})$' is the only one newly added term in Eq. (4a). This calculated quality-adjusted average distance ($\bar{d}_{it}^{a1}$) replaces the original average distance in the second and third step. The variable QR_{rt} refers to the quality ranking of universities by province from zero to 29 with decreasing number of invention patent applications filed by universities in each province under the assumption that universities from the same provinces are of the same quality. The effect of quality differentials between university research on corporate patenting is reflected in the quality decay parameter (δ). A positive value of δ means that only universities with the best quality will be counted fully as relevant universities for companies, while universities with lower quality will be counted in Eq. (4a) as if fewer universities existed. We assume δ equal to 0.01 rank^{-1} as our base value, meaning that universities with a quality of one level lower than the best ones are considered as if there were only 99% of the existing universities relevant for companies instead of the full population of universities, assuming the same geographic distance from companies to the best universities and to the universities with a one level lower quality. To check robustness, we consider δ equal to 0.005 rank^{-1} and 0.05 rank^{-1} as well.

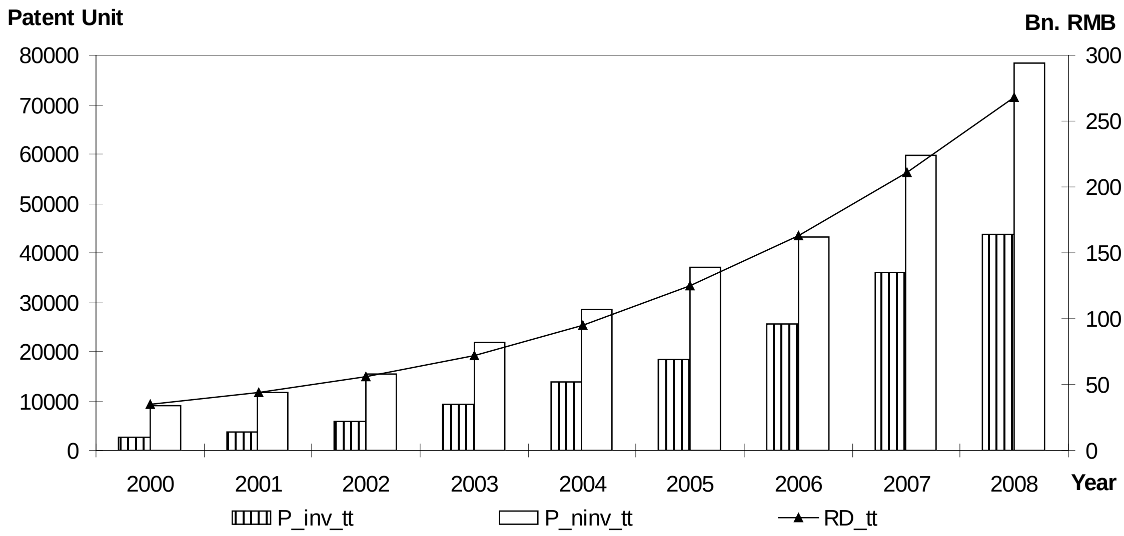
The second concept differs from the first concept only in the first step to construct the new variable:

$$\bar{d}_{it}^{a2} = (-\tfrac{1}{\gamma})\log[\sum_{j=1}^{J} QL_{rt}(NO_{jt}^{uni} \Big/ \sum_{j\in r} NO_{jt}^{uni})\exp(-\gamma DIS_{ij})] \tag{5}$$

The new element QL_{rt} refers to the number of invention patent applications filed by universities in province *r* at the time *t*. Given the same number of universities existing in city *j1* and city *j2*, both located at the same distance from a company in city *i*, universities in city *j1* provide more academic knowledge for that company than universities in city *j2* if the number of invention patent applications allocated to the universities in city *j1* is higher than that in city *j2*. As above, we assume that universities from the same province are of the same quality, indicating that the number of invention patent applications allocated to universities in each city is determined by the city's share of universities in the same province in addition to the total number of provincial academic invention patent applications. The quality-adjusted average distance obtained, $\overline{d}_{it}^{a2}$, replaces the corresponding $\overline{d}_{it}^{a1}$ in Eq. (4b) and (4c) thereby deriving the quality-adjusted accessibility measure ($ACCE_{rt}^{a2}$).

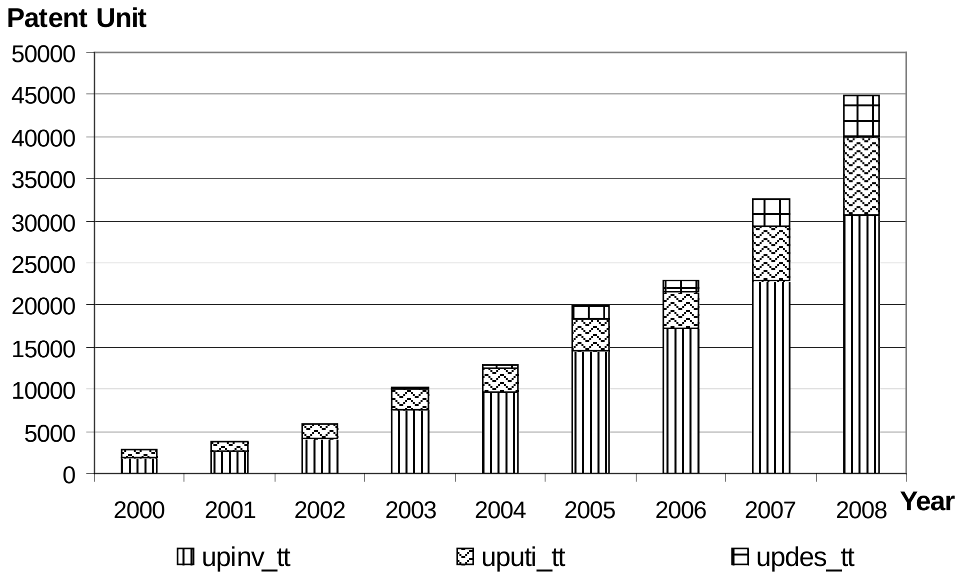
Appendix B

Figure B1 – Total corporate patent applications (invention vs. non-invention) and industrial R&D expenditure



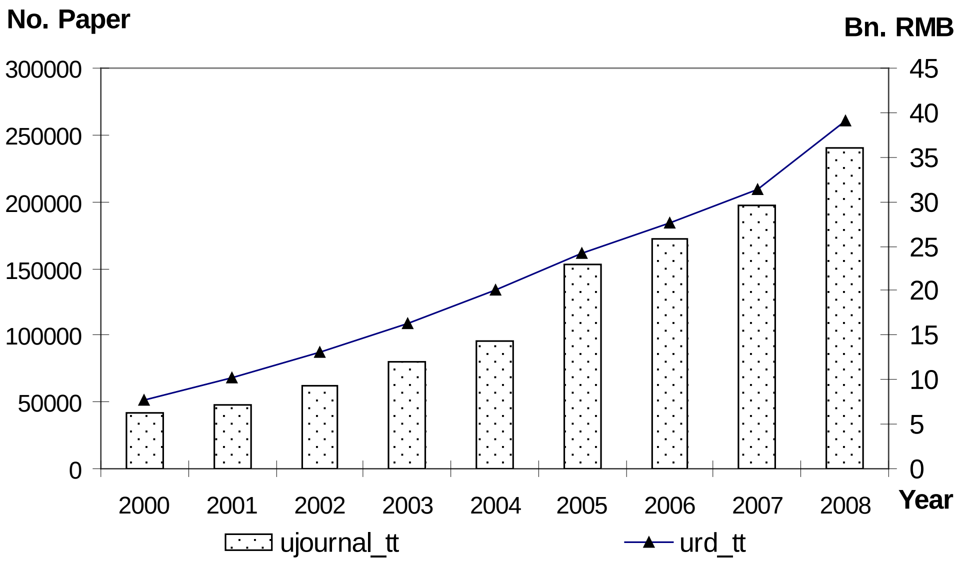
Note: Sums of the corresponding province-level statistics of 30 provinces in China are presented here. Original data source: NBSC-CNSYST (various years). Own presentation.

Figure B2 – Total patents (invention, utility model and external design) filed by universities



Note: Sums of the corresponding province-level statistics of 30 provinces in China are presented here. Data source: SIPO-SARP (various years). Own presentation.

Figure B3 – Total academic journal publications and universities' R&D expenditure



Notes: Sums of the corresponding province-level statistics of 30 provinces in China are presented here. The articles here refer to the Chinese scientific papers taken by major foreign referencing system such as SCI (Science Citation Index), EI (Engineering Index) and ISTP (Index to Scientific & Technical Proceedings). Data source: NBSC-CNSYST (various years). Own presentation.

Table B1 – Key descriptive statistics of variables considered in regression models

Variable		Mean	Std. Dev.	Min	Max	Obs
lnP_all[1]	overall	6.17	1.59	1.61	10.41	300
lnP_all = ln[P_all]	between		1.34	3.02	8.93	30
Note: P_all in unit	within		0.89	3.77	7.96	10
lnP_inv[1]	overall	5.01	1.64	0.69	9.75	270
lnP_inv = ln[P_inv]	between		1.39	1.70	8.23	30
Note: P_inv in unit	within		0.90	2.53	6.81	9
lnP_ninv[1]	overall	6.94	1.58	1.00	10.68	270
lnP_ninv = ln[exp(1)*(1+P_ninv)][7]	between		1.38	3.40	9.60	30
Note: P_ninv in unit	within		0.80	4.54	9.15	9
lnRD[1]	overall	11.85	1.49	7.21	15.23	300
lnRD = ln[RD]	between		1.31	8.40	14.16	30
Note: RD in 10,000 RMB	within		0.75	9.76	13.61	10
ACCE[2]	overall	36.42	19.45	-31.20	88.61	270
Note: 1 year lag, base value for gamma	between		17.97	7.24	85.34	30
	within		8.07	-13.12	62.52	9
INDCON[3]	overall	54.35	4.62	45.75	72.81	267
Note: INDCON: index * 100	between		4.33	48.36	66.46	30
	within		1.75	48.88	60.70	8.9
lnICT[3]	overall	1.94	0.55	1.00	3.32	267
lnICT = ln[exp(1)*(1+ICT)][7]	between		0.53	1.15	3.16	30
Note: ICT: share * 100	within		0.16	1.25	2.96	8.9
lnHEDU[4,6]	overall	1.66	0.55	-0.15	3.41	300
lnHEDU = ln[HEDU]	between		0.48	0.94	3.13	30
Note: HEDU: share * 100	within		0.28	0.33	2.22	10
lnPOP[4]	overall	3.51	0.78	1.63	4.58	300
lnPOP = ln[POP]	between		0.79	1.68	4.55	30
Note: POP in mio.	within		0.04	3.35	3.65	10
lnOPEN[4]	overall	2.88	1.05	1.15	5.19	300
lnOPEN = ln[OPEN]	between		1.03	1.63	4.99	30
Note: OPEN: ratio * 100	within		0.25	2.07	3.53	10
lnFOR[4]	overall	2.18	0.83	0.11	3.80	300
lnFOR = ln[FOR]	between		0.83	0.56	3.75	30
Note: FOR: share * 100	within		0.17	1.35	2.69	10
ACCE_a1_upinv[2,5]	overall	33.65	20.35	-35.59	88.38	270
Note: 1 year lag, base values for delta and	between		19.00	2.42	85.17	30
gamma	within		7.98	-15.28	59.16	9
ACCE_a1__upjournal[1,2]	overall	33.53	20.36	-36.59	88.58	270
Note: 1 year lag, base values for delta and	between		18.98	1.62	85.31	30
gamma	within		8.07	-15.89	59.75	9
ACCE_a1__urd[1,2]	overall	33.54	20.38	-36.60	88.58	270
Note: 1 year lag, base values for delta and	between		19.00	1.66	85.31	30
gamma	within		8.05	-15.88	59.56	9
ACCE_a2__upinv[2,5]	overall	37.57	105.63	-1420.18	164.39	270
Note: 1 year lag	between		55.80	-132.03	139.28	30
	within		90.20	-1250.58	229.06	9
ACCE_a2__ujournal[1,2]	overall	100.90	40.15	5.72	212.53	270
Note: 1 year lag	between		37.73	29.27	199.51	30
	within		15.21	33.95	138.76	9
ACCE_a2__urd[1,2]	overall	163.63	35.92	51.03	261.54	270
Note: 1 year lag	between		33.20	104.20	249.12	30
	within		14.86	89.99	196.42	9
lnSALES[1]	overall	16.85	1.18	13.95	19.73	270
lnSALES = ln[SALES]	between		1.03	14.64	18.70	30
Note: SALES in 10,000 RMB, 1 year lag	within		0.62	15.53	18.39	9
lnCAPOUT[1]	overall	4.19	0.51	3.04	5.22	270
lnCAPOUT = ln[CAPOUT]	between		0.28	3.60	4.65	30
Note: CAPOUT: ratio * 100, 1 year lag	within		0.42	2.76	4.88	9

Notes: [1]Source of data or core data for calculating the variables: NBSC-CNSYST (various years). [2]Source of data or core data for calculating the variables: NBSC-CCSY (various years). [3]Source of data or core data for calculating the variables: Provincial Statistical Yearbooks for all provinces except for Tibet (various years). [4]Source of data or core data for calculating the variables: NBSC-CNSY (various years). [5]Source of data or core data for calculating the variables: SIPO-SARP (various years). [6]Data of *HEDU* in 2001 are average values calculated from the data of *HEDU* in 2000 and 2002, since the base data needed to calculate *HEDU* in 2001 are not available. [7]In case of P_ninv (ICT) two (eight) original observations are zero.