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# The impact of conference ranking systems in computer science: a comparative regression analysis

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**Abstract** Nowadays, conference publications have gained importance both quantitatively and qualitatively. People are seeking ways to distinguish the quality and impact of different conferences. Some bibliometrics like conference impact factor have been proposed to assess them. Meanwhile, associations in some countries have implemented several projects to build conference ranking systems that classify conferences based on certain quality measures. The Computing Research and Education Association of Australasia and China Computer Federation lists are two such well-known and widely used conference rating systems. They can serve as a guide when researchers need to publish their work. At the same time, they can influence researchers' publication decisions. In this paper, we try to find out how publication patterns in different countries have been influenced by these two lists as well as by some other factors. A random-effect Negative Binominal Regression Model is used to identify the level of the impact caused by different factors.

**Keywords** Computer science · Ranking system · Conference · Influence factor · Multiple regression

## Introduction

Scientific publications have long played an essential role in evaluating academic researchers in terms of recognitions and rewards (Feist 1997). Though there are various venues for researchers to share their findings, journals and conferences are the two most

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frequent choices. Apart from counting the number of papers that one has published, evaluating how good they are has become a more challenging task. The Impact Factor (IF) of a journal is currently one of the most popular indicators used to assess conference quality (van Wesel 2016). Based on IF and its variants, several journal ranking methods have been proposed and studies have found evidences that this journal rank corresponds well with subjective ratings of journal quality (Sønderstrup-Andersen and Sønderstrup-Andersen 2008).

Besides journal publications, conferences have also been important venues for researchers to exchange ideas and findings. Therefore, it is equally necessary to find proper ways to assess the quality of scientific conferences, but currently no consensual means of measurement has been as widely adopted as IF for journals (Vrettas and Sanderson 2015). Several researchers have taken efforts to develop systems to assess conferences. For example, Martins et al. (2010) proposed some numerical values and conducted a study to evaluate the quality of scientific conferences by using existing journals. Based on their analysis, they proposed several quality metrics related to conferences and proved that those metrics are suitable for conference quality measurement (Martins et al. 2010). Similarly, Loizides and Koutsakis (2017) recently proposed a conference classification approach based on its papers' impact and their authors' *h*-indexes, and achieved a very comparable classification.

The importance of conferences is particularly augmented in the field of computer science as several bibliometric studies have revealed that conference papers in this subject perform better, both quantitatively and qualitatively, than papers in other disciplines (Freyne et al. 2010). Due to the importance as well as lack of a widely accepted measurement of the quality of conference publications, several efforts have been devoted to creating a ranking list of computer science conferences, and many associations have started projects to evaluate conference quality. At the end of 2006, the Computing Research and Education Association of Australasia (CORE) launched one of the first projects to build a ranking system for computer science conferences. In their system, conferences are classified into four groups, i.e., *A**, *A*, *B*, and *C*. Later in 2012, China Computer Federation (CCF) also developed a ranking system containing three classifications and it divided all those venues into ten different subfields.

Considering the fact that ranking lists will probably be used not only to serve as a proxy for quality measurement but also to evaluate researchers (Küngas et al. 2013), there is no doubt that they will have an impact on researchers' publication behaviors. Since these rankings are developed by different national associations, it is reasonable to ask several questions about them: (1) What are the impacts of ranking systems on the paper publishing process? (2) Are they more likely to have "local" effects or "global" ones? (3) What are other factors that researchers of different countries care about when publishing papers? (4) What do the ranking systems bring us, or in other words, what are the consequences of these systems?

In this study, we considered authors of each country as a group and used the number of papers published by a country in different conferences to measure their publication behaviors. The characteristics of the conferences were described by their classifications in CCF and CORE rankings, along with various factors based on the quantity and quality of papers published in them. By examining which of these factors lead to a larger number of papers being published by a country, we identified their impact in different countries. Our study aimed to find out whether and to what extent the classifications and other factors influence authors' publishing behaviors and their differences among countries. The study mainly focused on how CCF has influenced the behaviors of Chinese researchers compared to CORE. Other factors were analyzed through a regression analysis with an international comparison. We used DBLP and Microsoft Academic Search to collect more than 700,000 papers published in 521 conferences that appear in CCF or CORE from 2005 to 2016. Relevant citation information and details of more than 800,000 authors were also used to conduct the analysis and make comparisons. We hope that this work can provide insight into the pros and cons of ranking systems and where they can lead us.

In this paper, we first review several related works about journal and conference assessment concerning ranking systems and publication patterns, along with other scholars. We then introduce the dataset of our experiment and present the results of some preliminary analyses in the section "Dataset". Before the section "factors to characterize a conference," we propose some factors concerning the quantity and the quality of papers published in a conference, and examine whether they have any significant impacts, as well as how important those impacts are.

## Related work

Since the importance of publication quality is highly emphasized, people started to find ways to measure publication quality and impact. In 1955, Garfield proposed what is currently one of the most important indicators, IF Garfield (1955), to evaluate peer-reviewed academic journals. IF is mainly based on citation analysis (Holsapple and O'Leary 2009) and has now become a widely used indicator in evaluation. Other IF based variants such as *h*-index (Hirsch 2005), *y*-factor (Bollen et al. 2006), and the recently proposed Euclidean index (Perry and Reny 2016) have also been investigated. The global recognition of metrics based on citation analysis significantly assists decision-making processes regarding awarding prizes, allocating funds and promotions (Costas and Bordons 2007).

Another important publication option is conference proceedings as they have several advantages such as "providing fast and regular publication of papers and bringing researchers together" (Franceschet 2010). Particularly in the field of computer science, many studies have shown that conferences are at least as important as journals (Larsen and Von Ins 2010; Eckmann et al. 2011; Vrettas and Sanderson 2015; Qian et al. 2017). As such many researches about measuring computer science conferences' reputations have been conducted, and a first impact analysis was presented to highlight the issue by Clausen and Wormell (2001). Later on, Zhuang et al. (2007) proposed a method to automatically determine prestigious conferences using the characteristics of its program committee. Similarly, Yan and Lee (2007) considered evaluating the quality of a conference by referring to the similarity between its papers with high-quality seeds. Martins e-t al. Martins et al. (2010) tested the popular metrics for journals and proposed several factors designed for conferences. At the same time, several national associations proposed means to assess conference quality. Among them, CCF and CORE are two well-known ranking systems implemented by China and Australia respectively.

Besides publication evaluation, many works are concerned with research productivity and publication patterns worldwide or of a specific country (Gu 2002; Kumar and Garg 2005; He and Guan 2008; Chen and Guan 2010; Barbosa et al. 2017; Perlin et al. 2017). They found that researchers from different countries may act similarly to an extent, but their behavior can also be significantly different. For example, Guan and Ma observed that the ratio of publications in domestic conferences and journals were notably high in some countries but not as much in some others (Guan and Ma 2004). Similarly, Harzing and

Giroud (2014) divided countries into different groups and found that different countries have very different research profiles.

The difference in publication patterns may be related to decisions on where to publish one's own work, which are supposed to be subjective and made by researchers themselves. However, this behavior may be influenced, and even dominated by some extrinsic factors (Park et al. 2014). For example, nowadays, the publication in which a work appears is indicative of a researchers level of career advancement. When researchers are rewarded for publishing in several specific venues, habits which promote this behavior are naturally selected (Smaldino and McElreath 2016). Furthermore, scientists are currently facing intense competition and are burdened by several social and regulatory demands. In this context, recognition is a crucial need and they may make various compromises under this pressure (Martinson et al. 2005). Thus, it is important to study how ranking systems can influence scientists.

Based on those previous works, we conducted a study on the number of papers published in different conferences to try to identify how they can be influenced by classifications in ranking systems (CCF and CORE) and other factors including the subfield of a conference, annual average number of papers published by the conference, average number of authors, maximum and average *h*-index of all authors present, conference impact factor (CIF) and conference location. We were interested in how these can influence researchers' publication behaviors, which are mainly reflected in the quantity of publications in different conferences. We focused on the differences between countries and used regression models for each to identify the impacts of those factors considered.

## Dataset

### Dataset configuration

CCF is a national academic association in China which was established in 1956. They released a publication ranking list in 2012, dividing some well-known international computer science conferences and journals into 10 subfields (1. Computer systems and high-performance computing; 2. Computer networks; 3. Network and information security; 4. Software engineering, software, programming language; 5. Databases, data mining, and information retrieval; 6. Theoretical computer science; 7. Computer graphics and multimedia; 8. Artificial intelligence and pattern recognition; 9. Human computer interaction and ubiquitous computing; and 10. Miscellaneous). In this list, conferences are classified into three, represented by classes *A*, *B* and *C*. Top international conferences and journals are classified as *A*, famous journals and conferences with significant impact as *B*, and important conferences and journals as *C*. In 2014, CCF made some small shifts in this ranking and the present list is available on the CCF website.[1] In order to classify these conferences and journals, CCF examined the quality of conferences and journals along with other factors. However, quality changes constantly, while this list can only be updated occasionally. Hence, it can only be considered a list of recommendations that computer science researchers can refer to.

The CORE Conference Ranking is an ongoing activity that provides assessments of major conferences in computing disciplines. The rankings are managed by the CORE Executive Committee, with updates processed from time to time by a subcommittee

[1] www.ccf.org.cn.

established as needed. Similar to CCF, conferences are divided into four major classifications, i.e. *A**, *A*, *B*, and *C*. According to the CORE website,[2] classification *A** refers to a flagship conference, which is a leading venue in a discipline. Following this, *A* refers to an excellent conference, and highly respected in a discipline; *B* refers to a good conference, and well regarded in a discipline; and *C* refers to other ranked conference venues that meet minimum standards. Besides these 4 classifications, they also have two special marks, i.e., Australasian and Unranked, which refer to a conference for which the audience is primarily Australians and New Zealanders and a conference for which no ranking decision has been made, respectively. These conference rankings are determined by a mix of indicators, including citation rates, paper submission and acceptance rates, and the visibility and research track record of the key people hosting the conference and managing its technical program.

AW Harzing compared Microsoft Academic Search (MA) with other databases and concluded that MA's performance was significantly better than WoS and at least equal to Scopus (Harzing 2016; Harzing and Alakangas 2017). He also suggested that "Google Scholar includes coverage of non-standard research outputs, such as Publish or Perish software, thus providing additional citations for unique publications. Besides, Google Scholar has more citations for all of the overlapping publications, and substantially more in some cases." Besides, Hug et al. (2017) found that the publication records in Microsoft Academic have grown from 83 million in 2015 to 140 million in 2016. They concluded that the metadata in MA is more structured and considerably richer than in Google Scholar (GS). Recently, MA started a cooperation with Aminer, an academic social network miner constructed by Tsinghua University which aims to provide comprehensive search and mining services for researcher social networks. This cooperation will further improve its performance. So, we decide to use MA as our source of data.

In this research, we first collected the CCF and CORE conference lists. We then matched the names of conferences that appear in both lists via DBLP,[3] considering that the name can be different in those two lists even if it is the same conference. In this step, we ignore conferences marked as Australasian and Unranked. Next, we retrieved papers published in those conferences from 2005 to 2016 along with relevant information about authors, affiliations and citations from Microsoft Academic Search.[4] After data pre-treatment and cleaning, our final dataset consisted of: (1) Paper.rar, which included 728,425 papers and relevant citation information; (2) Author.rar, containing details of 833,925 authors; and (3) Conferences.rar, with 521 conferences in at least one of the two ranking systems. Table 1 summarizes the number of conferences in different classifications according to CCF and CORE. When a conference's name did not appear in the list, it was given a classification *X*. Our data is available on Github.[5] 30 out of 32 conferences classified as *A* in CCF are classified as *A** in CORE and the two left are classified as *A*. More than half of the conferences classified as *A** in CORE are classified as *A* in CCF. It is obvious that the two ranking systems agree on the top conferences. On the contrary, the classifications of other conferences vary greatly. This inconsistency makes it possible to identify the different impacts the two ranking systems have.

[2] www.core.edu.au.

[3] https://dblp.uni-trier.de.

[4] https://academic.microsoft.com.

[5] https://github.com/XianchengLI/PaperData.

**Table 1** Number of conferences in different classifications according to CCF and CORE

| CCF_classification | CORE_classification | | | | | |
|---|---|---|---|---|---|---|
| | *A** | *A* | *B* | *C* | *X* | All |
| *A* | 30 | 2 | 0 | 0 | 0 | 32 |
| *B* | 17 | 54 | 13 | 3 | 7 | 94 |
| *C* | 2 | 32 | 37 | 11 | 19 | 102 |
| *X* | 5 | 47 | 120 | 114 | 0 | 293 |
| All | 54 | 135 | 170 | 128 | 26 | 521 |

The most commonly used direct indicator to describe the research output and scientists' behavior is the number of papers published. Many studies have used this as a measure of productivity. In this study, we conducted a comparative analysis on the number of papers published in several selected countries. We chose China, Australia, Germany, India and the US because China and Australia have released the CCF and COER list, India is one of the most populous developing countries as well as one of most rapidly growing, like China, and the USA and Germany are science-giants, representing the highest academic level in the world. First of all, we wanted to study the characteristics of the overall number of publications published by the five countries. The publication counts during the period 2005–2016 are given in Table 2. An analysis of the total output indicates that the US took absolute predominance among all five countries: it constituted more than a quarter of the world output, while Germany constituted about one fifth of the USA's. China occupies the second ranking with a total number of publications which is the sum of Australia's, India's and Germany's. India has the lowest absolute number among the five countries.

However, in the degree of growth rate, except for China and India, the other three countries have a relatively declining trend in publication volume. India has a significant growth rate in 2006 (50%), 2009 (40%), and 2012 (50%), while China occasionally has a greater absolute number growth, namely 2000 in 2009 and 1000 in 2012. Some periodic fluctuations exist because conferences can be biennial or triennial. If the volumes of 2 years are combined, as presented in Table 3, we find that India has positive growth rates during 2 years.

Guan and Gao (2008) use Gini coefficients to measure the distribution of journal papers quantitatively for different countries. Their work shows that journal papers in bioinformatics are concentrated in several large and reputed journals (Guan and Gao 2008). We believe the same phenomenon exists for conference papers, so we used the number of publications published in different conferences each year by different countries and evaluated the degree of concentration for conference papers in computer science. Table 4 shows that the Gini coefficient of the five countries varies from 0.45 to 0.82, which means papers they published also have a certain degree of concentration. China, India and Australia have higher Gini coefficients than scientifically leading countries like Germany, and the US. The Gini coefficients of these five countries reflect a trend of convergence: lower Gini coefficients are growing while higher Gini coefficients are declining. This may indicate that researchers across the world are more agreed about conferences' reputations than before.

**Table 2** Number of papers from each country published in different years

| Year | Australia | China | Germany | India | US | Total |
|---|---|---|---|---|---|---|
| 2005 | 1590 | 5652 | 2390 | 539 | 17,618 | 53,985 |
| 2006 | 1750 | 6038 | 2672 | 835 | 18,011 | 58,509 |
| 2007 | 1699 | 5846 | 2939 | 704 | 17,991 | 59,053 |
| 2008 | 1738 | 5715 | 3268 | 1010 | 17,595 | 60,382 |
| 2009 | 1626 | 7819 | 3639 | 1001 | 17,816 | 63,738 |
| 2010 | 1836 | 7512 | 3860 | 1116 | 17,949 | 64,631 |
| 2011 | 1759 | 5939 | 3783 | 978 | 18,211 | 62,753 |
| 2012 | 1783 | 6922 | 3841 | 1473 | 16,984 | 63,071 |
| 2013 | 1877 | 6296 | 3755 | 1344 | 16,083 | 61,024 |
| 2014 | 1616 | 7085 | 3820 | 1550 | 16,015 | 61,721 |
| 2015 | 1608 | 7083 | 3592 | 1708 | 15,613 | 59,757 |
| 2016 | 1488 | 8573 | 3540 | 1622 | 15,772 | 59,801 |
| Total | 20,370 | 80,480 | 41,099 | 13,880 | 205,658 | 728,425 |

**Table 3** Growth rate of paper count in different years

| Year | Australia | China | Germany | India | US |
|---|---|---|---|---|---|
| 2008 | 0.028 | 0.011 | 0.184 | 0.198 | 0.001 |
| 2010 | 0.007 | 0.250 | 0.172 | 0.190 | 0.005 |
| 2012 | 0.023 | 0.192 | 0.016 | 0.136 | 0.016 |
| 2014 | 0.014 | 0.039 | 0.006 | 0.153 | 0.096 |
| 2016 | 0.128 | 0.145 | 0.062 | 0.140 | 0.023 |

**Table 4** Gini coefficients of publication numbers in different conferences for different countries

| Year | Australia | China | Germany | India | US |
|---|---|---|---|---|---|
| 2005 | 0.788 | 0.814 | 0.621 | 0.840 | 0.432 |
| 2006 | 0.772 | 0.786 | 0.607 | 0.828 | 0.436 |
| 2007 | 0.768 | 0.782 | 0.560 | 0.826 | 0.428 |
| 2008 | 0.781 | 0.767 | 0.578 | 0.823 | 0.446 |
| 2009 | 0.767 | 0.766 | 0.536 | 0.835 | 0.433 |
| 2010 | 0.789 | 0.766 | 0.541 | 0.832 | 0.447 |
| 2011 | 0.780 | 0.764 | 0.570 | 0.789 | 0.444 |
| 2012 | 0.802 | 0.734 | 0.550 | 0.815 | 0.473 |
| 2013 | 0.776 | 0.738 | 0.570 | 0.802 | 0.472 |
| 2014 | 0.772 | 0.719 | 0.599 | 0.816 | 0.491 |
| 2015 | 0.824 | 0.743 | 0.559 | 0.778 | 0.491 |
| 2016 | 0.813 | 0.730 | 0.577 | 0.774 | 0.495 |
| Mean | 0.786 | 0.759 | 0.572 | 0.813 | 0.457 |

## The influence of CCF list

Since 2010, which is when the CCF list was published, Chinese researchers seem to put more effort into listed conferences, while ignoring the others to some degree. To measure the extent of this influence, we used the concept of Activity Index (AI) that was first proposed by Frame (1977) to evaluate the relative research efforts a country put into a specific subfield. A transformative expression was used in a comparative study in computer science (Guan and Ma 2004). We considered subsets of conferences instead of subfields, namely conferences in the CCF list and those not in it, and the expression of Transformative Activity Index (TAI) of a country is:

$$\mathrm{TAI} = (C_i/C_o)/(W_i/W_o) \times 100 \tag{1}$$

where $C_i$, denotes the number of papers in a given subset in year i published by a country; $C_o$, denotes the number of all papers in a given subset published by a country; $W_i$, denotes the number of papers in a given subset in year i published by all countries in the world; $W_o$, denotes the number of all papers in a given subset published by all countries in the world.

TAI is a relative indicator which shows a country's relative paper count compared to the world's average. When a country's paper count in the given subset is equal to the world average, TAI = 100. TAI > 100 and TAI¡ < 100 respectively indicate higher and lower than the average (Guan and Ma 2004). Tables 5 and 6 are respectively the values of TAI for conferences in and not in the CCF list. Except for China, the other four countries display the same trend in both subsets, namely TAI of Australia and the US is declining, while that of India and Germany is growing. As for China, TAI is declining when we consider conferences not in CCF and growing when considering conferences in CCF. This phenomenon is particular to China and it means the CCF ranking system does have a significant effect on Chinese researchers' publication behavior.

## Preliminary paper count analysis

In the field of computer science, the number of papers published in different conferences vary greatly, and this seems to be the dominant factor influencing a country's paper count in a conference. However, we are more concerned about the relative paper count of different countries than the absolute number. We use a Normalize Coefficient (NC) which equals to the paper count of a conference divided by the average paper count of all conferences in our dataset in a specific year. We then calculate the Normalized Paper Count (NPC) for different countries which equals to the quotient of the paper count and

**Table 5** TAI of conferences in CCF list

| Year | Australia | China | Germany | India | US |
|---|---|---|---|---|---|
| 2005 | 110.03 | 44.25 | 82.39 | 46.06 | 121.33 |
| 2006 | 104.08 | 68.04 | 81.40 | 67.79 | 111.22 |
| 2007 | 103.38 | 75.98 | 87.15 | 63.87 | 109.99 |
| 2008 | 92.17 | 68.74 | 98.70 | 80.97 | 109.02 |
| 2009 | 91.39 | 90.96 | 105.93 | 58.32 | 102.10 |
| 2010 | 103.25 | 89.48 | 104.69 | 103.87 | 101.30 |
| 2011 | 94.31 | 87.63 | 108.48 | 81.85 | 100.50 |
| 2012 | 98.33 | 105.18 | 100.34 | 128.04 | 96.44 |
| 2013 | 109.97 | 112.47 | 108.88 | 118.16 | 91.65 |
| 2014 | 97.71 | 133.79 | 105.31 | 135.50 | 86.04 |
| 2015 | 107.12 | 136.70 | 106.11 | 147.33 | 91.53 |

**Table 6** TAI of conferences not in CCF list

| Year | Australia | China | Germany | India | US |
|---|---|---|---|---|---|
| 2005 | 100.53 | 124.92 | 75.01 | 56.29 | 111.74 |
| 2006 | 108.19 | 109.71 | 80.58 | 79.88 | 107.71 |
| 2007 | 101.45 | 97.49 | 89.37 | 61.07 | 107.53 |
| 2008 | 109.22 | 95.61 | 93.41 | 92.05 | 97.42 |
| 2009 | 89.41 | 120.92 | 97.20 | 97.95 | 99.18 |
| 2010 | 99.65 | 115.00 | 107.12 | 79.90 | 95.56 |
| 2011 | 104.08 | 83.80 | 105.27 | 81.42 | 107.62 |
| 2012 | 103.62 | 95.42 | 116.12 | 118.32 | 92.76 |
| 2013 | 111.73 | 79.63 | 109.02 | 114.65 | 92.93 |
| 2014 | 92.17 | 81.18 | 114.81 | 130.71 | 97.95 |
| 2015 | 88.34 | 85.48 | 106.82 | 154.13 | 91.15 |

NC. The expression of NPC and NC are given in Eqs. 2 and 3. This NPC will be used in the rest of this study. Variables and symbols used in this paper are given in Table 7.

$$\mathrm{NPC}_{\mathrm{country}}(\mathrm{con}, y) = \frac{\mathrm{PC}_{\mathrm{country}}(\mathrm{con}, y)}{\mathrm{NC}(\mathrm{con}, y)} \tag{2}$$

$$\mathrm{NC}(\mathrm{con}, y) = \frac{\mathrm{PC}(\mathrm{con}, y)}{\overline{\mathrm{PC}(y)}} \tag{3}$$

where $\mathrm{NPC}_{\mathrm{country}}(\mathrm{con}, y)$ indicates the NPC of country country in conference con at year $y$. We can calculate NPC for the 5 countries considered for the study. We first investigate the geometric mean NPC for different classifications and categories to examine the difference among them. Since normal mean value can significantly be influenced by a few large values, geometric mean is more appropriate for count data considering that high skewness usually exists in this kind of data (Zitt 2012). The calculability of log can be ensured by adding 1 to the NPC when some of the NPC values are zero (Fairclough and Thelwall 2015). Since the CCF list was first published at the end of 2010, we separated our data into two time periods—before 2013 and after 2013, which leaves 1 year, namely 2012, to wait

**Table 7** Symbols of dataset

| Symbol | Description |
|---|---|
| $s$ | The subfield of a given publication, $s \in \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ |
| $c$ | The classification of a given publication, $c \in \{A, B, C\}$ |
| $y$ | The year a publication was published |
| $p$ | The time period, $p \in \{\mathrm{before2013}, \mathrm{after2013}\}$ |
| con | A conference |
| $\mathrm{ConferenceSet}(c, s, p)$ | The conference set, where $s$ is the subfield, $p$ is the time period, and $c$ is the domain classification |
| $n(c, s, p)$ | The number of conferences in conference set $\mathrm{ConferenceSet}(c, s, p)$ |

for a spread of the CCF list. Now we can define the geometric mean NPC for a subfield in a classification $\overline{\mathrm{NPC}}(\mathrm{con}, c, s, p)$ as follows:

$$\overline{\mathrm{NPC}}_{\mathrm{country}}(p, c, s) = \left( \prod_{\mathrm{con} \in \mathrm{ConferenceSet}(c,s,p)} (\mathrm{NPC}_{\mathrm{country}}(\mathrm{con}) + 1) \right)^{\frac{1}{n(c,s,p)}} \quad (4)$$

Figure 1a–e each contain 27 bars distributed into three classifications and nine subfields in CCF. For instance, the leftmost bar of Fig. 1a represents $\overline{\mathrm{NPC}}_{\mathrm{China}}(C, 1, \mathrm{Before\,2013})$.

After investigating the details from Fig. 1a, a general trend can be found—before 2013, no significant difference of $\overline{\mathrm{NPC}}_{\mathrm{China}}$ can be seen among different classifications in all subfields except subfield 7. The $\overline{\mathrm{NPC}}_{\mathrm{China}}$ after 2013 has grown significantly compared to that before 2013. Besides, a significant difference in $\overline{\mathrm{NPC}}_{\mathrm{China}}$ appears after 2013, that is, $\overline{\mathrm{NPC}}_{\mathrm{China}}$ in classification A is higher than it is in classification B which is higher than that in classification C. According to Fig. 1b–e, the relative status of $\overline{\mathrm{NPC}}_{\mathrm{Germany}}$ and $\overline{\mathrm{NPC}}_{\mathrm{US}}$ among classifications are consistent before and after 2013. $\overline{\mathrm{NPC}}_{\mathrm{Australia}}$ in subfields 5 and 8 has grown a lot while the rest stay at the same level. $\overline{\mathrm{NPC}}_{\mathrm{India}}$ in subfield 2 classification A is extraordinarily high compared to other subfields. Except for this abnormal value, the relative status of $\overline{\mathrm{NPC}}_{\mathrm{India}}$ among classifications are consistent before and after 2013.

Figure 2 contains the growth rates $\overline{\mathrm{NPC}}$ of five countries constructed similar to Fig. 1a, except that in each subfield 5 markers are used to represent different countries. For instance, the triangle on the top of Fig. 2 represents the $\overline{\mathrm{NPC}}_{\mathrm{China}}(A, 9)$, which is the geometric mean NPC for CCF class $A$ conferences in subfield 9. In classification $A$, the number of subfields where the growth rates of $\overline{\mathrm{NPC}}_{\mathrm{China}}$ are above 100% is 4 while that in classification $B$ is 2 and in classification $A$ is 1. This is consistent with our conclusion from Fig. 1a–e. Except the growth rate of $\overline{\mathrm{NPC}}_{\mathrm{India}}$ in subfield 2 classification A, all other values fluctuate near 0, which does not show a clear correlation with CCF classification.

## Factors to characterize a conference

### Factor description

#### *CCF and CORE classifications*

Conference rating lists are usually proposed by national associations and serve as a guide when researchers need to publish their work. The quality of a researcher's work may be assessed by the classification of the conferences that published them. This means of assessment can have a strong effect on researchers' publication behaviors. In our study, we mainly analyzed how the CCF and CORE lists affected local researchers' behaviors by comparing this with other countries.

#### *Conference impact factor*

The most widely accepted way to measure the quality of a conference is using citation information. It is widely accepted that citations of papers published by a venue has a strong positive correlation with its quality. Based on the use of IF in journal publications, Martins et al. (2010) proposed the CIF. "CIF is a redefinition of IF that uses a larger temporal

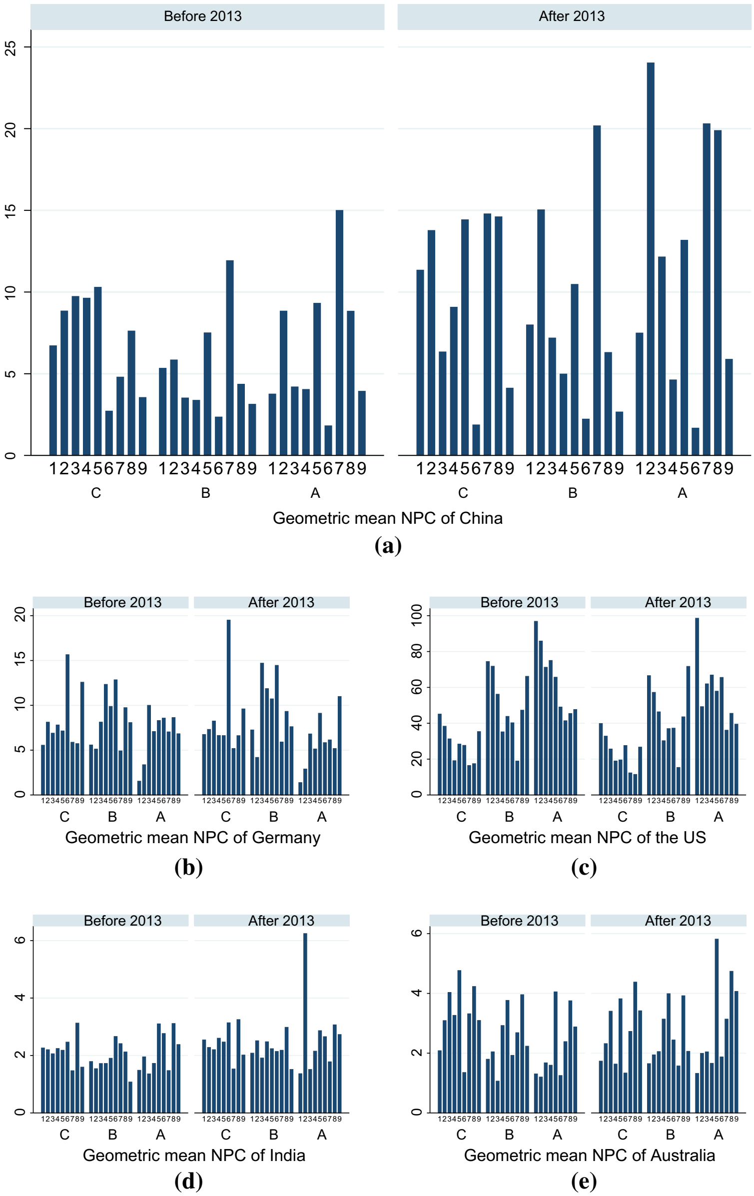


**Fig. 1** Geometric mean NPC from different CCF classifications and categories for sets of conferences after 2013 and before 2013. **a** Geometric mean NPC of China from different CCF classifications and categories, **b** geometric mean NPC of Germany from different CCF classifications and categories, **c** geometric mean NPC of the US from different CCF classifications and categories, **d** geometric mean NPC of India from different CCF classifications and categories, **e** geometric mean NPC of Australia from different CCF classifications and categories

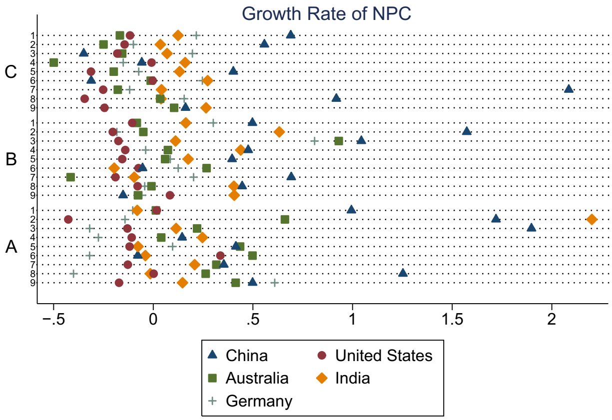


**Fig. 2** The growth of Geometric mean NPC for CCF grouped by CCF classification and subfield

window, increasing the probability of obtaining available data for the conferences being evaluated" (Martins et al. 2010). CIF measures the quality of a conference based on one aspect and can complement and serve as a comparison to the two classifications.

*Annual average number of papers published in a conference*

The annual average number of papers published in a conference is an estimation of its size. It is an essential complement to CIF since the latter cannot capture the size of a conference. Moreover, some conferences can have a few papers with high citation rate, which leads to a relatively higher CIF for smaller conferences. Here, it's worth noting that the size of a conference does not reflect its quality since there are examples of large conferences of low quality, despite the general tendency for low quality conferences to be smaller and high-quality conferences to be larger (Martins et al. 2010). Besides, some researchers may look for larger conferences as it is easier for their work to be accepted or because their co-workers had published works in those conferences. In these cases, this factor can be a good reflection of researchers' publication choices.

*Number of authors per paper*

In modern society, big projects are often completed by groups rather than individuals. Collective efforts lead to advancements in science. Gazni et al. (2012) describe international collaboration in their study, which shows that western countries are more likely to cooperate with each other. Besides, knowledge of a paper is more likely to reach other researchers through the authors (Abt and Garfield 2002) which means papers with more authors can have larger audiences. The number of authors per paper reflect the collaboration preferences in a conference, which may attract authors with same preferences. Guan's work shows that collaboration patterns differ from country to country (Guan and Ma 2007). Based on these facts, it is reasonable to believe that the number of authors per paper in a conference will influence researchers' choice of venues. In this paper, we use the number of authors per paper in a conference to measure this influence.

*Maximum and average h-index of all authors*

Many studies have proved that the reputation and impact of a publication is related to the *h*-index of its authors, and an author's *h*-index can represent his/her reputation (Onodera and Yoshikane 2014). Conferences offer the opportunity to discuss one's work with peers. When highly-reputed peers decide to attend a specific conference, other researchers may be more willing to join them. The maximum and average *h*-index of all authors reflect the highest and average reputation of participants in a conference respectively, and have the potential of influencing researchers' choices.

*Location of a conference*

Guan and Ma (2004) observe that the ratio of publications published in domestic journals and conferences are remarkable for most countries, especially China. We intuited that attending a conference convened overseas costs a lot more than one which is convened inland. Hence, we believe the location where a conference is convened can also influence its number of publications. In our study, we distinguish conferences as "inland" and "overseas". The variable dom is used to denote this factor.

*Subfield*

As shown in the preliminary analysis, the profile of $\overline{\text{NPC}}$ varies from subfield to subfield. In fact, different countries may focus on different subfields and this is mainly decided by various factors such as government policies and the needs of the public. Thus, it is reasonable to assume that the subfield of a conference may influence the number of papers published in it in a country.

The above factors of a conference are denoted as (1) CCF_classification, (2) CORE_classification, (3) CIF, (4) conference_average_author_number, (5) conference_average_paper, (6) conference_max_h_index, (7) conference_average_h_index, (8) location, (9) subfield. In this study, we use a multiple regression model to analyze the impacts of these factors.

## Regression analysis

*Constructing categorical variables from continuous variables*

To study the impact of these factors on NPC and to obtain a result comparable with the classifications in CCF and CORE, we classified these factors with continuous values into different categories, namely cat_cif, cat_conference_average_author_number (cat_caa), cat_conference_average_paper (cat_cap), cat_conference_max_h_index (cat_max_h), and cat_conference_average_h_index (cat_avg_h). We categorized conferences into 4 groups according to those factors using 0.25, 0.5 and 0.75 quantiles. Hence, every category contains approximately 25% of all conferences. The categorical variables constructed are given in Table 8.

Similar to Tables 1 and 9 summarizes the number of conferences in the different CCF and CORE classifications, compared with cat_cif. When a conference's name did not appear in the list, it was given a classification *X*. Conferences held in different years are considered as different (for e.g., SIGMOD 2012 and SIGMOD 2014 are different

**Table 8** Results of variable conversion

| cat_cif | cif | Freq. | Percent | Cum. |
|---|---|---|---|---|
| 1 | (0, 0.53] | 657 | 24.95 | 24.95 |
| 2 | (0.53, 1.13] | 657 | 24.95 | 49.91 |
| 3 | (1.13, 2.35] | 659 | 25.03 | 74.93 |
| 4 | (2.35, $+\infty$] | 660 | 25.07 | 100 |
| **cat_avg_h** | **conference_average_h_index** | **Freq.** | **Percent** | **Cum.** |
| 1 | (0, 3.30] | 669 | 25.41 | 25.41 |
| 2 | (3.30, 4.80] | 659 | 25.03 | 50.44 |
| 3 | (4.80, 6.77] | 647 | 24.57 | 75.01 |
| 4 | (6.77, $+\infty$] | 658 | 24.99 | 100 |
| **cat_max_h** | **conference_max_h_index** | **Freq.** | **Percent** | **Cum.** |
| 1 | (0, 21] | 664 | 25.22 | 25.22 |
| 2 | (21, 29] | 684 | 25.98 | 51.2 |
| 3 | (29, 37] | 658 | 24.99 | 76.19 |
| 4 | (37, $+\infty$] | 627 | 23.81 | 100 |
| **cat_caa** | **conference_average_author_number** | **Freq.** | **Percent** | **Cum.** |
| 1 | (0, 2.98] | 667 | 25.33 | 25.33 |
| 2 | (2.98, 3.31] | 656 | 24.91 | 50.25 |
| 3 | (3.31, 3.65] | 641 | 24.34 | 74.59 |
| 4 | (3.65, $+\infty$] | 669 | 25.41 | 100 |
| **cat_cap** | **conference_average_paper** | **Freq.** | **Percent** | **Cum.** |
| 1 | (0, 57] | 665 | 25.26 | 25.26 |
| 2 | (57, 98] | 643 | 24.42 | 49.68 |
| 3 | (98, 189] | 671 | 25.48 | 75.16 |
| 4 | (189, $+\infty$] | 654 | 24.84 | 100 |

conferences). Several agreements between classifications and cat_cif can be found—most class *A* conferences in CCF and *A** class conferences in CORE are classified in the highest category according to CIF. With the decrease in classification in CCF and CORE, the ratio of conferences classified in lower categories in cat_cif increases. Meanwhile, inconsistency exists—several class *C* conferences in CCF or CORE have been classified here into the highest category. This inconsistency makes it possible to identify the impacts of our various means of assessments.

**Table 9** Number of conferences in different classifications according to CCF and CORE

| cat_cif | CCF classification | | | | CORE classification | | | | | All |
|---|---|---|---|---|---|---|---|---|---|---|
| | *X* | *C* | *B* | *A* | *X* | *C* | *B* | *A* | *A** | |
| 1 | 561 | 83 | 13 | 0 | 30 | 327 | 237 | 62 | 1 | 657 |
| 2 | 443 | 183 | 31 | 0 | 35 | 167 | 298 | 137 | 20 | 657 |
| 3 | 297 | 197 | 151 | 14 | 74 | 87 | 222 | 243 | 33 | 659 |
| 4 | 88 | 79 | 327 | 166 | 37 | 39 | 76 | 262 | 246 | 660 |
| Total | 1389 | 542 | 522 | 180 | 176 | 620 | 833 | 704 | 300 | 2633 |

*Regression model selection*

The dependent variable of our study is NPC, which can be considered as count data, and the Poisson Regression Model(PRM) is often used for modelling count data. However, “a persistent problem with Poisson models is that they often exhibit over dispersion, where the variance of the response variable is greater than the mean, resulting in a poor fit to the data” (Moskowitz and Chun 2015). A generalization of PRM is the Negative Binominal Regression Model (NBRM), in which over dispersion is denoted by $\alpha$, the dispersion parameter. When $\alpha = 0$, NBRM reduces to the PRM (Hilbe 2011). We performed a test of over dispersion by $H0 : \alpha = 0$ for NPC of different countries and the results showed that $\alpha$ is significantly different from 0, which means H0 is rejected and over dispersion exists. So we used NBRM as our regression model. Our data is divided into two parts, namely before and after 2013. Each part contains conferences over 3 years (2010–2012 and 2014–2016), which means our data can be treated as “panel data”. Panel data contains a large number of data points and can improve the efficiency of estimates by reducing collinearity among expletive variables and increasing degrees of freedom (Cheng 2014). Stata provided us a negative binomial model for panel data. Fixed-effects (FE) and random-effects (RE) models are widely used for panel data. The differences between these two have been discussed by Field (2003) and Borenstein et al. (2009). The basic distinction here is that “FE models assume apriori that exactly the same population value underlies all studies in the meta-analysis, while RE models allow for the possibility that population parameters vary from study to study” (Schmidt et al. 2009). To decide which one of those two models are more suitable for the given data, the ’Hausman specification test is commonly employed. It is based on the idea that “the set of coefficient estimates obtained from the fixed-effects estimation taken as a group should not differ systematically from the set derived via random-effects estimation under the null hypothesis that the unobservable, individual-specific effects and the regressors are orthogonal” (Frondel and Vance 2010). Stata provided us a’ Hausman specification test for panel data and the results showed that the random-effects model was suitable for our data.

After these analyses and tests, we preferred random-effects NBRM to analyze our data. In Stata, random-effects NBRM is represented by “xtnbrm” and random-effect by “re”. We use this command and the percentage change is calculated when the categorical variable changes from the base to another (Qian et al. 2017).

## Discussion

### Factor 1: CCF classification of publications

Taking CCF classification as an example, keeping all other variables constant and taking classification $X$ as the base, the percentage change in the expected NPC can be calculated when the classification changes to another. The results in Tables 10 and 11 are in accordance with our assumption. Before 2013, if we investigate NPC_China, a conference classified as $C$, $B$ or $A$ in the CCF list increased the NPC_China by 168, 160 and 154% respectively, which are significant numbers. However, little difference existed between different classifications. After 2013, the values are 185, 241 and 341%, which are greater than those of the time period before 2013. Meanwhile, a hierarchical increase appears—the percentage change increases with the classification of a conference in CCF. This hierarchical increase did not exist before 2013 and the most important difference between those two time periods is the existence of CCF list. As for the NPC of other countries, the impact of CCF classifications do not change much after 2013 compared to before 2013. We also cannot observe any patterns between classifications. This leads us to the conclusion that CCF classifications do have a strong impact on Chinese researchers' publication behaviors—they tend to publish more in conferences listed in CCF and even more in conferences with higher classifications in the list.

### Factor 2: CORE classification of publications

Similar to CCF classifications, CORE classifications also influence Australian researchers' behavior—conferences classified as $B$, $A$ or $A*$ increased the NPC_Australia by 26, 73 and 96% respectively before 2013. The difference is that a conference classified as C in CORE decreases NPC_Australia by 33%, which means Australian researchers do not take class $C$ as a measure of high quality, and they prefer to attend other conferences with better reputations even if they are not in the CORE list. After 2013, the hierarchical impact of classifications still existed on NPC_Australia, only that most percentage changes are negative. As shown in Table 3, the number of papers published in Australia are not increasing, while the research efforts of developing countries like China and India are growing persistently. Under these circumstances, the relative number of papers published in conferences with good reputation is decreasing, which may lead to the negative percentage changes. There is an interesting finding about NPC_China—before 2013, a quasi-hierarchical impact of CORE classification existed on NPC_China (the percentage changes are 23, 67, 31 and 71% respectively). However, after 2013, this impact suddenly disappeared. This could easily be explained—before the CCF list was published, Chinese researchers might have referred to the CORE list to gauge conferences' quality. Shortly after the CCF list was published, Chinese researchers did not need to refer to CORE list anymore since they had their own list, which met their needs better.

### Factor 3: conference impact factor

CIF can be used to measure a conference's impact by using the citation information of papers published. Unlike the ranking systems mentioned above, CIF is a more "objective" factor because it can easily be calculated without subjective evaluations. The percentage change of NPC in scientifically leading countries like the US and Germany are strongly

**Table 10** xtNBRM: Percentage change in expected NPC compared with a base for the set of conferences before 2013

| Factors | NPC_China | NPC_Australia | NPC_US | NPC_Germany | NPC_India |
|---|---|---|---|---|---|
| *Cat_avg_h* | | | | | |
| 1 | Base | | | | |
| 2 | − 21.93* | 12.99 | 28.32** | 69.82** | − 12.88 |
| 3 | − 29.35** | 29.53 | 60.78** | 111.28** | − 38.6** |
| 4 | − 54.87** | − 14.43 | 101.48** | 100.9** | − 40.29** |
| *Cat_max_h* | | | | | |
| 1 | Base | | | | |
| 2 | 22.51* | 3.06 | 9.92* | − 2.67 | 17.68 |
| 3 | 37.05** | 4.02 | 21.36** | − 15.91* | 12.05 |
| 4 | 55.77** | 28.63 | 20.93** | − 10.52 | 35.69* |
| *Cat_caa* | | | | | |
| 1 | Base | | | | |
| 2 | 46.77** | 20.93* | 0.45 | − 1.66 | − 0.06 |
| 3 | 65.87** | 28.76* | 0.72 | − 10.03 | − 23.17* |
| 4 | 46.43** | − 1.70 | 7.00 | − 18.73* | − 32.59** |
| *Cat_cif* | | | | | |
| 1 | Base | | | | |
| 2 | − 8.18 | − 11.46 | 12.04 | 21.13* | 65.88** |
| 3 | − 34.45** | − 25.36* | 17.20** | 20.92* | 38.15* |
| 4 | − 37.70** | − 35.10* | 20.93** | 25.59* | 76.45** |
| *Cat_cap* | | | | | |
| 1 | Base | | | | |
| 2 | 81.29** | 23.54 | 4.29 | 7.03 | 41.68** |
| 3 | 131.68** | 90.23** | 7.45 | 5.5 | 116.98** |
| 4 | 250.99** | 116.89** | 13.23* | 26.57** | 226.61** |
| *CCF_classification* | | | | | |
| *X* | Base | | | | |
| *C* | 168.37** | − 50.46** | 69.27** | − 33.09** | 24.2 |
| *B* | 160.88** | − 59.87** | 113.25** | − 40.23** | 22.39 |
| *A* | 154.68** | − 73.2** | 85.66** | − 60.38** | 36.04 |
| *CORE_classification* | | | | | |
| *X* | Base | | | | |
| *C* | 23.34 | − 33.24 | 10.2 | 32.17 | 24.48 |
| *B* | 67.65** | 26.81 | − 2.64 | 32.81* | 6.52 |
| *A* | 36.35 | 73.12* | 15.31 | 79.2** | − 25.74 |
| *A** | 71.31* | 96.93* | 46.38* | 74.24** | − 32.33 |
| *Conference_location* | | | | | |
| Overseas | Base | | | | |
| Inland | 171.64** | 194.46** | 34.46** | 68.83** | 933.51** |
| *Computer science subfield* | | | | | |
| 1 | Base | | | | |
| 2 | − 8.65 | 36.87 | − 11.4 | 17.66 | − 6.79 |
| 3 | 27.39 | − 22.06 | − 17.62 | 63.63* | − 23.4 |

**Table 10** continued

| Factors | NPC_China | NPC_Australia | NPC_US | NPC_Germany | NPC_India |
|---|---|---|---|---|---|
| 4 | − 16.71 | 146.55** | − 46.65** | 85.83** | − 23.14 |
| 5 | 9.97 | 203.07** | − 42.32** | 53.87** | 7.68 |
| 6 | − 38.62 | − 21.46 | − 43.44** | 127.43** | 60.78 |
| 7 | − 5.81 | 74.87 | − 57.15** | 30.65 | − 11.64 |
| 8 | − 19.55 | 209.03** | − 49.45** | 32.93 | − 1.1 |
| 9 | − 58.83** | 41.51 | − 18.02 | 108.32** | − 54.08* |

*Significant at 5%; **significant at 1%

Subfield: 1—computer systems and high-performance computing; 2—computer networks; 3—network and information security; 4—software engineering, software, programming language; 5—databases, data mining, and content retrieval; 6—theoretical computer science; 7—computer graphics and multimedia; 8—artificial intelligence and pattern recognition; 9—human–computer interaction and ubiquitous computing

positively correlated with cat_cif both before and after 2013. However, for countries with "local" ranking systems like China, the percentage change of NPC caused by different categories of CIF are all negative. In the analysis of factor 1, we know that the Chinese put more research effort into class *A* conferences after 2013. But the impact of CIF did not change much after 2013 compared to before 2013. This leads us to the conclusion that researchers' publication behaviors of countries with ranking systems are less influenced by CIF. The impact of CIF on NPC_India is singular: NPC_India was positively correlated with cat_cif before 2013. However, after 2013, these correlations became negative. This may have been caused by the increasing number of publications published by Indian researchers.

## Factor 4: annual average number of papers published in the conference

The results in Tables 10 and 11 show that academically-leading countries like the US and Germany are not influenced by the size of a conference, while other countries tend to publish more work in larger conferences. China and India published more in larger conferences before 2013.

## Factor 5: maximum and average *h*-index of all authors

According to Tables 10 and 11, the influence of the highest *h*-index of all participants in a conference is generally positive in all countries except Germany. This influence is most significant on China and India. This means that the reputation of the best scientists can attract more authors to attend a conference. On the other hand, the influence of the average *h*-index of all authors in a conference varies from country to country, that is, for developing countries like China and India, the influence is negative while for developed countries like the US and Germany, it is positive. NPC_Australia is an exception since the influence is not significant. This shows that researchers from developing countries care more about the most well-known participants in a conference rather than their average research level, while researchers from developed countries take both into consideration.

**Table 11** xtNBRM: Percentage change in expected NPC compared with a base for the set of conferences after 2013

| Factors | NPC_China | NPC_Australia | NPC_US | NPC_Germany | NPC_India |
|---|---|---|---|---|---|
| *Cat_avg_h* | | | | | |
| 1 | Base | | | | |
| 2 | − 24.45** | 5.06 | 28.01** | 29.07** | − 13.14 |
| 3 | − 41.06** | 1.11 | 38.64** | 35.31** | − 6.41 |
| 4 | − 53.73** | − 29.88 | 57.73** | 19.95 | − 41.4** |
| *Cat_max_h* | | | | | |
| 1 | Base | | | | |
| 2 | 22.5* | 3.06 | 9.92** | − 2.67 | 17.68 |
| 3 | 37.05** | 4.02 | 21.36** | − 15.91 | 12.05 |
| 4 | 55.77** | 28.63 | 20.93** | − 10.52 | 35.69** |
| *Cat_caa* | | | | | |
| 1 | Base | | | | |
| 2 | 60.04** | − 1.36 | 7.05 | − 3.3 | − 4.03 |
| 3 | 112.09** | 27.29 | 8.07 | − 10.28 | 9.35 |
| 4 | 168.27** | 16.39 | 3.88 | − 15.38 | − 7.95 |
| *Cat_cif* | | | | | |
| 1 | Base | | | | |
| 2 | 3.72 | − 0.28 | 24.81** | 45.73** | − 9.39 |
| 3 | − 26.81** | − 10.37 | 34.35** | 98.22** | − 17.54 |
| 4 | − 37.48** | − 36.05* | 62.54** | 74.93** | − 18.24 |
| *Cat_cap* | | | | | |
| 1 | Base | | | | |
| 2 | 35.09** | 52.17** | 1.74 | − 7.73 | 43.03** |
| 3 | 77.70** | 101.37** | 17.51** | 9.74 | 98.85** |
| 4 | 121.87** | 157.52** | 21.67** | 29.67** | 166.12** |
| *CCF_classification* | | | | | |
| *X* | Base | | | | |
| *C* | 185.19** | − 74.04** | 64.13** | − 25.92* | 0.72 |
| *B* | 241.84** | − 64.53** | 105.69** | − 25.38 | 12.67 |
| *A* | 341.37** | − 68.05** | 70.93** | − 55.17** | 28.71 |
| *CORE_classification* | | | | | |
| *X* | Base | | | | |
| *C* | − 18.32 | − 62.49** | − 0.3 | − 0.56 | 33.06 |
| *B* | 12.63 | − 37.83* | − 11.17 | 14.56 | 28.95 |
| *A* | − 2.07 | − 1.1 | 2.81 | 40.25* | 0.99 |
| *A** | − 4.37 | 1.11 | 45.67* | 19.43 | − 0.55 |
| *Conference_location* | | | | | |
| Overseas | Base | | | | |
| Inland | 89.53** | 472.19** | 39.22** | 64.95** | 320.16** |
| *Computer science subfield* | | | | | |
| 1 | Base | | | | |
| 2 | 15.13 | 67.94 | − 16.16 | − 3.85 | 11.16 |
| 3 | − 5.44 | 123.10 | − 25.03 | 84.53 | − 13.44 |

**Table 11** continued

| Factors | NPC_China | NPC_Australia | NPC_US | NPC_Germany | NPC_India |
|---|---|---|---|---|---|
| 4 | − 33.89 | 96.29 | − 42.03 | 40.41 | − 3.95 |
| 5 | 8.01 | 226.3 | − 48.24 | 52.31 | − 4.71 |
| 6 | − 66.41 | 42.3 | − 34.45 | 101.01 | 48.29 |
| 7 | 0.38 | 69.12 | − 63.92 | 22.82 | − 47.71 |
| 8 | 14.54 | 381.36 | − 55.31 | 29.36 | 37.14 |
| 9 | − 71.72 | 193.91 | − 19.21 | 59.87 | − 37.05 |

*Significant at 5%; **significant at 1%

Subfield: 1—computer systems and high-performance computing; 2—computer networks; 3—network and information security; 4—software engineering, software, programming language; 5—databases, data mining, and content retrieval; 6—theoretical computer science; 7—computer graphics and multimedia; 8—artificial intelligence and pattern recognition; 9—human–computer interaction and ubiquitous computing

## Factor 6: number of authors per paper

The impact of the number of authors per paper in a conference shows a country's collaborative status. The results in Tables 10 and 11 are consistent with Guan's work concerning the field of computer science (Guan and Ma 2004)—scientists in this field in Asian countries prefer to work in groups, while those in occident countries are more inclined to work separately or with only one collaborator. The influence of the average number of authors is the highest on Chinese authors, particularly after 2013.

## Factor 7: location where a conference is convened

The results in Tables 10 and 11 verify our assumption that the location where a conference is convened can influence its number of publications, and this influence is strongly positive for all countries considered. For example, before 2013, a conference convened domestically increased the $NPC_{India}$ enormously by 933%. As for other countries, the percentage changes varied from 34 to 193%. After 2013, the percentage change of India and China decreased to 320 and 89% respectively, while those for other countries slightly increased. This shows that Asian countries display a tendency to increase their international scientific communication.

## Factor 8: subfield

As different countries may focus on different subfields, the impact of different subfields can reflect the research efforts of different countries. From Tables 10 and 11, we can identify the main subfields that different countries focus on. In Australia, the main subfields are software engineering, software, programming language; databases, data mining, and content retrieval; and artificial intelligence and pattern recognition. This is consistent with our finding in Fig. 1e. In the US, researchers publish more papers in computer systems and high-performance computing. In Germany, the main subfields are network and information security; theoretical computer science; and human-computer interaction and ubiquitous computing. As for China and India, no significant differences can be found among subfields. Again, this may be caused by the rapid development in those countries.

## The influence of the pattern changes caused by CCF ranking

We have confirmed that CCF rankings have modified the publication patterns of Chinese researchers. We still need to investigate the differences between classifications and the consequences of these changes. In Table 12, we separated our result of Chi_NPC according to CCF classifications. For each classification, the first value is the percentage change before 2013 and the second one is that after 2013. Conferences of some classifications may not cover all categories of average and maximum $h$-index, in these cases, no value is given in this table. The result shows that the impacts of those factors discussed above are sometimes very different according to classifications. Among the five factors in Table 12, namely Cat_cap, Cat_avg_h, Cat_max_h, Cat_caa and Conference_location, only the impact of number of authors per paper is not affected by CCF classification. This means most Chinese researchers in computer science are working in bigger groups than before. As for the factor "annual average number of papers published of the publication", its impact is decreasing in class $B$ and $C$ conferences as well as those not in CCF list. However, the biggest class $A$ conferences attract more publications with a 161% percentage change. The negative influence of average $h$-index of all authors in a conference become more significant in class $C$ and A conferences and less significant in class $B$ conferences. The influence of the maximum $h$-index of all authors in a conference nearly disappears after 2013 except for class $C$ conferences. The most important differences exist for the factor "location where a conference is convened". We have found that the location of the conference affects the number of publications for all countries and its impact on Chinese researchers is decreasing. But if we take the classification into consideration, we can find that the decreasing trend are not shown in class $C$ conferences. However, for top conferences classified as A in CCF, the influence of this factor disappears. This lead to the conclusion that for researchers who are capable of publishing in top conferences, they do not care much where a conference is convened, and they just choose the ones with high quality and reputation.

To measure the consequences of changes relevant to CCF list, similar to the above mentioned Transformative Activity Index (TAI), we define three metrics—PCI (Publication Co-authorship Index), PARI (Publication Author Reputation Index) and PEI (Publication Efficiency Index)as follows:

$$\mathrm{PXI} = \frac{\left(\sum\limits_{s \in \mathrm{PublicationSet}(i,c,p)} C_s / n(i,c,p)\right)}{\left(\sum\limits_{s \in \mathrm{PublicationSet}(\mathrm{world},c,p)} C_s / n(\mathrm{world},c,p)\right)} \times 100 \qquad (5)$$

where $C_s$, denotes the counting value of a paper $s$ in a given subset. For PCI, PARI and PEI the equations are the same except that the counting values are number of authors, number of authors' $h$-index and number of citations received respectively; $\mathrm{PublicationSet}(i,c,p)$, denotes the publication set, where $i$ is the country, $p$ is the time period, and $c$ is the domain classification; $n(i, c, p)$, denotes the number of publications in $\mathrm{PublicationSet}(i,c,p)$; PXI, is a relative indicator compared to the world average. When the counting value of a country

**Table 12** xtNBRM: Percentage change in expected NPC of China compared with base for the set of conferences before and after 2013

| chi_npc | Not in CCF | | Classification C | | Classification B | | Classification A | |
|---|---|---|---|---|---|---|---|---|
| *Cat_cap* | | | | | | | | |
| 1 | Base | | | | | | | |
| 2 | 60.65** | 33.06 | 53.62* | − 5.64 | 56.55* | 71.08** | 0.15 | 10.97 |
| 3 | 175.54** | 74.61** | 69.49* | 19.76 | 80.27* | 59.39* | − 27.79 | 24.77 |
| 4 | 303.49** | 137.19** | 60.55* | 42.17 | 210.5** | 125.15** | 74.66 | 161.72* |
| *Cat_avg_h* | | | | | | | | |
| 1 | Base | | | | | | | |
| 2 | − 12.25 | − 8.82 | − 16.35 | − 33.21** | − 71.29* | 20.31 | | − 64.35** |
| 3 | − 30.95* | − 35.92* | − 5.88 | − 44.46** | − 61.76 | − 11.35 | 57.99* | − 76.72** |
| 4 | − 46.89** | − 36.6 | − 48.92** | − 63.77** | − 76.61** | − 25.81 | − 37.3 | − 83.34** |
| *Cat_max_h* | | | | | | | | |
| 1 | Base | | | | | | | |
| 2 | 12.19 | 22.48 | 4.35 | 21.48 | 502.74* | − 17.15 | | |
| 3 | 36.04* | 27.11 | 8.59 | 43.56* | 409.6 | − 9.49 | 220.7* | 37.72 |
| 4 | 54.34** | 27.18 | 32.34 | 79.54** | 516.69 | 4 | 129.1* | 43.74 |
| *Cat_caa* | | | | | | | | |
| 1 | Base | | | | | | | |
| 2 | 42.29** | 26.61 | 47.24* | 241.45** | 75.2* | 268.16** | 57.4* | 273.05* |
| 3 | 55.33** | 92.59** | 77.44** | 335.59** | 156.54** | 354.28** | 16.74 | 233.64* |
| 4 | 12.95 | 142.42** | 91.25** | 417.48** | 126.01** | 505.49** | 43.88 | 334.15** |
| *Conference_location* | | | | | | | | |
| Overseas | Base | | | | | | | |
| Inland | 323.09** | 119.33** | 99.52** | 87.51** | 139.43** | 62.26** | 62.23** | 8.45 |

For each classification, the first value is the percentage change before 2013 and the second one is that after 2013. Conferences of some classifications may not cover all categories of average and maximum *h*-index, in these cases, no value is given in this table

*Significant at 5%. **Significant at 1%

in the given subset equals to the world average, PXI = 100. PXI > 100 and PXI < 100 indicate higher and lower than the average respectively.

Table 13 shows the values of PXI of the five countries. By comparing the values before and after 2013, consequences of the changes in Chinese researchers' publication patterns can be found. All the three metrics of China and Australia increased after 2013. The values of Germany and US stayed the same. However, for India, all metrics decreased. According to the change in PCI, Chinese researchers now work in bigger groups, and the number of papers published in non-CCF listed conferences have become the biggest. The change of overall PARI for China is not significant but differences exist between classifications. The PARI increases only in class *A* publications and decreased greatly in class *C* publications. It is obvious that groups which are capable of publishing in class *A* conferences are growing in reputation. On the other hand, the decrease may have been caused by new researchers with low *h*-indexes who are trying to publish papers in CCF listed conferences. Considering the overall decrease in India, this can be considered unavoidable when the publication numbers are improving, and will be profitable in the long term since new researchers are involved. Among the three metrics, PEI is a direct indicator of publications impact, and China has a greater improvement than other countries from 57.55 to 66.91. Although far below the world average, Chinese researchers are making major progress especially in top conferences classified as A and B in the CCF list: from 62 to 72 and 70 to 76 respectively. A hierarchical pattern emerges after 2013 in China in both PARI and PEI, which can be seen as the direct consequence of CCF ranking. Besides this, the decrease of PEI in class *C* publications can be explained the same way as it was for PARI. According to the three metrics, we find that developed countries are always doing well but are not making any significant improvements.

## Conclusions

In this study, we conducted a comparative analysis of NPC in five selected countries (China, Australia, the US, Germany and India) for sets of computer science conferences separated by time period, i.e., before and after 2013. We focused on the publication patterns of authors in different countries and used several factors to characterize conferences. This kind of work concerning conferences is rarely undertaken since the assessment of conferences itself varies a lot. Our choice of factors is based on several objective metrics proposed in previous works and two well-known ranking systems, which make our study objective and meaningful. In addition, our approach does not involve any subjective means of evaluation, which opens up the possibility of using our method for other datasets using different metrics for further analyses.

In our study, the most important factors are classifications in CCF and CORE, along with CIF. These are direct assessments of conferences' quality, calculated or made by associations. By comparing the impacts of those factors on NPC of different countries, we can outline a series of phenomena. Most of those phenomena can be explained by considering the academic contexts of different countries. Besides this, we investigated other widely used factors, namely maximum and average *h*-index of all authors, number of authors per paper, location where a conference is convened and subfield. With our random effect NBRM results, we can give answers to the questions posed in Sect. 1 (Q1: What are the impacts of ranking systems on papers publishing process? Q2: Do they more likely to have a "local" effect or "global" one? Q3: What are other factors that researchers of

**Table 13** PXI of five countries before and after 2013

| | PCI | PARI | PEI |
|---|---|---|---|
| China | | | |
| *All classifications* | | | |
| Before 2013 | 110.13 | 69.32 | 57.55 |
| After 2013 | **115.75** | 70.26 | **66.91** |
| *Not in CCF* | | | |
| Before 2013 | 105.16 | **57.14** | **56.89** |
| After 2013 | **112.58** | 54.33 | 54.71 |
| *Classification C* | | | |
| Before 2013 | 117.67 | **85.04** | **66.76** |
| After 2013 | 117.78 | 69.43 | 58.88 |
| *Classification B* | | | |
| Before 2013 | 121.09 | **78.46** | 62.43 |
| After 2013 | 122.43 | 76.85 | **72.56** |
| *Classification A* | | | |
| Before 2013 | 111.98 | 85.59 | 70.65 |
| After 2013 | **114.01** | **88.01** | **76.82** |
| Australia | | | |
| *All classifications* | | | |
| Before 2013 | 93.75 | 108.13 | 77.39 |
| After 2013 | **97.76** | **121.09** | **85.85** |
| *Not in CCF* | | | |
| Before 2013 | 91.74 | 123.65 | 98.12 |
| After 2013 | **96.16** | **133.41** | 98.84 |
| *Classification C* | | | |
| Before 2013 | 94.35 | 111.71 | 90.69 |
| After 2013 | **99.61** | **123.39** | **94.18** |
| *Classification B* | | | |
| Before 2013 | **99.89** | 98.8 | 66.67 |
| After 2013 | 98.59 | **115.09** | **88.16** |
| *Classification A* | | | |
| Before 2013 | 98.16 | 113.44 | **87.9** |
| After 2013 | **101.57** | **120.72** | 83.57 |
| US | | | |
| *All classifications* | | | |
| Before 2013 | 100.38 | 130.07 | 153.98 |
| After 2013 | 99.87 | 131.57 | 154.32 |
| *Not in CCF* | | | |
| Before 2013 | 100.65 | 121.55 | 135.85 |
| After 2013 | 99.87 | **124.59** | 129.96 |
| *Classification C* | | | |
| Before 2013 | 98.28 | 120.48 | 130.63 |
| After 2013 | 98.09 | **127.17** | 131.9 |

**Table 13** continued

| | PCI | PARI | PEI |
|---|---|---|---|
| *Classification B* | | | |
| Before 2013 | 99.87 | 119.07 | 133.76 |
| After 2013 | 99.14 | 120.55 | 134.43 |
| *Classification A* | | | |
| Before 2013 | 100.7 | 117.39 | 130.87 |
| After 2013 | 99.31 | 118.49 | **135.85** |
| Germany | | | |
| *All classifications* | | | |
| Before 2013 | 98.76 | 111.7 | 104.73 |
| After 2013 | 96.82 | 113.04 | 106.67 |
| *Not in CCF* | | | |
| Before 2013 | **99.48** | 128.56 | 116.86 |
| After 2013 | 96.34 | 128.38 | 122.57 |
| *Classification C* | | | |
| Before 2013 | 96.94 | 108.51 | 107.84 |
| After 2013 | 96.36 | **113.59** | **118.22** |
| *Classification B* | | | |
| Before 2013 | **98.13** | 99.71 | 95.27 |
| After 2013 | 95.69 | **104.71** | **101.47** |
| *Classification A* | | | |
| Before 2013 | 100.12 | 103.3 | **108.11** |
| After 2013 | 101.32 | 101.43 | 101.13 |
| India | | | |
| *All classifications* | | | |
| Before 2013 | **88.67** | **61.5** | **59.96** |
| After 2013 | 84.34 | 52.43 | 48.4 |
| *Not in CCF* | | | |
| Before 2013 | **88.66** | **74.45** | **85.69** |
| After 2013 | 85.18 | 65.3 | 80.84 |
| *Classification C* | | | |
| Before 2013 | **94.4** | 63.22 | **80.81** |
| After 2013 | 84.14 | **69.17** | 69.18 |
| *Classification B* | | | |
| Before 2013 | 88.88 | **68.47** | **52.6** |
| After 2013 | 86.92 | 45.89 | 39.12 |
| *Classification A* | | | |
| Before 2013 | 82.07 | **39.12** | **35.18** |
| After 2013 | 80.94 | 32.3 | 23.94 |

The bigger values among those before and after 2013 are in bold, but when the two values are not very different (difference within 2), none of them are in bold and the value is considered not changed different countries care about when publishing papers? Q4: what are the consequences of the use of ranking systems?) Once these four questions were answered, we went on to find clues to the reasons for these differences. A discussion of the results of our study is presented in Sect. 4.3. To summarize: (1) In response to the first question, the impact of CCF classifications on Chinese researchers' publication behaviors is significant; they tend to publish a lot more in conferences with higher classifications in CCF and to some extent ignore those not listed. Researchers in India may also refer to CCF when deciding where to publish their works. CORE classifications also influence Australian researchers' behaviors but not as significantly. Thus, the conclusion is that ranking systems will change the publication patterns but the impacts of them varies from country to country. (2) The answer to the second question is that the impact of a ranking system is more "local" than "global". In other words, a ranking system constructed by a country can significantly influence the publication behaviors of researchers within it. However, its influence on the publication behaviors of researchers outside the country is less. It may serve as a reference for researchers in other countries but can never dominate their choices. This conclusion is true for both CCF (China) and CORE (Australia). As for other countries, sometimes a positive correlation does exist between a conference's classification and NPC. However, the level of this correlation never showed a hierarchical increase with the increase of a conference's classification. An exception can be found—before 2013, a quasi-hierarchical impact of CORE classification existed on NPC_China. But after 2013, those impacts suddenly disappeared. A possible reason is that before publishing the CCF list, Chinese researchers may have referred to the CORE list to distinguish conferences on the basis of quality. Shortly after publishing the CCF list, Chinese researchers did not need to refer to the CORE list anymore since they had their own list, which met their needs better. (3) Answering the third question, all the factors considered influenced the publication patterns of authors in one or more countries, only the degree of influence varies. Two common factors among all countries are the location of a conference and the average number of papers published in a conference. All countries tended to publish more papers in conferences which were convened inland or had a higher average number of papers. This is a consequence of the relatively low cost of attending a domestic conference and the relatively better reputation of larger conferences. Asian countries display a trend of increasing their international scientific communication. Concerning participants in a conference, Asian countries care more about well-known participants attending a conference while occidental countries care about both the average and high reputation of all participants. NPC for scientifically leading countries like the US and Germany are strongly positively correlated with CIF, while NPC for developing countries are either negatively or insignificantly correlated with it. As for collaborative patterns, computer science scientists in Asian countries prefer to work in groups, while those in occident countries prefer to work separately or with only one collaborator. The impact of subfields show the focus areas of different countries and the results are listed in 4.3.8. (4) To study the consequences of ranking systems, we examined CCF and found that it has brought major progress for China, and the impact of publications in top conferences are improving. However, we cannot ignore the decrease in the quality of publications in lower class conferences. This may be favorable in the long run since it could attract more researchers to attend these conferences, but this requires further study. Therefore, CCF rankings bring big changes to Chinese researchers and have positive impacts in the process of keeping up with the more scientifically leading countries.

Many studies on the impact of journals' IF and ranking have been conducted. Considering the increase in the importance of conferences, we attempted to find the impact of ranking systems and several other factors on them as well. In our work, we analyzed in detail how CCF has influenced the publication decisions of Chinese researchers. A preliminary analysis of the number of papers published in conferences listed and not listed in CCF was conducted using AI. We then conducted a regression analysis using random-effect NBRM to evaluate the different impacts of several factors concerning conference quality and popularity. We found that ranking lists do have a strong impact on researchers' publication behaviors. Moreover, it appears that CCF classifications have nearly dominated the choices of Chinese researchers. In fact, the list published by CCF has guided researchers in China for years, and it has accelerated the process of publishing more papers in top conferences as well as improving the quality of those publications. Countries with higher research levels have already established several standards to assess a conference and once a stable means of assessment is established, new rankings do not greatly influence their judgement. The analysis in this study about the influence of the CCF list, the first national assessment for conferences, is far from the end. It should be taken further to compare its influence on Chinese journal publications and conference publications. Differences can exist between them as assessment for journals existed before the publication of the CCF list, unlike for conferences.

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