COOPERATION AND DISCRIMINATION IN ACADEMIC PUBLISHING

A thesis submitted for the degree of Doctor of Philosophy

by

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ABSTRACT

This thesis consists of four essays in collaboration and discrimination. The first essay examines the role of collaboration as a determinant of publication productivity in the field of economics, measured by means of citations, journal rank, and journal impact factor. The analysis employs cross-sectional data of 1,512 journal publications published in 2012 in 16 economics journals. The findings show a positive effect of team size on publication productivity, whereas research teams consisting of only one gender perform better in terms of research quality than gender-mixed teams. The analysis also indicates a negative relationship between female-dominated teams and research productivity.

The second essay examines the impact of physical attractiveness on productivity. As literature found a strong impact on wages and career progression, it can be either due to discrimination in favour of good-looking people or can reflect an association between attractiveness and productivity. We utilise a context of academic publishing where there is no or limited face-to-face interaction. Using data on 2,800 authors, the results suggest that physical attractiveness has significantly important benefits. The third essay also considers the effect of physical attractiveness, as assessed based on pictures of top scientists, on their probability of winning the Nobel Prize. In contrast, the results show that attractiveness is negatively correlated with the probability of being awarded the Nobel, with the magnitude of this effect being not negligible.

The fourth essay analyses the subsequent publication success (i.e., the probability to publish in top journals, the publication productivity) of the contenders in a best paper prize awarded at an academic conference to see whether the winners' papers fare better than those that failed to get the prize, measured by rank and impact factor of the journal, and citations. We employ the data of nominees for the Distinguished CESifo Affiliate prize between 2008 and 2015. The findings indicate that winning has a positive effect on the quality of journals they published as well as the publication productivity, suggesting that scholars who succeed in their early stage of academia tend to success later compared to those who are not outstanding.

This thesis contributes to the literature on publication productivity and discrimination in academia by extending the existing literature on these issues. In this context, we explore the determinants of research productivity in economics (e.g., gender, nationality, seniority and others) and how those characteristics impact on productivity. We also investigate the role of beauty, and the presence of appearance-based discrimination, in determining research productivity among mainstream academics. We then re-examine the role of physical attractiveness at the top of the distribution of productivity, among Nobel Prize candidates/winners. Finally, we examine inequality in scientific research outcomes and the role of the so-called Matthew Effect. The findings shed light on the issues of collaboration, discrimination and inequality in academia.

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DECLARATION

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CHAPTER ONE

INTRODUCTION

Publications are becoming increasingly important in academia because of the reward system in place there. For example, publications are generally used to determine who gets hired, receives tenure or gets promoted, and whose funding application gets approved. In other words, research productivity is considered as a key indicator of productivity of scholars. Its quantity and quality can be measured by various means such as publication rates, citations, journal quality, and altmetrics. In social sciences, including economics, the number of citations received by others is one of the most commonly used measurements of peer recognition of a publication because it reflects the impact of that contribution onto peers (Laband and Piette, 1994). It also affects the author's market value out of academia (i.e., prestige, position in society). In addition, a university’s publications are used to indicate its national and international reputation at the institutional level and the funding amount for the institution can be based on publication productivity. For instance, the greater annual publication rates produced by academics may increase departmental funding (Silvestre *et al*., 2016). Consequently, these are the reasons why researchers endeavour to produce a high-quality publication. To achieve publication productivity, research production is the substantial topic that should be considered.

Scientific knowledge production has changed dramatically over the past few decades, from being dominated by single authors or small teams of researchers to a situation where most papers are co-authored, sometimes involving relatively large research teams (Davidson and Carpenter, 1979; Luukkonen *et al*., 1992; Wuchty *et al*., 2007; Hwang, 2008). Collaboration brings about numerous benefits due to the exchange of knowledge, skills, technologies, specialised instruments, equipment and software, and/or data. The knowledge outcomes of such collaboration have been increasing as a consequence; therefore, it is assumed by the previous studies regarding the importance of collaboration that increases research productivity (Narin, Stevens and Whitlow, 1991;

Katz and Hicks, 1997; Goldfinch, Dale and DeRouen, 2003; Lee and Bozeman, 2005; Wuchty *et al*., 2007; Sooryamoorthy, 2009; Börner *et al*., 2010). The benefits of such collaboration have been accepted widely as team's diverse backgrounds and perspectives tend to produce better results; however, those potential benefits may be neutralised by coordination issues (Stahl *et al*., 2010; Hackman, 2011) as dealing with many authors is similar to herding cats (Hellawell and Hancock, 2001). In this case, the approach on how authors in research teams collaborate to achieve research productivity is important to understand. Research teams generally are not formed randomly: the selection of co-authors should be motivated by their (expected) ability to contribute to the subject at hand, personal preferences, ease of communication (e.g. linguistic ability and/or cultural similarity) and the like. The characteristics of the research team, therefore, should be at even more important for the quality of the research and the impact of characteristics of the team for developing effective strategies in research production is of interest. The characteristics of author teams that we consider are gender, nationality, seniority, academic rank, and team size; and we examine their impacts on publication productivity in economics, measured by means of citation counts, journal ranking lists, and the journal impact factor (JIF). The following questions, therefore, form the basis for this study: (1) what are the factors (i.e., gender, nationality, seniority, academic rank, and team size) that determine the teams' productivity; and (2) how do these factors affect productivity? The answers to this question should be informative to researchers who conduct, lead or serve in decision-making in research production.

Another issue which emerges when dealing with a number of diverse people in a group or community is discrimination. A large amount of research regarding discrimination in the labour market investigates the differences in the outcomes by ethnicity, gender, religion, and other characteristics. Discrimination based on observable characteristics is illegal while appearance-based discrimination is not currently illegitimate and it has been the subject of litigations in recent years (Andreoni and Petrie, 2008). In parallel, the academic studies investigate this issue in various areas such as psychological experiments (Solnick and Schweitzer, 1999; Eckel and Wilson, 2004; Mobius and Rosenblat, 2006; Wilson and Eckel, 2006; Andreoni and Petrie, 2008) and sports (Callaway, 2009; Williams *et al*., 2010; Postma, 2014). Economic studies focus mostly on the correlation between beauty and labour-market outcomes such as the probability of employment (Watkins and Johnston, 2000; Dipboye and Dhahani, 2017), promotion and wages (Harper, 2000; Bowles *et al*., 2001; French, 2002; Mobius and Rosenblat, 2006; Fletcher, 2009; Scholz and Sicinski, 2015) to examine both the presence of discrimination and the potential role of beauty as a productive factor. The latter is interesting due to the contrasting assumptions drawn from the previous findings, according to which either beautiful people are more intelligent than those who are unattractive (Langlois *et al*., 2000; Zebrowitz *et al*., 2002; Kanazawa and Kovar, 2004), or beauty is an innate characteristic (Slater *et al*., 2000) and as such is not a strong factor of performance. By focusing on a field in which merit should play a crucial role and the potential for taste-based discrimination should be very limited or non-existent, e.g., academic publishing, it should be possible to examine whether beauty is correlated with productivity or not. For instance, if employers and co-workers use beauty to discriminate, attractive researchers may face better employment and promotion prospects, may have an easier time to find co-authors or become members of established teams. However, their good looks should not translate into higher publication rates, higher impact factor or especially into higher citation rates: editors, referees and readers do not usually meet the author face to face, and referees, who play an instrumental role in the process of turning manuscripts into publications, often do not even know who the authors are. So far, the evidence on this matter is scarce. In other words, we investigate this issue in academic publishing where the beauty of authors should not have significant effects on their research productivity. The questions, therefore, form the basis for this study: (1) is there a relationship between physical attractiveness and productivity in academic publishing, a context characteristic by the low degree of face-to-face interactions; and (2) how does the physical attractiveness affect productivity? Towards this end, we begin the analysis by investigating whether the effect of beauty exists in our sample and we then examine the extent of the effect of beauty on research productivity. Again, publication productivity is measured by means of citation counts, journal ranking lists, and the journal impact factor (JIF).

There is now an extensive body of literature that finds that physically attractive people receive non-negligible benefits in the labour market and other areas. For example, physical attractiveness has an important effect on one's well-being: attractive people tend to be happier and more content than their less attractive peers. We aim to add additional evidence to the literature on the effect of physical attractiveness in another area of academia. Specifically, we consider scientists who were predicted to win the Nobel Prize in physics, chemistry, medicine and economics between 2002 and 2014. The predictions are based on the reports by the Thompson Reuters Science Watch Hall of Citation Laureates, and reflect how often the scientists' work gets cited. Some but not all of the scientists highlighted by the Hall of Citation Laureates do go on to win the Nobel Prize. Likewise, some of the actual Nobel Prize winners are scientists overlooked by the Hall of Citation Laureates. The question, therefore, forms the basis for this study: does physical attractiveness have any bearing on whether a top scientist gets the Nobel Prize? The answer to this question will be evidence supporting the assumption raised by the previous literature that beauty is a reliable proxy for productive traits.

Another form of discrimination in scientific research, we recall the Matthew Effect attributed to Robert K. Merton in 1986 to explain inequality in the scientific community. In principle, it refers to the accumulated advantage whereby those who already have attained certain and reputation status, in turn, continue to fare well whereas those without the benefits of similar status struggle to attain recognition (Merton, 1968). In other words, scholars who succeed early in their academic career should also fare better later. The idea of the Matthew Effect has been applied widely in various fields, for example, it is linked to the notion that the rich get richer and the poor get poorer (Marx, 1844) and reflects the difference in academic performance among students (Stanovich, 1986; 2000). To address this issue, we aim to determine whether explicit ranking of research quality (i.e. being a winner of the best-paper prize at a competition), which is a form of early success, is informative as a predictor of subsequent publication success. The questions, therefore, form the basis for this study: (1) does winning impacts on the probability of being published in a high-quality journal; and (2) does winning impacts on publication productivity? To this end, we employ data of aspiring researchers nominated for the best paper award at CESifo area conferences, so-called the Distinguished CESifo Affiliate Award. We use the journal ranks listed in the ABS Academic Journal Quality Guide 2015 and journal impact factor as a measure of the journal quality. Again, we investigate the relationship between winners and publication productivity when they get published in those journals measured by citations, journal rank, and journal impact factor. The findings of this study aim to indicate correlation between being the winner and their later publication success and to observe the role of Matthew effect in this area.

The aforementioned questions have heretofore not been addressed adequately in scientific knowledge production; therefore, this thesis aims to examine the role of collaboration and discrimination in academia. Consequently, this thesis is based on four essays in the area of collaboration and discrimination. Specifically, **Chapter 2** endeavours to shed light on the determinants of collaborative research productivity. We collect detailed information on papers, and their authors, published in 2012 in 16 economics journals listed in Association of Business Schools (ABS) Journal Quality Guide (2010). The number of citations, obtained from Scopus and Google Scholar databases, received is considered as a basic indicator for productivity of a research team. However, citation index only is inadequate to represent team productivity comprehensively; thus journal impact factor and renowned ranking lists (i.e., Keele ranking and ERA ranking) are also included as productivity measures. To analyse the impact of author-team characteristics on research productivity, quantile regression which is robust to outliers, is employed as the main regression. We also run a linear regression as a robustness check. The statistical analysis reveals a negative relationship between gender diversity and research productivity, in other words, gender-mixed teams appear less productive than gender-homogenous teams. Similarly, the findings show a significant negative effect of the female-dominance in teams on productivity. There is a significant positive relationship between the number of authors in the team and the productivity in economics publications, in other words, multi-author publications are of higher quality than single-author publications. Regarding the relationship between academic rank diversity and research productivity, the significant correlation is not found. With seniority, we find a positive relationship between the percentage of senior author and productivity and a negative effect of average seniority on productivity, both in the conditional-mean model only. Finally, no relationship between nationality diversity and research productivity is found.

Chapter 3 extends the previous literature with regard to the role of physical attractiveness in the labour market. We investigate the impact of physical attractiveness in shaping publication productivity in academic publishing which is a context where physical attractiveness plays no or very limited role (i.e., the peer-review process is, as a rule, free of face-to-face interactions). The analysis is based on the same data base of articles and authors that we used in Chapter 2. We had these photos rated for the authors' attractiveness by survey participants, with 20 assessors rating each photo. We examine the extent to which physical attractiveness correlates with research productivity using weighted productivity, average productivity and average normalised citations as outcome measures. The results strongly suggest that being more attractive increases the probability to produce high-quality publications. In other words, the attractiveness of authors appears to be a productive factor. In respect of the location and shape shifts, the results show a stronger positive effect on research productivity for the middle and upper quantiles than in the lower quantiles. All in all, the attractiveness of authors has a significantly positive effect, which is stronger for the authors of better ranked and more often cited articles. Another strong predictor is the team size which also has a significantly positive effect on productivity in all models and measurements, that is, increasing in team size increases the possibility to produce the higher quality of the publication as confirmed in Chapter 2.

Due to the significantly positive effect of the physical attractiveness of authors on research productivity, **Chapter 4** aims to re-examine the role of physical attractiveness on the academics' activities, in particular their probability of winning the Nobel Prize. We employ the data of top scientists in four scientific disciplines (i.e., physics, chemistry, medicine and economics) who actually received the Nobel Prize, and the scientists who were reported as being most likely to win this award listed in the Thompson Reuters Science Watch Hall of Citation Laureates website, in both cases between 2002 and 2014 to examine the relationship between the physical attractiveness of scientists and the probability to win the Nobel Prize. University students who participated in this exercise were shown the pictures of scientists on the screen and were asked to rate the physical attractiveness of the person in the picture spontaneously. The probit regression model is used to analyse whether attractiveness has an impact on the probability that a top scientist receives the Nobel Prize. The findings report that being more attractive reduces the probability of receiving the Nobel Prize. The possible explanations are addressed as discrimination by which the selection committee would consider attractive scientists as less devoted, or the attractive scientists have more alternative activities besides hard work.

Chapter 5 examines the subsequent publication success of the nominees in the best paper prize awarded at an academic conference to see whether the winners' papers fare better than those that failed to get the prize. We consider the probability to publish in good journals and the productivity of the paper published as the measures of publication success. The data of nominees for the Distinguished CESifo Affiliate prize for the best paper presented at the CESifo conferences between 2008 and 2015 is used to analyse the impact of the winner. Controlling for nominee's personal background, conference type, and article background, the results of our analysis obtained from the ordered probit model (for the probability to publish in good journals) and the linear regression model (for the productivity of the paper published) suggest that young economists with the prize awarded tend to publish their work in the higher ranked journals and their works are likely to be of higher quality measured by citations, journal rank, and journal impact factor.

Finally, **Chapter 6** summarises the main findings and proposes several limitations of this thesis. Also, the suggestions regarding the further research on this topic in ways beyond the scope of this thesis are addressed.

This study aims to shed more light on a rather unexplored topic with respect to collaboration and discrimination in academia. Although, the topics of the determinants of productivity in academics, the impact of physical attractiveness on economics outcomes, and the inequality in academia have been investigated at least partially elsewhere, putting these topics together provides adds to the existing knowledge. We hope this thesis will be useful to several parties in order to devise regulation against beauty-based discrimination, and to manage research teams successfully, not only among academics but also in other areas of the labour market.

CHAPTER TWO

COLLABORATION AND RESEARCH IMPACT: THE CASE OF ECONOMICS PUBLICATIONS

2.1 Introduction

Scientific knowledge production has changed dramatically over the past few decades, from being dominated by single authors or small teams of researchers to a situation where most papers are co-authored, sometimes involving relatively large research teams. There are numerous benefits of working in a team: the team members benefit from division of labour reflecting their relative skills, particularly when their skills are complementary, and share proprietary technologies, specialised instruments, equipment and software, and/or data. Team size has been increasing over time, and knowledge outcomes of such collaboration have been increasing as a consequence. This shift leads to a question of how research collaboration impacts the quality of scientific publications. Does research collaboration result in a higher average quality of publications, more publication output (without affecting quality), or both?

The academic community has long been interested in the impact of collaboration on productivity, with the latter typically measured by means of publication rates and citation counts. In contrast, the impact of characteristics of co-author teams on research productivity has received less attention, especially in social sciences. This ignores a potentially important aspect of research collaboration. Research teams are not formed randomly: the selection of co-authors should be motivated by their (expected) ability to contribute to the subject at hand, personal preferences, ease of communication (e.g. linguistic ability and/or cultural similarity) and the like. The characteristics of the research team, therefore, should be at even more important for the quality of the ensuing research as the size of the team.

The answer to the question whether collaboration produces the higher quality publication in economics is beyond an exercise in academic curiosity. The importance of research quality is clearly explained as it has a market value to scholars in both a monetary and nonmonetary value such as wage or wage increments, professional standing, visibility, recognition, prestige, and prizes. These benefits would be of interest to economists particularly early stage academics if research team could produce higher-quality research. Many universities and grant-giving institutions believe that collaboration and research quality is positively correlated; they reward collaboration and promote it as a policy issue by offering their incentive structures for co-publications. Therefore, the findings of this study could provide substantial answers to this policy debate and research team managers.

This study aims to examine what characteristics of author teams (i.e., gender, nationality, seniority, academic rank, and team size) affect publication productivity in economics and how they impact the research outcomes, including citation counts, journal ranking lists, and the journal impact factor (JIF). Our results highlight the benefits of collaboration: larger teams, holding other factors constant, produce better research. Quality of publications appears to depend also on the gender mix of the research team: groups of co-authors of the same gender appear to do better than gender mixed teams. In contrast, teams composed of individuals of different academic rank or nationality do not fare any better or worse than teams that are more homogenous with respect to these characteristics.

The next section reviews the literature on the relationship between collaboration and research productivity. Section 3 discusses the methodology of this study including data, variables, and empirical model. Section 4 presents the descriptive statistics and results. The final section contains concluding remarks.

2.2 Literature review

Collaboration among researchers creates benefits in several ways. It produces intellectual benefits through knowledge and information sharing. It can bring about financial savings with respect to training cost and infrastructure building, and encourages better use of existing resources. Several studies attempt to identify the relationship between co-authorship and its impact on publication productivity. They generally find a positive relationship between them, that is, collaborative activities enhance research productivity measured by the numbers of publication and citation counts (Narin, Stevens and Whitlow, 1991; Katz and Hicks, 1997; Glänzel and Schubert, 2001; Hollis, 2001; Goldfinch, Dale and DeRouen, 2003; Beaver, 2004; Sooryamoorthy, 2009; Larivière *et al*., 2015). Durden and Perri (1995) employed time series data on annual economics publications over 24 years and find that the number of co-authored publications and the number of total publications are positively correlated. They conclude that collaboration increases both research productivity in total and per-capita article production. Abramo, D'Angelo and Caprasecca (2009), similarly, show that collaboration increases research productivity. Despite the evidence supporting the positive impact of collaboration on productivity, some contradictory effects of collaboration have also been identified. Working together on a project can reduce research expenses, yet an unavoidable consequence of collaboration is transaction costs because of the need to communicate with the other team members. Furthermore, access to physical facilities does not ensure that members will make the most of the facilities and cannot guarantee the success of the project. Although heterogeneity of team members improves decision quality, large teams with diverse members may make achieving consensus in decision-making difficult and time-consuming. As a consequence, team size can boost the frequency of interpersonal conflict, which obstructs team collaboration (Amason and Schweiger, 1994). Accordingly, diversity of team members with respect to attributes such as seniority and nationality are negatively connected with team outcomes (Gazni and Didegah, 2011; Stvilia *et al*., 2011). Human management, therefore, takes a significant role in such collaborative circumstances.

When many researchers collaborate in the same team, they are required to support each other to complete tasks, share resources, and finish projects on time. It challenges project managers to deal with large complex collaborative teams to maximise the team's abilities and minimise the weaknesses posed by their composition. Thus, understanding what characteristics of collaborative teams that could impact research productivity is necessary as it helps the research team managers to manage their teams to increase quality of the ensuing publications.

2.2.1 Gender diversity

When economists mention about the "gender gap", they usually point to differences in the outcomes that male and female achieve in the labour market. This gap seems to exist in the industrialised world even in the area of research as women fall behind men in many respects. Cole and Zuckerman (1984), therefore, highlight gender differences in research productivity as the "productivity puzzle". The attention to gender issues in academia initially mainly related to discrimination concerning employment and pay. In particular, there are fewer women in academia than men, and this disparity is particularly pronounced in the higher positions. European Commission (2006) reports that there is only one female academic for every 3.5 men working in the top academic ranks. Furthermore, the proportion of women in the scientific committees working in the European Community is about 20%, but in only 10% of cases, women were consigned to the leadership of these committees. Regarding the ability to achieve senior status, female academics remain at a considerable disadvantage compared to male colleagues. They are less likely than male peers to secure career paths such as full-time positions, tenure, and senior academic ranks (Mathews and Andersen, 2001; Corley and Gaughan, 2005). Robinson (2006) concludes that women are less likely to get PhD; therefore, there are few senior female academics. The findings from the Committee on Science, Engineering, and Public Policy report that for over three decades, more than 30% of PhDs were awarded to women but only 15.4% of full professors at the top research institutions are women (National Research Council, 2007).

With respect to research output, there is evidence which supports the proposition that female academics are less productive than male colleagues when considering publication rates (Fox, 1983; Cole and Zuckerman, 1984; Long, 1987; Lee and Bozeman, 2005). Kyvik (1995) studies data on scientists in the Norwegian university system and reveals that women produce on average 20% fewer publications than their male counterparts over a three-year period. A New Zealand study also confirmed that male academics were out-publishing females (Brooks, 1997). However, results from the previous literature suggest also that there is a relationship between productivity and academic rank, and the fact that women are working at lower ranks than men can explain their lower level of productivity. Without considering academic rank, men display higher productivity than women (Cole and Zuckerman, 1984; Long, 1992; Abbot, 2000). Given that a large number of studies note that publication rates of academic women are lower, on average, than those of men, gender can at least describe the disparities between genders regarding income and promotion opportunities. The study by Bentley (2003) suggests that the publication rate of women was lower than that of men because they were less likely to set up professional and collegial networks.

Concerning the relationship between gender and research quality, the results from the previous literature are mixed. Some studies argue that the impact of publications written by men and women is about the same (Long and Fox, 1995; Bordons *et al*., 2003; Mauleón and Bordons, 2006; Gonzalez-Brambila and Veloso, 2007). Other studies indicate higher impact of women's publications in particular scientific disciplines (Long, 1992; Borrego *et al*., 2010). Patents from women were found to have a higher impact than those of men (Whittington and Smith-Doerr, 2005). These studies provide support to the proposition that men focus on publication quantity, whereas women focus more on publication quality. Nevertheless, some studies show evidence that publications of women receive, on average, fewer citations than men's (Turner and Mairesse, 2005; Peñas and Willett, 2006). Even in the stereotypical perception, the gender of author affects the evaluation of articles or abstracts in which women are perceived to be less competent than men (Knobloch-Westerwick, Glynn and Huge, 2013; Krawczyk and Smyk, 2016).

Some gender gaps stem from difficulties with finding suitable co-authors as there are few female academics and they are likely to coordinate with the same-gender peers (Bentley, 2003). In this context, the role of networks is examined as there are inequities, particularly in gender. In academia, male researchers have systematically larger and stronger networks (Ding, Murray and Stuart, 2006; Monroe *et al*., 2008) and they may be reluctant to assist or collaborate with female peers (Gersick, Dutton and Bartunek, 2000). Moreover, females tend to concern with duties which hinder publication productivity. For instance, family responsibilities during childbearing years negatively impact on earning and career advancement of female academics (Mathews and Andersen, 2001; Suitor, Mecom and Feld, 2001; Bentley, 2003; Robinson, 2006; Prozesky, 2008; Sabelis and Schilling, 2013). Other significant factors include women spending their time on administration tasks and teaching (Maske, Durden and Gaynor, 2003). Men are considered as knowledge producers and more direct to research while women are considered as reproducers and more concern in teaching (Poole, Bornholt and Summers, 1997; Bagilhole and White, 2003).

The differences across disciplines in research productivity can also be substantial. Asmar (1999) obtained quantitative data from 1993 questionnaires from PhD graduates in eight Australian universities and qualitative data from other sources to investigate the research experiences of male and female academics at an early stage of their careers. The author finds that women are not on an equal footing with men; however, the stereotypical views of academic women's disadvantages are diminishing over time. The paper also casts new light on an important issue, namely, the effect of discipline. Most males in the sample were clustered in "hard sciences" where collaboration, team-driven research and informal mentoring are strongly supported, while female academics were in the humanities and social sciences where the nature of work is individualistic and person-oriented, with emphasis on solo monographs, and a low publication rate. The findings suggest that once research discipline is controlled for; the gender differences are considerably lower. In other words, the observed differences reflect disciplines, not gender. Abramo, D'Angelo and Caprasecca (2009) use bibliometric indicators on male and female academics working in Italian universities in scientific-technological disciplines. Their study confirms significant gender differences in research productivity; however, they are smaller than those reported in the previous contributions. They point out that gender differences decline over time, and confirm the presence of inter-disciplinary differences. The performance of women does not appear inferior in some scientific disciplines: Tower, Plummer and Ridgewell (2011) investigate the top six international journals across science, business, and social science, and find no gender difference in productivity when the percentage of female joining academia was factored in. In Journal Impact Factor ratings for both genders, there were also no statistically significant differences; thus quality differences were not a gender issue but rather a discipline difference. Otherwise, the unidentified disparity might be involved in discrimination in the publication process.

2.2.2 Size of author-team

Team size is one important issue that has been investigated regarding its impact on research performance. As contribution is divided among the team members, it is expected that more research contributors would cause the faster completion of the project. Also, large teams may encourage sharing of specialised knowledge and skills within the team together with having a stronger internal review to correct errors, which should result in higher quality of research outcomes. On average, publications by more than one author indeed appear to be of higher quality than single-author publications. Several studies support this assumption and conclude that there is a positive relationship between the number of team members and the scientific outcome (Beaver, 2004; Adams *et al*., 2005; Lee and Bozeman, 2005; Wuchty, Jones and Uzzi, 2007; Martín-Sempere, Garzón-García and Rey-Rocha, 2008; Sooryamoorthy, 2009; Fischbach, Putzke and Schoder, 2011; Gazni and Didegah, 2011). Hollis (2001) finds a positive relationship between the number of authors and the quality, length, and frequency of publications. However, after discounting the team size, the relationship between co-authorship and outcome attributable to the individual is negative.

Contrary to the evidence discussed above, a negative relationship between size and research productivity has also been found, that is, increasing team size lowers team productivity (Petersen *et al*., 2012). Publications with more authors do not necessarily receive more citations (Medoff, 2003; Haslam *et al*., 2008; Hinnant *et al*., 2012). Bergh and Perry (2006) conclude that team size is not a strong predictor of citation rates. Lead articles, placed at the beginning of a journal, are typically produced by a single author or a few authors (Piette and Ross, 1992, von Tunzelmann *et al*., 2003). According to the analysis of research institutes by the National Research Council (CNR) in Italy, the size of these institutes has a negative effect on scientific performance in three of six disciplines, which are chemistry, environment and engineering. The study also indicated that all productivity indicators decline with size and the smaller groups are more cost-efficient (Bonaccorsi and Daraio, 2002). Bridgstock (1991) studies 656 publications in four Australian science journals and confirms a negative relationship between team size and output. Also, the negative result occurs mainly in the social sciences, which are sometimes described as a "soft science" while most of the positive results obtain for "hard sciences". Abramo, D'Angelo and Caprasecca (2009) present similar results, whereby the relationship between the number of team members and outcome is strongly positive in industrial and information engineering fields only.

2.2.3 Seniority

Seniority is generally considered as an important element in research production because it is associated with social-hierarchical status, community prestige, research experience, as well as access to funding and other resources. Senior authors can act as intellectual and financial drives behind the project. According to team dynamics, having the notable senior scholars in the research team may raise the possibility of publication as well as affect the editorial review process, which leads to a higher number of citations (Haslam *et al*., 2008). This notion brings about the assumption that seniority within author team may affect intramural dynamics and leads to productive research. Also, seniority is related to the degree of researchers' integration and consolidation among the team members. Martín-Sempere, Garzón-García and Rey-Rocha (2008) argue that senior members tend to collaborate with larger teams and bring about the higher level of productivity. Literature has been examining the connection between research teams and productivity. They generally indicate seniority by the number of years since a scholar has received the doctoral degree or another key career milestone (Martín-Sempere, Garzón-García and Rey-Rocha, 2008) and the amount of time that members have been working in a particular team or institution (Cohen and Zhou, 1991). Also, Cohen and Zhou (1991) conclude that seniority negatively impacts on the level of interaction among team members. Applying different methods of seniority measurement may reflect different results, for example, Baldi (1998) measured seniority by the team's percentage of full professors and found no significant interaction between academic rank and the number of citations received.

2.2.4 Academic rank

A related issue to seniority is academic rank. Research teams are often comprised of researchers with different academic ranks. Academic rank is thought to be highly related to research productivity because promotion relies considerably on evidence of productivity. Productive researchers are both likely to attain a higher rank and serve as the head of the team. Consequently, they have better access to funds and projects (Bordons *et al*., 2003). Various scholars have investigated the effect of academic rank on scientific productivity and found a significant difference in productivity by varying rank. Their studies confirm a positive impact of academic rank on publication rates; in other words, full professors have a higher rate of publication than associate professors and assistant professors (Dickson, 1983; Kyvik, 1990; Martín-Sempere, Garzón-García and Rey-Rocha, 2008). Concerning the relationship between academic rank and research quality, there appears to be a positive impact of academic rank on both publication rates and citation counts (Shaw and Vaughan, 2008; Ben-David, 2010). Bordons *et al*. (2003) investigate the impact of publications by gender and academic rank in Natural Resources and Chemistry disciplines using the average impact factor of journals. They find that publication rate of full professors is higher than that of the lower professional ranks.

2.2.5 Nationality diversity

The mixture of knowledge and skills from several countries should be beneficial for scientific knowledge production. When human capital and physical resources from different backgrounds and cultures are combined, a rich blend of scientific inputs is generated. Various reasons could explain the benefits of collaboration, for instance, it enables researchers to work on many projects concurrently and encourages researchers to expand the scope of their research topics by integrating knowledge and skills from experts in different disciplines. The impact of nationality on research collaboration has been examined because international collaboration is considered to enhance visibility and research productivity. Previous studies concluded that publications with international collaborative teams are cited more frequently, on average, than those from domestic collaboration (Narin, Stevens and Whitlow, 1991; Schmoch and Schubert, 2008; Sooryamoorthy, 2009). Bordons *et al*. (1996) study the relationship between international collaboration and quality of publications in Spanish biomedical field and conclude that internationally co-authored papers appear to be higher in quality, and international teams are more productive than domestic ones. Abramo, D'Angelo and Solazzi (2011) investigate international collaborations of researchers from Italian university for the period 2001 to 2005 and take each researcher as the unit of analysis. Assuming that co-authorship is a proxy of research collaboration, the results show a positive impact of international collaboration on either research productivity or average output quality. Barjak and Robinson (2008) investigate the extent to which researchers in the life sciences make use of knowledge from different research cultures and its effects. Considering the quantity and quality aspect, they find a positive relationship between international collaboration and outcomes. The most successful teams consist of members from different countries and have a moderate level of team diversity. Narin, Stevens and Whitlow (1991) compare domestic versus multinational teams and find that biomedical papers from teams with a high level of nationality diversity gain more citations than those with less diversity. Katz and Hicks (1997) employ the data from various science and technology fields in the United Kingdom. They conclude that using citation index as a productivity measurement; publications by large teams with domestic researchers only but involving different institutions had the most impact. They also find that works produced by local and international members are cited more than those produced by single authors or only domestic collaborations. In contrast, other studies present evidence that internationally collaborated publications are not highly cited (Gazni and Didegah, 2011; Rey-Rocha *et al*., 2001). Cummings and Kiesler (2005) suggest that the difficulty of international collaborations might be lessened by gathering researchers into closer geographic proximity. Geographic proximity, in turn, might mitigate problems caused by cultural or linguistic barriers, which can be found in multi-national research teams.

2.3 Methodology

2.3.1 Data

The sample data of this study are obtained from 1,512 publications published in 2012 in 16 economics journals: American Economic Review, Economic Journal, Quarterly Journal of Economics, European Economic Review, Journal of Public Economics, Journal of Comparative Economics, Journal of Economic Dynamics and Control, Journal of Economic Behavior and Organization, Journal of Development Economics, Labour Economics, Applied Economics, European Journal of Political Economy, Economic Modelling, Contemporary Economic Policy, Open Economies Review, and German Economic Review. The journals were selected so as to cover the full range of academic journals in economics, from leading journals to relatively low ranked ones. Special issues of these journals are excluded from the analysis because the selection criteria for including papers in special issues may be different from regular issues. We collect detailed information on the publication (i.e., name of article, volume, issue, start page, end page, author number, citation rate, journal ranking index, journal impact factor) and the author or all co-authors (i.e., name, affiliation, gender, institution and country of first degree and PhD, the year of first-degree award and PhD, academic rank) from multiple sources such as personal website, curriculum vitae, and institutional website. The research team, a collaborative group of economists contributing to research production, is defined as the main unit of analysis. The summary statistics for all data are reported in Appendix A.

2.3.2 Variables

Measurement of research productivity

Research productivity is a key indicator for performance appraisement in economics as well as other fields. It can be measured by several means. In the context of research production, research can be compared to an input-output process in which researchers and financial resources are considered as inputs. Outputs are categorised into two types; tangible (e.g. publications, patents, and presentations) and intangible (e.g., knowledge, skills, and consulting activities) so that it is important to utilise an accurate output measurement because it can account for the real contribution of the researchers in their works. Measuring research productivity is a complicated task because it can be assessed and monitored at many levels and for various purposes. At the micro-level, for instance, universities and research institutions consider the number of publications and citations as a measurement of researchers' performance. The previous publications of individual are considered in the evaluation process and also have an effect on salary and promotion. At the macro-level, governments take research output into account when deciding on how to allocate research funds (Gonzalez-Brambila and Veloso, 2007). In general, the quantity aspect of research productivity can be measured by publication rates whereas citation rates including the journal impact factors reflect the quality aspect.

Although citation indexes have generally been considered as indicative of research quality, there are some arguments about the effectiveness of such indexes (Hirsch, 2007), with various alternative means of impact becoming widely used such as journal impact factor and the H-index. The H-index shows either the number of publications per researcher or citation counts per publication. While the H-index attempts to correct for the weaknesses of the citation index, it does not adjust for some collaboration specific factors (Petersen *et al*., 2012). Therefore, citation analysis remains a primary metric for quality appraisal (Schmoch and Schubert, 2008). Citation-based metrics continue to serve as a basis for funding and tenure decisions as well as for measuring the relative standing of journals (Haslam *et al*., 2008; Ioannidis, 2008). Hurley, Ogier and Torvik (2013) argue that the "identification of certain collaboration patterns leading to higher citation counts would be considered a significant contribution to bibliometrics and would offer a potential method for normalization of citation numbers in order to arrive at a more accurate tool for impact measurement". As a rule, journal articles are perceived as a seal of approval by the wider community confirming that the paper has been judged by the journal editors to be a particular importance.

2.3.2.1 Dependent variable

Productivity in this study focuses on the publication impact in term of quality rather quantity. To this effect, various indices are applied to measure the productivity of research. Specifically, a weighted productivity index used in this paper combines normalised citations from Scopus and Google Scholar (together with a weight of 50%), normalised journal ranking from Excellence in Research for Australia (ERA) and the Keele list from Keele University (together 30%), and normalised journal impact factor from Thomson Reuters Journal Citation Reports (20%). As an alternative, we also use average productivity, calculated using the same set of indexes as the weighted productivity but with equal weights. The list of all indices used in this analysis is as follows;

1. Citation Index

The citation numbers gathered from Scopus and Google Scholar databases are used to construct a citation index. To take account of the different scales of these two databases, the citation counts are normalised by dividing them by the maximum citations observed in the sample. This results in citations based on each source ranging from 0 to 1. The citation index then is constructed as the average of normalised citations per publication from both databases. Given that the publications used in this research were published in 2012, the cut-off dates for the citation counts from Scopus and Google Scholar were 11th October 2013 and 27th October 2013, respectively.

2. Journal impact factor

The Journal Impact Factor (JIF) is an assessment applied to journals and commonly refers to the average number of citations obtained during a given year for the articles published in that journal during the previous two years. In general, citable items are articles, reviews, proceedings, or notes; however, editorials or letters to the editor are excluded. The impact factor was introduced in 1960 by Dr Eugene Garfield, the founder of the Institute for Scientific Information (ISI) which is currently part of Thomson Reuters and it was used as an index to select journals to the ISI database. In 1975

Thomson Reuters started to publish the Journal Citation Reports (JCR) after applying journal statistical data only in-house for many years. The Journal Citation Reports (JCR) offers a systematic channel to evaluate, rank, categorise, and compare journals with quantifiable and statistical information based on cited rate of articles. The journal impact factor, as a combination of impact metrics, and millions of cited and citing journal data points compiled by the JCR, helps users assess the actual position of the journal. The journal impact factor (JIF) provided by the ISI Journal Citation Reports (JCR) is used in this study, and the calculation is expressed as follows;

$$JIF = \frac{\text{Total cites received this year for the articles published in the journal in the previous two years}}{\text{Total number of articles published in the journal in the previous two years}}$$

3. Journal ranking lists

Another method to determine the quality of publications is comparing subjective perceptions of journal rank. A number of journal ranking lists are available. Journal ranking is one of the metrics that determines how a journal performs compared to other journals in the same field. Publications in higher-ranked journals are more likely to be cited and receive a high impact score consequently. In general, it is assumed that the more renowned the journal, the stricter the publishing process. That is to say, an article, which is accepted by the editors of a high-ranked international journal, will be perceived as being of higher quality than an article accepted in a lower-ranked journal. This reflects the significant role of journal reputation in scientific research. Journal ranking lists are broadly used in academic communities to evaluate quality and impact of academic journals. The rankings indicate the position of a journal among all journals within its discipline and the relative difficulty of publishing in it. Several journal ranking lists are widely used to assess journal quality in business and economics. In this study, the Excellence in Research for Australia (ERA) and the Keele list from Keele University are applied to measure the impact of journals.

We use the Keele and ERA lists for measuring research productivity by means of journal rank in this thesis. The reasons for this selection are due to the fact that the Keele list is produced so as to mirror economist's views. This list was originally conceived to serve the Department of Economics at Keele University. Although the Keele list is obsolete as it provides information for the year 2006, it has been widely used to evaluate the quality of economics publications in the UK. Moreover, the Keele list puts the focus on economics and on theoretical journals whilst the Association of Business Schools (ABS) list focuses on business and management (Hudson, 2013). We also use the Excellence of Research in Australia (ERA) list, an active journal ranking lists compiled by the Australian government, as a measurement of research productivity regarding journal-ranking to provide a guide to quality. It is a benchmark for journal evaluation and is widely used in many countries (e.g., in the UK). The list continuously comes along with a set of enhancements with regard to maintaining the rigour and comparability. Importantly, the list reflects international prestige, which serves to encourage academics not to be espouse a single-country's research focus.

Figure 2-1 Explication of productivity variable

Determinants of research productivity

The objective of this study is to identify the factors that determine the authors' productivity. Previous contributions suggest several possible relationships between author-team diversity and their productivity.

D1: Gender diversity within the author team

Previous research points out that gender diversity might have either positive or negative effect on team research productivity. A higher level of gender diversity might bring about high-quality research, particularly in cognitive tasks. However, such diversity might also raise the probability of intra-team difficulties because of dissimilarity between genders and emotional conflict within teams (Pelled, Eisenhardt and Xin, 1999). The gender diversity index is calculated as follows;

$$Gender\ diversity = \frac{the\ number\ of\ the\ minority\ gender\ in\ team}{the\ number\ of\ the\ majority\ gender\ in\ team}$$

The index thus ranges between 0 (only one gender is represented in the team) to 1 (both genders are equally represented in the team).

As an alternative measure of gender diversity, we also use the Herfindahl index:

$$Hgender = \sum_i s_i^2$$

where s_i refers to the share of the group i in the author team (in this case, there are two groups, males and females). For homogenous teams, the Herfindahl index takes the value of one. At its lower bound, the index approaches zero, with lower values representing greater heterogeneity. We compute similar indexes to capture also the diversity with respect to academic rank and nationality in the author teams (see below). Note that, by construction, single-author teams are perfectly homogenous and therefore always have the Herfindahl index equal to one.

D2: Female dominance of author team

The previous literature suggests that females tend to be more collaborative but less competitive than males, which should make them better collaborators (Berdahl and Anderson, 2005). The recent studies also pointed out a significant advantage for female dominated teams (Woolley *et al*., 2010; Dasgupta, Scircle and Hunsinger, 2015). Dasgupta, Scircle and Hunsinger (2015) added that having more females in teams allows them to participate more actively, shrug off worries, and feel confident than other teams. It would be expected that more females in the research team should boost collaboration in the team and produce a higher quality of publications as a consequence. The female dominance index is calculated from;

$$Female\ dominance = \frac{the\ number\ of\ female\ authors\ in\ team}{the\ number\ of\ author(s)\ in\ team}$$

The female dominance index also ranges from 0 (no female collaborators in the research team) to 1 (team composed entirely of women).

D3: Size of team

Some researchers conclude that there is no correlation between team size and publication productivity (Seglen and Aksnes, 2000, Haslam *et al*., 2008). Furthermore, previous research found that the bigger the size of the team, the higher the level of difficulty in coordination (Beaver, 2004). However, there is also numerous evidence that the citation rates for an article increases as a consequence of greater team size (Lawani, 1986; Katz and Hicks, 1997; Baldi, 1998; Gazni and Didegah, 2011). We therefore include the number of co-authors participating in the research team as an explanatory variable.

D4: Academic rank diversity within the author team

Academic rank is thought to be an important factor in research production because higher academic rank tends to be associated with greater research experience, as well as better access to resources and greater prestige. Many studies find that academic rank has a positive association with research impact, that is, full professors have a tendency to produce more high impact publications compared to associate professors or assistant professors (Bonzi, 1992; Adkins and Budd, 2006; Shaw and Vaughan, 2008). However, full professors also have to contribute more of their time to other administrative tasks in their faculties or institutions. Therefore, their workload might mitigate innovation and motivation of senior academics in research production. The rank diversity index is calculated as follows;

$$Rank\ diversity = \frac{the\ number\ of\ academic\ ranks\ in\ team}{the\ number\ of\ author(s)\ in\ team}$$

The maximum value that this index can attain is thus 1 (each author is of different rank), while lower values indicate relatively homogenous research teams.

As with gender diversity, we also compute the Herfindahl index of rank diversity (see above for the formula).

D5: Seniority within the author team

Seniority might heighten the researcher's status; however, it might hinder the interaction with other co-authors (Cohen and Zhou, 1991). As senior researchers have more experience, connections, and prestige, they are more likely to participate in broader projects and research networks. Therefore, they tend to be members of larger teams and those larger teams bring about more productive research effort (Martín-Sempere, Garzón-García and Rey-Rocha, 2008). To identify author team seniority, we consider two group-level indexes: full professor percentage and average professional age of all authors in the team where the professional age was derived as the number of years since the individual has received their doctoral degree until the publication year (2012).

D6: Nationality diversity within the author team

Nationality diversity in scientific research production is thought to be beneficial regarding supplement resources, a variety of knowledge, and a pool of skills. Scholars claim that internationally collaborated papers are more highly cited (Narin, Stevens and Whitlow, 1991; Schmoch and Schubert, 2008; Sooryamoorthy, 2009). However, some researchers argue that papers with the higher number of foreign collaborators are not highly cited (Rey-Rocha *et al*., 2001). The nationality diversity index is calculated from;

$$Nationality\ diversity = \frac{the\ number\ of\ nationalities\ in\ team}{the\ number\ of\ author(s)\ in\ team}$$

As with rank diversity, the maximum value of this index is 1 (each author is of different nationality) while lower values indicate relatively homogenous research teams.

Again, we also use the Herfindahl index of nationality diversity (see above for the formula) as an alternative measure of the nationality mix in the author team.

2.3.2.2 Independent variables

The independent variables reflect the author-team characteristics and another indicator:

Gender

- Gender diversity
- Female dominance of author team

Team size

- Number of author(s) in team

Academic rank

- Academic rank diversity

Seniority

- Average seniority
- Percentage of senior authors in team

Nationality

- Nationality diversity

Other indicator

- Publication length (page count)

Table 2-1 Description of variables

Variable	Definition
Dependent variable	
w_productivity	Weighted citation index, impact factor, and journal rank in Keele and ERA Lists
avg_productivity	Average of citation index, impact factor, and journal rank in Keele and ERA lists
Independent variables	
sexdiv	Gender diversity; value varies from 0 to1; 0 < sexdiv < 0.5 is low level of gender diversity; 0.5 < sexdiv < 1 is high level of gender diversity
femdom	female dominance of author team; value varies from 0 to1; 0 < femdom < 0.5 is male-dominated team; 0.5 < femdom < 1 is female-dominated team
teamsize	Number of author(s) in team
rankdiv	Academic rank diversity; value varies from 0 to1; 0 < rankdiv < 0.5 is low level of rank diversity; 0.5 < rankdiv < 1 is high level of rank diversity
seniorpercent	Percentage of full professors in team
avgseniority	Average professional age* of all author in team
natdiv	Nationality diversity; value varies in a range of 0 to1; 0 < natdiv < 0.5 is low level of nationality diversity; 0.5 < natdiv < 1 is high level of nationality diversity
publength	Publication length; number of pages of the interested publication

*professional age was derived from the number of years since an individual has received a doctoral degree until the publication year (2012)

Table 2-2 List of dummy variable values and codes

Gender

Values	Value codes
Male	0
Female	1

Academic rank

Values	Value codes
Assistant professor	1
Associate professor	2
Full professor	3
Others	9

Ethnicity*

Values	Value codes
White	1
Black	2
South Asian**	3
East Asian***	4
Middle Eastern	5

*Ethnicity was determined by the author based on the author's picture, name and country of origin.

**This ethnic group is classified as the population of South Asia, which are the nations of India, Pakistan, Sri Lanka, Bangladesh, Bhutan, Nepal, and Maldives.

***East Asian people are classified as those who live in Asian countries other than South Asia or the Middle East.

Considering a reference group for dummy variables, male is defined a reference group for gender; white is defined a reference group for ethnicity; and professor is defined a reference group for academic rank. Table 2-4 shows a descriptive statistics of authors by rank, gender, and journal. Table 2-5 shows a distribution of authors of sixteen journals by gender and academic rank.

2.3.3 Model specification

There are two measurements for research productivity in this study; weighted productivity and average productivity. The weighted productivity is considered as a main dependent variable in this study. The average productivity is considered as a benchmark for research productivity, and it is calculated by averaging the three indexes as for the weighted productivity index. And the specification of the research productivity equation is:

$$Productivity_i = \alpha + \beta 1{*}GenderDiversity_i + \beta_2{*}FemaleDominance_i + \beta_3{*}TeamSize_i + \beta_4{*}RankDiversity_i + \beta_5{*}AverageSeniority_i + \beta_6{*}SeniorPercentage_i + \beta_7{*}NationalityDiversity_i + \beta_8{*}PublicationLength_i + \varepsilon_i \quad (1)$$

where $Productivity_i$ denotes the research productivity, $GenderDiversity_i$ ranges from 0 to 1; the value comes to zero refers to low level of gender diversity and the value comes to one refers to high level of gender diversity, $FemaleDominance_i$ ranges from 0 to 1; the value below 0.5 refers to male-dominated team and the value above 0.5 refers to female-dominated team, $TeamSize_i$ signifies the number of authors in the research team, $RankDiversity_i$ ranges from 0 to 1; the value comes to zero refers to low level of rank diversity and the value comes to one refers to high level of rank diversity, $AverageSeniority_i$ denotes the average professional age of all authors in team, $SeniorPercentage_i$ is the percentage of full professors in team, $NationalityDiversity_i$ ranges from 0 to 1; the value comes to zero refers to low level of nationality diversity and the value comes to one refers to high level of nationality diversity, $PublicationLength_i$ is the number of pages of the publication. α is the level of non-qualified research productivity.

2.4 Results

2.4.1 Descriptive statistics

The descriptive analysis shows that the number of co-authored publications is much higher than single author publications. In 16 journals, only 388 of 1,512 publications, or 25.7%, are single-author publications while 74.3% of all publications are joint publications. Across all journals, more than 60% of all articles are co-authored publications, and the average of normalised citations per co-authored publication is higher than that of single author publications. Team size ranged from one to eight authors, and two-author publications are the largest category of all publications (655, or 43.3%). The citation numbers gathered from Scopus database for 1,512 publications ranged from 0 to 28 while those from Google database ranged from 0 to 356. Finally, only 5.59% of authors have published more than one publication in our sample.

Table 2-3 Number and percentage of publications and average number of citations for publications with different number of author(s)

Number of author(s)	Number of publications	Percentage of publications
1	388	25.66
2	655	43.32
3	360	23.81
4	90	5.952
5	15	0.992
6	2	0.132
7	1	0.066
8	1	0.066
Total	1,512	100

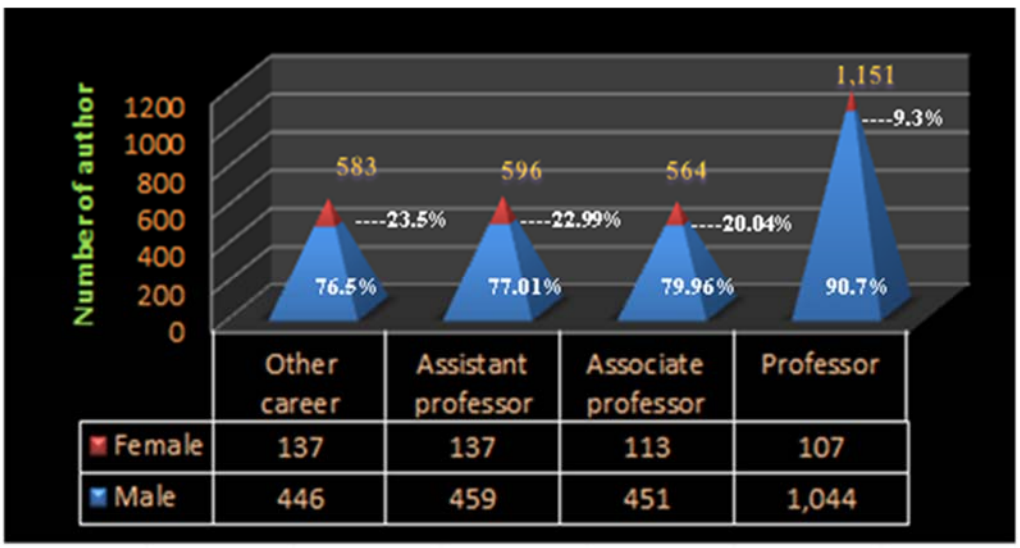
Table 2-4 Descriptive statistics of authors by position, gender, and journal

Position	**Gender**	American Economic Review	Economic Journal	Quarterly Journal of Economics	European Economic Review	Journal of Public Economics	Journal of Comparative Economics	Journal of Economic Dynamics and Control	Journal of Economic Behavior and Organization	Journal of Development Economics	Labour Economics	Applied Economics	European Journal of Political Economy	Economic Modelling	Contemporary Economic Policy	Open Economies Review	German Economic Review	**Total**	**Total (both genders)**
Full Professors	**M**	130	45	50	82	52	19	73	113	52	31	150	30	131	30	33	23	1,044	1,151
	F	10	7	4	11	5	2	6	15	6	1	21	4	10	3	1	1	107	
Associate Professors	**M**	47	16	12	36	23	11	25	41	32	7	80	10	90	14	6	1	451	564
	F	12	2	1	9	6	2	7	16	5	5	21	2	21	2	1	1	113	
Assistant Professors	**M**	60	20	13	40	31	11	28	46	21	10	52	16	84	13	5	9	459	596
	F	19	3	6	7	6	6	7	13	14	9	18	3	18	3	3	2	137	
Others*	**M**	31	37	11	27	14	17	34	36	31	24	50	14	82	12	16	10	446	583
	F	8	6	7	12	6	2	6	14	15	8	19	4	19	3	4	4	137	
Total	**M**	268	118	86	185	120	58	160	236	136	72	332	70	387	69	60	43	2,400	2,894
	F	49	18	18	39	23	12	26	58	40	23	79	13	68	11	9	8	494	
Total (both genders)		317	136	104	224	143	70	186	294	176	95	411	83	455	80	69	51		2,894

Table 2-5 Distribution of authors of sixteen journals by gender and academic rank

Rank	**Male**	**Female**	**Total**
Assistant professor	459	137	596
Associate professor	451	113	564
Professor	1,044	107	1,151
Other career	446	137	583
Total	2,400	494	2,894

Figure 2-2 Proportion of male and female academics in each tenure rank



Note: This figure is based on data of 2,894 authors from 16 economics journals

2.4.2 Findings

First, each variable used in the analysis has been checked for normality of distribution using Shapiro–Wilk normality test and Shapiro–Francia normality test. The results of these tests indicate that response variables are not normally distributed ($p < 0.0001$). Nonparametric methods are suitable techniques to deal with the response that is not normally distributed because they can provide a comprehensive view of relationship (Cade and Noon, 2003; Koenker and Hallock, 2001).

Table 2-6 Normality of distribution by variable

Panel A: Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
w_productivity	1,512	0.9293	64.9150	10.5050	0.0000
avg_productivity	1,512	0.9411	54.0680	10.0440	0.0000
sexdiv	1,277	0.9681	25.0720	8.0570	0.0000
femdom	1,277	0.9681	25.1030	8.0600	0.0000
teamsize	1,512	0.9800	18.3790	7.3280	0.0000
rankdiv	913	0.9632	21.3440	7.5510	0.0000
seniorpercent	1,268	0.9967	2.5450	2.3360	0.0097
avgseniority	928	0.9097	53.1660	9.8100	0.0000
natdiv	913	0.9877	7.0900	4.8320	0.0000
publength	1,512	0.8510	136.9200	12.3830	0.0000

Note: The normal approximation to the sampling distribution of W is valid for 4<=n<=2000.

Panel B: Shapiro-Francia W' test for normal data

Variable	Obs	W'	V'	z	Prob>z
w_productivity	1,512	0.9309	67.1700	9.8990	0.0000
avg_productivity	1,512	0.9429	55.5510	9.4520	0.0000
sexdiv	1,277	0.9739	21.7400	7.1690	0.0000
femdom	1,277	0.9747	21.0620	7.0950	0.0000
teamsize	1,512	0.9877	11.9680	5.8400	0.0000
rankdiv	913	0.9637	22.3510	7.0820	0.0000
seniorpercent	1,268	0.9981	1.5770	1.0590	0.1447
avgseniority	928	0.9106	55.9510	9.1830	0.0000
natdiv	913	0.9970	1.7950	1.3340	0.0911
publength	1,512	0.8512	144.8150	11.7070	0.0000

Note: The normal approximation to the sampling distribution of W' is valid for 10<=n<=5000.

For this reason, a Spearman correlation is selected to analyse the relationship between all variables (see Table 2-7), and a quantile regression[1] with the 50th percentile is selected to analyse the impact in this study instead of the classical ordinary least squares regression. The dependent variables (i.e., weighted productivity and average productivity) appear to be highly correlated according to the Spearman correlation (see Table 2-7); therefore, the two variables are analysed separately. The impact of author team characteristics on weighted productivity and average productivity according to OLS and median regression are presented in Table 2-8 and Table 2-9 respectively. The other variables; gender diversity, female dominance, team size, academic rank diversity, percentage of full professor in the team, average professional age, nationality diversity, and article length are considered as independent variables in the models.

1 The quantile regression is described in more detail in Chapter 2 (Methodology Section).

2.4.2.1 OLS and Median Regression Results

To analyse the impact of author-team characteristics on research productivity, quantile regression which is robust to outliers is employed as the main regression, with the dependent variable (i.e., weighted productivity and average productivity) taking values from 0 to 1. We also run OLS regression as a robustness check. The median-regression model, or the 0.5th quantile, is the simplest quantile regression model to understand. It provides the conditional median of the dependent variable given the independent variables and constitutes a natural alternative to the linear-regression model that fits the conditional mean. It is natural to compare OLS and median regressions because they both endeavour to model the central location of the response distribution and the interpretation of the median-regression coefficient is similar to that of the linear-regression coefficient. In this study, we use bootstrapping approach for estimation of standard errors because the i.i.d. restricts to the assumption that expects no shapeshift of the response. Therefore, the more flexible approaches such as bootstrapping should be applied to estimate standard errors as it allows flexible errors and offers a numerical solution to the complex asymptotic method. Besides, the bootstrapped point estimates are analogous to the asymptotic approach, but they are likely to give smaller or larger standard errors than those from the asymptotic standard errors approach. In other words, the bootstrap reports a lower level of precision of the estimate at the 0.5th quantile than the asymptotic estimate (Koenker, 2005; Hao and Naiman, 2007).

We start by including all variables in the same regression. Publication length appears to be a strongly significant predictor of publication quality. However, this variable may itself be a product of the research-team characteristics: larger teams or those with more senior authors, for example, may write longer papers. We therefore omit this variable from columns 3 to 8, to allow the regressions to give greater weight to the other variables that can be correlated with publication length and productivity alike. Furthermore, as gender diversity and female dominance are closely related to each other, we first include both in the same regression (columns 3-4) and then consider their effects separately (columns 5-8).

Table 2-7 Spearman correlation matrix

	w_prod~y	avg_pr~y	sexdiv	femdom	teamsize	rankdiv	senior~t	avgsen~y	natdiv	puble~h
w_productivity	1									
avg_productivity	0.9976***	1								
sexdiv	-0.0419	-0.0405	1							
femdom	-0.0025	-0.0020	-0.7198***	1						
teamsize	0.2098***	0.2070***	-0.3647***	0.1263***	1					
rankdiv	-0.1288***	-0.1289***	0.2750***	-0.1220***	-0.5892***	1				
seniorpercent	0.1010**	0.0999**	-0.0500	-0.1029**	0.3125***	-0.0976**	1			
avgseniority	0.0362	0.0354	-0.0795*	-0.0738*	0.3125***	-0.1620***	0.6444***	1		
natdiv	-0.0181	-0.0204	0.1506***	-0.0484	-0.2607***	0.2336***	0.0024	-0.0916**	1	
publength	0.4676***	0.4681***	-0.0019	0.0083	0.1376***	-0.0629	0.0290	0.0094	-0.0235	1

Notes: * p<0.05, ** p<0.01, *** p<0.001

Table 2-8 Impact of author team characteristics on weighted productivity according to OLS and median regression

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)	(7) OLS	(8) QR(0.5)
sexdiv	0.0035	0.0171	0.0038	0.0015	-0.0166	-0.0460*		
	(0.0156)	(0.0220)	(0.0165)	(0.0422)	(0.0170)	(0.0225)		
femdom	-0.0153	-0.0228	-0.0415	-0.0739			-0.0370*	-0.0739*
	(0.0201)	(0.0281)	(0.0280)	(0.0542)			(0.0167)	(0.0348)
teamsize	0.0173*	0.0173	0.0290**	0.0453**	0.0282**	0.0460**	0.0289***	0.0453***
	(0.0077)	(0.0105)	(0.0109)	(0.0150)	(0.0106)	(0.0168)	(0.0086)	(0.0132)
rankdiv	0.0161	0.0053	0.0154	0.0185	0.0144	0.0100	0.0153	0.0185
	(0.0118)	(0.0162)	(0.0130)	(0.0284)	(0.0160)	(0.0256)	(0.0142)	(0.0271)
seniorpercent	0.0002	0.0002	0.0003*	0.0002	0.0003	0.0002	0.0003	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
avgseniority	-0.0010	-0.0005	-0.0022*	-0.0008	-0.0022*	-0.0008	-0.0023*	-0.0008
	(0.0008)	(0.0013)	(0.0010)	(0.0015)	(0.0011)	(0.0016)	(0.0009)	(0.0018)
natdiv	-0.0139	-0.0191	-0.0103	-0.0068	-0.0088	0.0017	-0.0101	-0.0068
	(0.0116)	(0.0151)	(0.0139)	(0.0313)	(0.0175)	(0.0319)	(0.0195)	(0.0316)
publength	0.0084***	0.0096***						
	(0.0004)	(0.0005)						
constant	0.0869***	0.0570	0.2330***	0.1830***	0.2320***	0.1820**	0.2330***	0.1830***
	(0.0239)	(0.0317)	(0.0314)	(0.0518)	(0.0313)	(0.0566)	(0.0259)	(0.0536)
N	611	611	611	611	611	611	611	611

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

The impact of the various diversity variables on research productivity is as follows. **D1** predicts a negative relationship between gender diversity within the author team and team research productivity. Considering columns 5 and 6, the statistical analysis reveals a negative correlation ($p<0.05$) between gender diversity and weighted productivity in the conditional-median model which is -0.0460, while the effect is not found in the conditional-mean model ($p=0.328$). An increase in gender diversity by one would translate into a decrease in weighted productivity by 0.0460, or approximately 19.25%.

D2 predicts a positive relationship between female dominance and team research productivity. Considering columns 7 and 8, the statistical analysis shows a significant negative effect of the female-dominated team on weighted productivity

($p<0.05$), both with OLS and quantile regression at 0.5th quantile. The coefficient of female dominance index in the conditional-median model, 0.0739, is higher than the coefficient in the conditional-mean model, which is 0.0370. That is, an increase in female dominance index by one reduces weighted productivity by 0.0739, or 31%.

D3 predicted a positive effect of an increase in team size on productivity. Considering columns 3 and 4, results of the analysis using weighted productivity as the dependent variable show a significant positive interaction ($p<0.01$) between the variables, both with OLS and quantile regression at 0.5th quantile. The coefficient of team size in the conditional-median model, 0.0453, is higher than the coefficient in the conditional-mean model which is 0.0290. Therefore, each additional co-author increases weighted productivity by 0.0453, or 18.95%.

D4 predicted a negative relationship between academic rank diversity and team research productivity. Results of the analysis using weighted productivity as the dependent variable indicate a positive correlation, but it falls short of statistical significance ($p=0.515$) in the conditional-median model. The insignificant positive relationship ($p=0.236$) is also confirmed in the conditional-mean model.

D5 predicted a positive relationship between seniority and research productivity. For seniority, two variables, percentage of senior authors and average seniority, are applied in the analysis. Using weighted productivity as a dependent variable, the results show a positive relationship between the percentage of senior author and productivity ($p<0.05$) in the conditional-mean model; however, it is not statistically significant in the conditional-median model ($p = 0.510$). On the other hand, the results show a negative effect of average seniority on weighted productivity ($p<0.05$) in the conditional-mean model; however, it is again not statistically significant in the conditional-median model ($p = 0.598$).

D6 predicted a negative relationship between nationality diversity and research productivity. The model using weighted productivity as the dependent variable shows a negative effect of nationality diversity on but they fall short of statistical significance in both the conditional-median model ($p = 0.826$) and the conditional-mean model ($p = 0.459$).

Table 2-8 measures gender, rank and nationality diversity by means of measures introduced above. In Table 2-9, we replace these with Herfindahl indexes. The Herfindahl index is a widely used measure of concentration (and competition) in industrial economics, defined as the sum of squared market shares. In our analysis, we use it to measure the homogeneity of author teams, where the relevant shares are those of the various categories: males and females with respect to gender, the four academic ranks, and nationalities. However, using this index to depict the diversity of author teams has three potentially important drawbacks. First, whereas in the market place, we would typically observe dozens or hundreds firms, we are considering author teams, the vast majority of which count no more than three members. Second, the nature of academic collaboration is non-random: co-authors tend to form teams with their colleagues and peers, so that many teams involve collaborators of the same nationality and often also rank. Third, one paper out of four in our sample is written by a single author and two out of three have no more than two co-authors. Single-author teams are, by definition, perfectly homogenous and the lowest possible value for a two-author team is 0.5. Hence, most of the author teams appear relatively homogenous according to the Herfindahl index.

These weaknesses may help explain the relatively disappointing results for diversity reported in Table 2-9. While team size and publication length remain strongly significant as determinants of publication quality, none of the Herfindahl indexes shows much significance. In further results, we added interaction terms between team size and the three Herfindahl indexes, to account for the fact that single-author teams all are perfectly homogenous. None of these interaction terms turned out significant, however, suggesting that the effect of author homogeneity is not dependent on team size.

The effect of covariates on the average productivity is reported in Appendix A-2. The results are in line with those reported in Table 2-8 particularly the team size variable, with the small difference in the effect and significance of covariates. However, the effect of gender diversity is not found in both the conditional-mean model and the conditional-median model with the average productivity while the negative effect of female dominance is found only in the conditional-median model.

Table 2-9 Impact of author team characteristics on weighted productivity according to OLS and median regression (Herfindahl indexes)

	(1) **OLS**	(2) **QR(0.5)**	(3) **OLS**	(4) **QR(0.5)**	(5) **OLS**	(6) **QR(0.5)**	(7) **OLS**	(8) **QR(0.5)**
hgender	-0.0089 (0.0275)	-0.0107 (0.0330)	0.0186 (0.0288)	0.0482 (0.0464)	0.0173 (0.0205)	0.0441 (0.0302)	-0.0075 (0.0176)	-0.0004 (0.0414)
femdom	-0.0159 (0.0151)	0.0004 (0.0209)	-0.0075 (0.0140)	0.0023 (0.0239)				
teamsize	0.0133 (0.0080)	0.0093 (0.0086)	0.0293*** (0.0083)	0.0405** (0.0150)	0.0325*** (0.0061)	0.0432** (0.0158)		
hrank	-0.0318 (0.0204)	-0.0124 (0.0247)	-0.0333 (0.0240)	-0.0431 (0.0511)	-0.0013 (0.0192)	0.0216 (0.0366)	-0.0639*** (0.0163)	-0.0620* (0.0300)
senior_autpercent	0.0002* (0.0001)	0.0003* (0.0002)	0.0004* (0.0002)	0.0007* (0.0003)				
avgseniority	-0.0010 (0.0006)	-0.0014 (0.0011)	-0.0018* (0.0009)	-0.0021 (0.0014)				
hnat	0.0252 (0.0262)	0.0457 (0.0286)	0.0137 (0.0315)	-0.0285 (0.0639)	0.0066 (0.0203)	0.0422 (0.0456)	-0.0039 (0.0245)	0.0032 (0.0601)
publength	0.0080*** (0.0005)	0.0095*** (0.0005)						
constant	0.1150* (0.0454)	0.0603 (0.0582)	0.2190*** (0.0523)	0.1980* (0.0952)	0.1650*** (0.0334)	0.0510 (0.0746)	0.3090*** (0.0271)	0.2630*** (0.0602)
N	909	909	909	909	1285	1285	1285	1285

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

2.4.2.2 Considering other individual conditional quantiles

We are also interested in the other quantiles of the distribution of productivity in addition to the median. The quantile regression estimates for weighted productivity across the quantiles are presented in Table 2-10. We can see that the team size increases research productivity across the productivity distribution excluding the 0.1^{th} and 0.9^{th} quantiles, with the strongest effect observed at $0.4\text{-}0.5^{th}$ quantiles. In other words, the number of co-authors matters little for the relatively unproductive and most productive teams alike while it is important for moderately productive teams.

Being a female-dominated team has a negative effect only at the 0.6^{th} quantile. For the full professor percentage, the positive effect only appears at the two highest quantiles. The average professional age of all author in the team likewise has a small negative impact at the three highest quantiles, that is, having more experienced co-authors in the team slightly impedes the ability to produce high-quality publications. A possible explanation for this somewhat counter-intuitive result is that senior authors have limited incentives to produce high-quality research, given that they face few career insecurities.

As before, replacing the diversity measures with the Herfindahl indexes of concentration results in little indication that homogenous and heterogeneous teams differ in terms of productivity (see Table 2-11). Again, this may be attributable to the low suitability of the Herfindahl index to this context.

The quantile regression estimates across quantiles using average productivity as the dependent variable is reported in Appendix A-3. The results are very much in line with the results reported in Table 2-10, with the small difference in the effect and significance of covariates.

Table 2-10 Quantile regression estimates for weighted productivity across quantiles

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
sexdiv	0.0009 (0.0126)	0.0020 (0.0179)	0.0147 (0.0264)	0.0131 (0.0289)	0.0015 (0.0352)	0.0292 (0.0302)	0.0020 (0.0392)	-0.0035 (0.0342)	0.0140 (0.0386)
femdom	0.0008 (0.0153)	-0.00856 (0.0332)	-0.0205 (0.0394)	-0.0656 (0.0452)	-0.0739 (0.0436)	-0.1130* (0.0477)	-0.0211 (0.0629)	-0.0320 (0.0514)	-0.0650 (0.0645)
teamsize	0.0157 (0.0092)	0.0262*** (0.0070)	0.0309* (0.0125)	0.0444* (0.0218)	0.0453*** (0.0136)	0.0239* (0.0116)	0.0345** (0.0113)	0.0343** (0.0121)	0.0203 (0.0185)
rankdiv	0.0072 (0.0106)	-0.0032 (0.0093)	0.0100 (0.0133)	0.0261 (0.0234)	0.0185 (0.0264)	0.0079 (0.0158)	0.0067 (0.0116)	0.0055 (0.0197)	0.0151 (0.0276)
seniorpercent	0.0001 (0.0001)	0.0001 (0.0002)	0.0002 (0.0002)	0.0000 (0.0004)	0.0002 (0.0004)	0.0003 (0.0003)	0.0005 (0.0003)	0.0008* (0.0003)	0.0010* (0.0004)
avgseniority	-0.0014 (0.0010)	-0.0010 (0.0008)	-0.0023* (0.0012)	-0.0002 (0.0019)	-0.0008 (0.0018)	-0.0020 (0.0012)	-0.0025* (0.0011)	-0.0039* (0.0016)	-0.0055* (0.0025)
natdiv	0.0044 (0.0068)	-0.0071 (0.0087)	-0.0333 (0.0219)	-0.0282 (0.0331)	-0.0068 (0.0326)	-0.0079 (0.0211)	-0.0034 (0.0185)	0.0033 (0.0238)	-0.0042 (0.0297)
constant	0.0997*** (0.0224)	0.0994*** (0.0217)	0.1300*** (0.0326)	0.1190* (0.0506)	0.1830*** (0.0497)	0.2960*** (0.0363)	0.2940*** (0.0348)	0.3380*** (0.0474)	0.4440*** (0.0577)
N	611	611	611	611	611	611	611	611	611

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Table 2-11 Quantile regression estimates for weighted productivity across quantiles (Herfindahl indexes)

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
hgender	-0.0064	0.0042	0.0084	0.0421	0.0482	0.0233	0.0356	0.0366	0.0226
	(0.0270)	(0.0253)	(0.0399)	(0.0542)	(0.0494)	(0.0529)	(0.0432)	(0.0344)	(0.0677)
femdom	0.0029	0.0004	0.0286	0.0064	0.0023	-0.0196	0.0038	0.0001	0.0137
	(0.0178)	(0.0137)	(0.0265)	(0.0189)	(0.0173)	(0.0372)	(0.0277)	(0.0167)	(0.0376)
teamsize	0.0156*	0.0220***	0.0262*	0.0296	0.0405**	0.0314*	0.0417***	0.0317***	0.0324*
	(0.0073)	(0.0055)	(0.0119)	(0.0185)	(0.0142)	(0.0151)	(0.0088)	(0.0096)	(0.0145)
hrank	-0.0093	0.0067	-0.0193	-0.0236	-0.0431	-0.0461	-0.0059	-0.0312	-0.0453
	(0.0192)	(0.0169)	(0.0346)	(0.0495)	(0.0483)	(0.0415)	(0.0244)	(0.0343)	(0.0536)
senior_autpercent	0.0000	0.0002	0.0003	0.0004	0.0007**	0.0004*	0.0003*	0.0005*	0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
avgseniority	-0.0024**	-0.0017*	-0.0023**	-0.0026	-0.0021	-0.0016	-0.0010	-0.0014	-0.0002
	(0.0008)	(0.0007)	(0.0009)	(0.0013)	(0.0012)	(0.0012)	(0.0010)	(0.0014)	(0.0017)
hnat	-0.0076	0.0231	0.0591	0.0536	-0.0285	0.0145	0.0035	0.0057	0.0206
	(0.0138)	(0.0124)	(0.0312)	(0.0485)	(0.0599)	(0.0445)	(0.0387)	(0.0384)	(0.0595)
constant	0.1330***	0.0867***	0.0873	0.1030	0.1980*	0.2580**	0.2340***	0.3070***	0.3700***
	(0.0386)	(0.0255)	(0.0618)	(0.0890)	(0.0865)	(0.0930)	(0.0671)	(0.0585)	(0.1053)
N	909	909	909	909	909	909	909	909	909

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

2.5 Conclusions

While collaboration nowadays becomes increasingly important in scientific research production, collaborative research production is generally more complex and less structured than single-authored work. This trend encourages teams including independently organised teams to interact with other associations for improving their works by getting feedback and peer-reviews (Douglas and Gardner, 2004; Stvilia *et al*., 2008). Effective cooperation requires careful concentration to target, operate, and manage the differences among co-operators (Benda *et al*., 2002; Eigenbrode *et al*., 2007).

This paper attempts to shed light on the determinants of collaborative research productivity. This study uses the number of citations received as a basic indicator for team productivity, which is obtained from Scopus and Google Scholar databases. However, citation index only is inadequate to represent team productivity comprehensively; thus other metrics and sources of data that can determine the quality of publications should be applied for measuring the productivity of teams' outcome (Stvilia *et al*., 2011). For this reason, journal impact factor and other renowned ranking lists (i.e., Keele ranking, ERA ranking) are also included in the analysis.

The statistical analysis reveals a negative relationship between gender diversity and research productivity: gender-mixed teams appear less productive than gender-homogenous teams. Similarly, the findings show a significant negative effect of the female-dominance in teams on productivity. There is a significant positive relationship between the number of authors in the team and the productivity in economics publications, in other words, multi-author publications are of higher quality than single-author publications. Regarding the relationship between academic rank diversity and research productivity, any significant correlation is not found. With seniority, we find a positive relationship between the percentage of senior author and productivity and a negative effect of average seniority on productivity, both in the conditional-mean model only. Finally, no relationship between nationality diversity and research productivity is found.

Future studies should examine more in-depth the effects of team composition (i.e., pattern and types of team associations) by interviewing team members to observe and collect qualitative data such as motivations for participating in the team. Because there are some omitted variables, which should be included in the analysis for bringing about a better comprehension to this topic. A more representative sample, which might be in different academic fields, should be used to investigate the relationship in the further studies. Moreover, a time period between the published year and cut-off date for citation counts should be left longer because this will provide enough time for some publications, which have not yet been cited so far to receive more citation rates. The next chapter, therefore, uses the update citation counts with the later cut-off date in the analysis. These suggestions should help further studies produce an adequate and comprehensive model to understand the association of composition of teams and research productivity.

Appendix A

Appendix A – 1 Summary statistics

Variable	N	Mean	Std.Dev.	Min	Max
women_number	1,277	0.363	0.608	0	5
men_number	1,277	1.712	0.925	0	5
sexdiv	1,277	0.179	0.345	0	1
femdom	1,277	0.173	0.296	0	1
teamsize	1,512	2.143	0.929	1	8
rank_number	1,268	1.603	0.638	1	4
rankdiv	913	0.629	0.417	0	1
senior_author_number	1,268	0.812	0.867	0	4
senior_author_percent	1,268	35.82	37.05	0	100
avgseniority	928	12.86	8.148	0	53
seniority_difference	1,268	6.860	9.533	0	48
nationality_number	1,268	1.159	0.379	0	3
natdiv	913	0.180	0.354	0	1
article_length	1,512	16.12	9.155	1	75
citations_scopus	1,512	1.373	2.475	0	28
normcite_scopus	1,512	0.049	0.088	0	1
citations_gscholar	1,512	11.45	27.08	0	356
normcite_gscholar	1,512	0.032	0.076	0	1
avgnormcite	1,512	0.040	0.077	0	0.964
rank_keele	1,512	2.693	0.822	1	4
normrank_keele	1,512	0.564	0.274	0	1
rank_era	1,512	3.330	0.603	2	4
normrank_era	1,512	0.665	0.302	0	1
jif	1,512	1.243	1.001	0.404	5.278
norm_jif	1,512	0.172	0.205	0	1
productivity	1,512	0.239	0.136	0	0.880
average_productivity	1,512	0.297	0.157	0	0.884
hgender	1,337	0.888	0.201	0.111	1
hrank	1,301	0.743	0.257	0.250	1
hnat	1,293	0.929	0.173	0.250	1

Appendix A – 2 Impact of author team characteristics on average productivity according to OLS and median regression

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)	(7) OLS	(8) QR(0.5)
sexdiv	0.0030	0.0197	0.0034	0.0216	-0.0190	-0.0528		
	(0.0211)	(0.0369)	(0.0253)	(0.0495)	(0.0148)	(0.0395)		
femdom	-0.0171	-0.0248	-0.0453	-0.0998*			-0.0414	-0.0914*
	(0.0293)	(0.0527)	(0.0310)	(0.0496)			(0.0227)	(0.0415)
teamsize	0.0191*	0.0207	0.0317**	0.0412*	0.0307*	0.0446**	0.0316**	0.0455*
	(0.0080)	(0.0141)	(0.0115)	(0.0206)	(0.0123)	(0.0165)	(0.0103)	(0.0195)
rankdiv	0.0192	0.0054	0.0184	0.0182	0.0174	0.0101	0.0183	0.0109
	(0.0144)	(0.0188)	(0.0155)	(0.0461)	(0.0172)	(0.0369)	(0.0157)	(0.0291)
seniorpercent	0.0002	0.0003	0.0003	0.0002	0.0004*	0.0002	0.0003	0.0003
	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0002)	(0.0005)	(0.0002)	(0.0004)
avgseniority	-0.0011	-0.0006	-0.0025*	-0.0011	-0.0025*	-0.0010	-0.0025*	-0.0011
	(0.0009)	(0.0019)	(0.0012)	(0.0022)	(0.0013)	(0.0025)	(0.0011)	(0.0020)
natdiv	-0.0126	-0.0220	-0.0087	-0.0065	-0.0072	-0.0021	-0.0085	0.0009
	(0.0142)	(0.0242)	(0.0172)	(0.0417)	(0.0165)	(0.0398)	(0.0184)	(0.0383)
publength	0.0090***	0.0107***						
	(0.0004)	(0.0006)						
constant	0.1350***	0.0967*	0.2920***	0.2750***	0.2910***	0.2680***	0.2920***	0.2660***
	(0.0273)	(0.0415)	(0.0352)	(0.0803)	(0.0362)	(0.0545)	(0.0309)	(0.0684)
N	611	611	611	611	611	611	611	611

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Appendix A - 2 (continued) The impact of author team characteristics on average productivity according to OLS and median regression (Herfindahl indexes)

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)	(7) OLS	(8) QR(0.5)
hgender	-0.0077	-0.0034	0.0220	0.0552	0.0179	0.0471	-0.0086	-0.0003
	(0.0290)	(0.0369)	(0.0347)	(0.0538)	(0.0210)	(0.0342)	(0.0187)	(0.0648)
femdom	-0.0154	0.0088	-0.0063	0.0061				
	(0.0170)	(0.0186)	(0.0196)	(0.0141)				
teamsize	0.0146*	0.0097	0.0318**	0.0450**	0.0347***	0.0583**		
	(0.0059)	(0.0096)	(0.0101)	(0.0151)	(0.0068)	(0.0185)		
hrank	-0.0381	-0.0245	-0.0397	-0.0529	-0.0046	0.0349	-0.0713***	-0.0498
	(0.0223)	(0.0319)	(0.0313)	(0.0545)	(0.0216)	(0.0508)	(0.0162)	(0.0571)
senior_autpercent	0.0003*	0.0004*	0.0004**	0.0010**				
	(0.0002)	(0.0002)	(0.0002)	(0.0004)				
avgseniority	-0.00130	-0.0019	-0.0021*	-0.0031*				
	(0.0007)	(0.0014)	(0.0010)	(0.0015)				
hnat	0.0229	0.0452	0.0106	-0.0562	0.0032	0.0478	-0.0080	0.0023
	(0.0268)	(0.0314)	(0.0360)	(0.0774)	(0.0254)	(0.0744)	(0.0269)	(0.0853)
publength	0.0087***	0.0108***						
	(0.0004)	(0.0005)						
constant	0.1710***	0.1050	0.2830***	0.2860**	0.2250***	0.0632	0.3790***	0.3090***
	(0.0463)	(0.0623)	(0.0638)	(0.1055)	(0.0427)	(0.1027)	(0.0223)	(0.0868)
N	909	909	909	909	1285	1285	1285	1285

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Appendix A – 3 Quantile regression estimates for average productivity across quantiles

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
sexdiv	0.0019	0.00204	0.0229	0.0214	0.0216	0.0415	-0.0025	0.0007	0.0000
	(0.0164)	(0.0166)	(0.0266)	(0.0337)	(0.0453)	(0.0439)	(0.0414)	(0.0377)	(0.0392)
femdom	-0.0002	-0.00693	-0.0305	-0.0838	-0.0998*	-0.1400*	-0.0348	-0.0589	-0.0394
	(0.0136)	(0.0295)	(0.0446)	(0.0529)	(0.0481)	(0.0669)	(0.0729)	(0.0653)	(0.0587)
teamsize	0.0131	0.0355**	0.0408	0.0530	0.0412*	0.0277*	0.0292**	0.0333**	0.0162
	(0.0151)	(0.0133)	(0.0228)	(0.0296)	(0.0168)	(0.0123)	(0.0110)	(0.0108)	(0.0142)
rankdiv	0.0060	-0.00161	0.0111	0.0257	0.0182	0.0067	0.0089	0.0153	0.0090
	(0.0259)	(0.0062)	(0.0227)	(0.0326)	(0.0354)	(0.0200)	(0.0156)	(0.0234)	(0.0337)
seniorpercent	0.0000	0.0000726	0.000266	0.000126	0.0002	0.0003	0.0005*	0.0009**	0.0010*
	(0.0003)	(0.0002)	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0005)
avgseniority	-0.0013	-0.000776	-0.00276	-0.000758	-0.0011	-0.0019	-0.0027**	-0.0048**	-0.0050*
	(0.0020)	(0.0010)	(0.0014)	(0.0023)	(0.0016)	(0.0010)	(0.0010)	(0.0017)	(0.0025)
natdiv	0.0027	-0.00535	-0.0380	-0.0295	-0.0065	-0.0162	-0.0003	0.0058	0.0052
	(0.0101)	(0.0097)	(0.0293)	(0.0438)	(0.0439)	(0.0222)	(0.0205)	(0.0246)	(0.0339)
constant	0.1480**	0.1170***	0.1610**	0.1650*	0.275***	0.3700***	0.397***	0.4370***	0.5390***
	(0.0450)	(0.0306)	(0.0499)	(0.0664)	(0.0573)	(0.0358)	(0.0288)	(0.0394)	(0.0534)
N	611	611	611	611	611	611	611	611	611

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Appendix A - 3 (continued) Quantile regression estimates for average productivity across quantiles (Herfindahl indexes)

	(1) Q(0.10)	(2) Q(0.20)	(3) Q(0.30)	(4) Q(0.40)	(5) Q(0.50)	(6) Q(0.60)	(7) Q(0.70)	(8) Q(0.80)	(9) Q(0.90)
hgender	-0.0034	-0.0011	0.0140	0.0557	0.0552	0.0031	0.0334	0.0581	0.0457
	(0.0415)	(0.0241)	(0.0549)	(0.0591)	(0.0509)	(0.0571)	(0.0345)	(0.0347)	(0.0568)
femdom	0.0032	-0.0005	0.0386	0.0208	0.0061	-0.0371	0.0065	-0.0027	0.0188
	(0.0400)	(0.0177)	(0.0321)	(0.0261)	(0.0269)	(0.0469)	(0.0261)	(0.0213)	(0.0340)
teamsize	0.0191	0.0207*	0.0332**	0.0395*	0.0450**	0.0374***	0.0344***	0.0303***	0.0340*
	(0.0104)	(0.0093)	(0.0120)	(0.0169)	(0.0148)	(0.0109)	(0.0074)	(0.0088)	(0.0134)
hrank	-0.0143	0.0060	-0.0145	-0.0233	-0.0529	-0.0351	-0.0211	-0.0465	-0.0510
	(0.0404)	(0.0271)	(0.0435)	(0.0633)	(0.0626)	(0.0385)	(0.0196)	(0.0391)	(0.0502)
senior_autpercent	0.0001	0.0001	0.0004	0.0005	0.0010***	0.0004	0.0005*	0.0006**	0.0003
	(0.0003)	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
avgseniority	-0.0033**	-0.0016	-0.0025*	-0.0027	-0.0031*	-0.0017	-0.0016	-0.0019	0.0000
	(0.0012)	(0.0011)	(0.0012)	(0.0015)	(0.0014)	(0.0013)	(0.0011)	(0.0014)	(0.0018)
hnat	-0.0155	0.0257	0.0703	0.0443	-0.0562	0.0275	-0.0102	-0.0010	0.0112
	(0.0273)	(0.0209)	(0.0450)	(0.0962)	(0.0689)	(0.0486)	(0.0318)	(0.0406)	(0.0477)
constant	0.1810**	0.1320***	0.1010	0.1330	0.2860**	0.3310***	0.3600***	0.3950***	0.4400***
	(0.0613)	(0.0335)	(0.0806)	(0.1126)	(0.0878)	(0.0891)	(0.0555)	(0.0569)	(0.0872)
N	909	909	909	909	909	909	909	909	909

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

CHAPTER THREE

BEAUTIFUL MINDS:
THE IMPACT OF BEAUTY ON RESEARCH PRODUCTIVITY IN ECONOMICS

3.1 Introduction

Economists have long been pointing out that wages depend on various characteristics such as gender, ethnicity, education and experience. The findings yield a broad range of factors which have been shown to have an important impact on earnings, some of which reflect workers' productivity (see, for example, the overview by Heckman, Lochner and Todd, 2006), while others reflect market returns to observable characteristics that should have little bearing on productivity (the seminal contribution on the economics of discrimination is Becker, 1971). In this context, another issue is the so-called 'halo effect' or 'physical attractiveness stereotype' whereby beauty also gets rewarded by higher wages. This observation was initially made by psychologists who argued that physical attractiveness serves as a signal for intelligence and sociable behaviour (Langlois *et al*., 2000; Zebrowitz *et al*., 2002; Kanazawa and Kovar, 2004). Evidence from trust and public goods games indeed confirms that physically attractive individuals are expected to be more cooperative and trustworthy than unattractive ones (Wilson and Eckel, 2006; Andreoni and Petrie, 2008).

Since physically attractive people are expected to behave better than unattractive people in social interactions, it is not surprising that attractiveness can have a positive return in the labour market. Physical attractiveness in the area of employment, beauty plays a significant role in securing interview call backs (Kraft, 2012), determining interviewers' judgments (Watkins and Johnston, 2000), and also has an important effect on wages (Frieze *et al*., 1991; Hamermesh and Biddle, 1994; Biddle and Hamermesh, 1998). The finding of a positive impact of beauty on labour market outcomes has been shown across all industries, both in high-visibility positions and low-visibility positions. We often see that occupations where attractiveness is likely to play a role (e.g. salespersons or newscasters) are filled by good-looking people. However, there is evidence supporting that the physical attractiveness bias also exists even for the positions that require a low degree of public exposure (Cash *et al*., 1977; Watkins and Johnston, 2000).

Although most results from the literature pointed out that unattractive candidates are considered less favourably than attractive ones, some studies showed findings opposing the beauty premium finding, the so-called 'Beauty is Beastly' effect. For instance, the reverse beauty bias was found for female candidates applying for traditionally masculine jobs so that attractive females were considered less favourably than unattractive ones (Cash *et al*., 1977; Heilman and Saruwatari, 1979; Johnson *et al*., 2010). Accordingly, Heilman and Saruwatari (1979) who introduced the "beauty is beastly" effect found that beauty is consistently beneficial for male candidates. However, beauty was an advantage only for female candidates who applied for traditionally female jobs. Attractive females were perceived as more feminine than unattractive ones; thus, it was a disadvantage for them when applying for a job that required masculine characteristics. Johnson *et al*., (2010) examined employment biases based on the attractiveness of applicants. They asked participants to match photos of attractive and unattractive men and women with job descriptions that they thought the applicant would fit in. As in previous studies, attractive men were matched with all sorts of jobs. However, attractive women were not seen as suitable for position considered traditionally male-dominated and where appearance was not regarded to be important (e.g., research and development manager, mechanical engineer, director of security, and hardware salesperson). Attractive women tended to be matched instead with jobs such as receptionists and secretaries.

Facial beauty seems to be a reliable proxy of underlying desirable behaviour as beauty is associated with a friendly appearance. Because people are social and have to get on with each other, friendliness is a feature that might be actively sought as it helps facilitate cooperation in the social environment. In other words, people desire to interact with friendly and cooperative people. Indeed, the preference for beauty appears innate: new-born infants also prefer to look at attractive faces. Experiments show that most babies spend more time focusing on attractive faces than on unattractive ones (Slater *et al*., 2000). Therefore, the association (actual or perceived) between beauty and being friendly, trustworthy, cooperative, and sociable might be the reason why employers have a preference for the better-looking people.

However, another explanation for the beauty premium is that it reflects discriminative preferences in favour of attractive people. Attractiveness is an important asset in those professions in which visual presentation (whether in face-to-face interactions or in the form of pictures or videos) is important. Performers (singers, actors, musicians and others) and even sportsmen tend to spend considerable resources and time on improving and maintaining their physical appearance. Clearly, these investments are not merely motivated by the desire to appear friendly and trustworthy.

Research investigating the beauty bias in employment decisions is important because of the extensive use of subjective appraisals in decision on hiring and promotions. While rules prohibiting employment discrimination based on factors unrelated to performance (e.g., gender, ethnicity, disability or age) are widespread, there are no such concerning discrimination based on physical attractiveness (Watkins and Johnston, 2000). Apart from the labour market aspect, physical attractiveness of individuals is also correlated with a wide range of outcomes including electoral success in politics (Berggren *et al*., 2010), in professional associations (Hamermesh, 2006), mating (Fisman *et al*., 2006), and happiness (Hamermesh and Abrevaya, 2013). These studies consistently find a positive impact of beauty on a broad range of outcome variables.

In this paper, we address the role of physical attractiveness in beauty-neutral situations without face-to-face interaction, where the counterparts are unaware of the individual's physical appearance. The publishing success of an author should be unrelated to the author's attractiveness, given that the peer review process is generally blind: the reviewer sees an article but does not meet the authors (or see their pictures), and often does not even have any identifying information about them (when the review process is double-blind). The attractiveness of authors therefore presumably should not be linked with publication productivity; instead, factors such as the author's intellectual ability and skills should be crucial. Hence, if the beauty bias is primarily driven by taste-based discrimination by employers (and other decision makers), there should be little or no evidence of a beauty bias in academic publishing. This question therefore forms the basis for this study: is there a relationship between physical attractiveness and productivity in academic publishing, a context characteristic by the low degree of face-to-face interaction? To this effect, we collect an extensive data set on 2,800 authors who published their work in one of 16 academic journals in economics in the course of 2012. The journals were selected so as to represent the broad spectrum of academic literature in economics, both with respect to quality as well as geographical coverage.

The rest of this paper is structured as follows: Section 2 discusses the relevant literature; Section 3 provides the data information, the methodology, and the empirical model. Section 4 presents the results with an emphasis placed on the impact of beauty on research productivity. Finally, Section 5 discusses the conclusion.

3.2 Literature review

Under ideal circumstances in the labour market, applicants should have an equal opportunity to be hired regardless of non-job related factors such as gender, race, religion, and skin colour. This is because these characteristics are irrelevant to labour productivity, which should be the main factor to be considered when making decisions on hiring, promotion or wage rates. That is to say, an unattractive candidate with equivalent educational qualifications and job experience should be given equal opportunity from potential employers as an attractive candidate. However, economists demonstrated the existence of discrimination in the labour market which has been shown in a vast amount of research. In recruitment, the literature shows evidence of discrimination against minority groups: African-Americans and Hispanics in the US (Cross *et al*., 1990; Bassanini and Saint-Martin, 2008), Indians, Pakistanis, West Indians and Africans in Britain (Bassanini and Saint-Martin, 2008), and non-Whites in White societies (Riach and Rich, 2002; Carlsson and Rooth, 2007; McGinnity and Lunn, 2011). With wages, economists endeavoured to verify the most relevant factors determining wages by regressing wages on various determinants such as gender, ethnicity, and human capital. Some of them even investigated health-related factors such as height and obesity. For instance, Harper (2000) showed evidence for a height premium; Harper (2000) and Rooth (2009) demonstrated the existence of an obesity penalty.

While economists focused on the relationship between socio-economic characteristics and labour market outcomes, the issue of physical attractiveness of an individual has been examined by psychologists widely. Laboratory studies explored the effect of beauty in different social interactions to indicate why beauty is a desirable trait. These experiments showed that attractive people were more cooperative in the public goods game (Andreoni and Petrie, 2008), were more trustworthy in the trust game (Wilson and Eckel, 2006), were offered a higher wages (Mobius and Rosenblat, 2006), and received a higher negotiation offers in the ultimatum game (Solnick and Schweitzer, 1999) than unattractive ones. According to Eckel and Wilson (2004), the physical attractiveness was often used as an alternative when forming an opinion about cooperativeness and trustworthiness of an unfamiliar person. Andreoni and Petrie (2008) add that the impact of beauty disappears when information about the real job performance of that individual is available, though the cooperativeness is expected to boost individual´s job performance. Moreover, the psychological literature also finds that attractive people are expected to be more intelligent than less attractive one (Langlois *et al*., 2000; Zebrowitz *et al*., 2002; Kanazawa and Kovar, 2004). An experiment by Zebrowitz *et al*. (2002) shows that beauty is a proxy for intelligence: the more attractive an individual is believed to be, the more intelligent he or she is assumed to be. They showed 804 photos to 24 research participants and asked them to state whether the person in the photo was intelligent or not. The results demonstrated a positive relationship between beauty and intelligence. The theoretical study of Kanazawa and Kovar (2004) provided further comprehension of the empirical study of Zebrowitz *et al*. (2002). They propose a theory that describes the reason why intelligence positively corresponds to physical attractiveness. Accordingly, more intelligent persons have greater possibility to attain higher socio-economic status than less intelligent ones. Higher-status individuals, in turn, have more chance to meet more beautiful women and get married to them, and pass on their intelligence and attractive genes to their children disproportionately.

Following the investigation of beauty effects in psychology, economists began to explore the impact of physical attractiveness on labour market outcomes. The general consensus seems to agree that beauty discrimination exists in the labour market, opening the question of the role played by physical attractiveness in job recruitment and wage determination. Regarding job recruitment, the literature shows that physical attractiveness has a positive impact on the possibility of employment success of candidates (Watkins and Johnston, 2000; Dipboye and Dhahani, 2017). Watkins and Johnston (2000) conclude that the more attractive a candidate, the greater the possibility of employment success. Furthermore, the correlation between physical attractiveness and earnings seems to be robust too (Frieze *et al*., 1991; Hamermesh and Biddle, 1994; Biddle and Hamermesh, 1998). Several studies (Harper, 2000; Bowles *et al*., 2001; French, 2002; Mobius and Rosenblat, 2006; Fletcher, 2009; Scholz and Sicinski, 2015) hypothesise that attractive people earn more than unattractive ones. However, findings concerning the effect of physical attractiveness on labour market outcomes by gender are mixed. Literature revealed that the gender difference regarding the impact of beauty on earnings are not found (Hamermesh and Biddle, 1994; Harper, 2000; Fletcher, 2009) while few studies revealed gender-specific impacts. The study by French (2002) indicated that a beauty premium exists only for females while Roszell, Kennedy and Grabb (1989) and Rooth (2009) found the beauty effects only for men.

Frieze, Olson and Russell (1991) investigate how physical attractiveness is associated with wages using longitudinal data of 737 MBA graduates. The results showed that more attractive males had higher starting wages than unattractive males and the difference persisted over time. For females, there was no effect of physical attractiveness on their starting salaries; however, attractive women fared better with respect to their earnings later in their careers. Hamermesh and Biddle (1994), who introduced the concepts of a “beauty premium” and a “plainness penalty”, found a significant beauty premium for both men and women. Specifically, attractive workers earn 10-15% more than unattractive workers. The study also showed evidence in accordance with the assumption that the beauty premium and the plainness penalty existed. According to the extent of the effect, they indicated that plainness penalty was around 5–10%, but on the other hand, the beauty premium was slightly smaller. A follow-up paper by Biddle and Hamermesh (1998) extended their earlier study using a large sample of law school graduates by tracing their earnings over time. They also found a positive relationship between physical attractiveness and wages based on the rating of matriculation photos. After five years of experience, physically attractive attorneys earned more than others, and the difference was impacted by the experience. Some studies showed evidence for only one effect. For instance, Harper (2000) found evidence for the plainness penalty only while Robins, Homer and French (2011) found evidence only for the beauty premium. Harper (2000) examined the effect of physical attractiveness of 7 and 11 year-olds on their labour market outcome after 26 and 22 years respectively, using British longitudinal data from the National Child Development Study (NCDS). He concluded that the importance of physical attractiveness for men was the same as it was for women. The plainness penalty for men (15%) was higher than for women (11%).

The bias in favour of good-looking people goes beyond the labour market. Hamermesh (2011) even reveals that attractive people have a higher possibility to get loan applications approved and to be offered lower interest rates than unattractive individuals with similar demographic characteristics (e.g., age, gender) or credit history. He concludes that lenders were willing to exchange more generous terms on loans, and comply with the situation that good-looking insurance sellers sold more insurance because of the bias against bad-looking insurance salespeople given by customers. The findings are consistent with the effect of "the pleasure of dealing with good-looking people". Research on this issue has been shown in several areas such as electoral success in politics (Berggren *et al*., 2010), electoral success in an organisation (Hamermesh, 2006), mating (Fisman *et al*., 2006), and happiness (Hamermesh and Abrevaya, 2013). Hamermesh (2006) used candidates' multiple appearances with different photographs accompanying ballots in the annual elections of the American Economic Association between 1996 and 2004. The results pointed out that an exogenous increase in beauty enhances the probability to be elected. Attractive people have the upper-hand also in politics. The field experiment conducted by Berggren, Jordahl and Poutvaara (2010) confirmed the existence of beauty advantage in elections in Finland. The candidates' physical attractiveness had a positive impact on the probability of being elected to serve in the parliament, that is, candidates, both male and female, who look better than their competitors, were more successful. However, there was no significant impact of physical attractiveness for incumbent candidates. The different from non-incumbent and incumbent candidates' results was probably due to the lack of reliable information about the non-incumbent candidates. Perceived competency and trustworthiness had less of an impact.

The question of the relationship between beauty and performance is being raised even in sports. Top athletes distinguish themselves through many attributes (e.g., hard work, fortitude, talent). However, attractiveness is considered as another trait of athletic performance (Callaway, 2009; Williams *et al*., 2010; Postma, 2014). Callaway (2009) presents a study conducted by New Scientist, indicating the correlations between perceived attractiveness and athletic performance of professional men's tennis players. The research team randomly picked 20 tennis players in the world top 100, with two players from each decile, based on the 2008 total ranking points. They asked a thousand New Scientist Twitter followers to rate the photos of the selected players, which were presented in a random order on a third-party website. The survey participants were asked about their gender and familiarity to each tennis player. The measurements of athletic performance in this study were: Association of Tennis Professionals (ATP) Tour ranking points for the 2008 season, and the winning percentage in the 2008 season. The research team first analysed the relationship between attractiveness and player's rank, and they found a small correlation between attractiveness and performance, however, it was not statistically significant. When using the percentage of matches each tennis player won in 2008 as a measurement, the result showed a weak correlation which was statistically significant. The research team were undecided over which measurement is more accurate to be a reliable proxy for tennis player's athletic performance. Ranking points is a good measure for players who compete in many tournaments but is unfair to those with injuries. On the other hand, winning percentages provide a real measure of ability but lack considering the quality of a player's opponents. Though this study was conducted informally and the measurement of athletic ability was ambiguous, the findings discovered the correlation between beauty and athletic performance.

Williams, Parka and Wieling (2010) examined the correlation between attractiveness and sports performance focusing on NFL quarterbacks. In this study, the passer ratings were considered as the performance measurement. The score ranged between 0 and 158.3, and it was obtained from several statistics including completed passes, yardage gained, and touchdowns. The researchers asked 60 female university students in Netherlands to rate the picture of quarterbacks who played in the 1997 season (30 photos), and those who played in 2007 season (58 photos). The results showed statistically significant correlations between good looks and passer ratings. However, the effects were small. The findings of this study are in line with the findings of tennis players from the New Scientist study. Postma (2014) collected 80 mugshots of long-distance cyclists in the 2012 Tour de France. He showed two sets of 40 pictures to each volunteer and asked them to rate the photos in three aspects which were attractiveness, likeability, and masculinity. Volunteers were also asked whether they recognized the cyclist or not. If recognized, the rating of that cyclist was excluded from the analysis. He points out that the correlation between attractiveness and likeability was not found. And likeable cyclists were neither more likely to win nor were perceived as more masculine. However, there was a relationship between attractiveness and performance. The findings support the idea that attractiveness is a plausible predictor of outcome, at least for men.

Due to the amount of solid research supporting the idea that beauty impacts on labour economics and other fields of interest (e.g., happiness, political success, mating, athleticism), some studies confirmed that physically attractive people are more successful than unattractive ones. Hamermesh (2011) points out that physically attractive people earn more than average-looking people, are employed sooner, are promoted more quickly, and have a tendency to get higher ranking jobs in companies. He also argues that attractive employees are likely to make more money for their organisations, and will be perceived as more successful accordingly.

The literature mentioned earlier offers explanations for the beauty effects in various fields. In psychology studies endeavour to clarify the beauty effect by linking beauty and intelligence with the hypothesis that more attractive people are thought to be more intelligent, friendly, and competent than others. And it also provides evidence to support that beauty is a reliable proxy for desirable behaviour. The economic studies focus on the correlation between beauty and employment differentials (e.g., interview rates, employment success, wages) to examine both the existing of employer discrimination and beauty as a productive factor. The latter is interesting due to the contrasting assumption draw from the previous findings, according to which either beautiful people are more intelligent than those who are unattractive, or that beauty is an innate characteristic and as such is not a strong factor of performance. By focusing on a field in which merit should play a crucial role and the potential for taste-based discrimination should be very limited or non-existent, such as professional sport or academic publishing, it should be possible to examine whether beauty is correlated with productivity or not. For instance, if employers and co-workers use beauty to discriminate, attractive researchers may face better employment and promotion prospects, may have an easier time to find co-authors or become members of established teams. However, their good looks should not translate into higher publication rates, higher impact factor or especially into higher citation rates: editors, referees and readers do not usually meet the author face to face, and referees, who play an instrumental role in the process of turning manuscripts into publications, often do not even know who the authors are. So far, the evidence on this matter is scarce. We investigate this issue in academic publishing where the beauty of authors should not have significant effects on their research productivity. Towards this end, we begin the analysis by investigating whether the effect of beauty exists in our sample and we then examine the extent of the effect of beauty on research productivity.

3.3 Methodology

3.3.1 Data

The sample data of this study is obtained from 1,512 publications published in 2012 in 16 economics journals listed in Association of Business Schools (ABS) Journal Quality Guide (2010) and is used to examine the relationship between physical attractiveness of author and research productivity. The selected journals are American Economic Review, Economic Journal, Quarterly Journal of Economics, European Economic Review, Journal of Public Economics, Journal of Comparative Economics, Journal of Economic Dynamics and Control, Journal of Economic Behavior and Organization, Journal of Development Economics, Labour Economics, Applied Economics, European Journal of Political Economy, Economic Modelling, Contemporary Economic Policy, Open Economies Review, and German Economic Review. The journals were selected randomly from the ABS list so as to each rank (between 1 and 4) is represented by four journals. Special issues of these journals are excluded from the analysis because the selection criteria for including papers in special issues may be different from the regular issues. Individual author is defined as the main unit of analysis in this study. We collect detailed information on 2,800 authors (i.e., name, affiliation, gender, race, institution and country of first degree and PhD, the year of first degree award and PhD, academic rank, and photo) and also the publication details (i.e., name of article, volume, issue, start page, end page, number of co-authors, citation count, journal rank, and journal impact factor). The information is collected from multiple sources such as personal webpage, curriculum vitae and institutional website. Thus, all of the information, including the author's photo (if available), were in the public domain at the time of data collection.

The authors in our sample are predominantly males. Among the 2,800 economists, males account for 82.6% and female account for only 17.4%. 8.5% of all authors published more than once in the journals included in our sample, and one published 5 papers in 2012 in the selected journals. Most of the authors, 40% of observations, are full professors, with each of the remaining three categories (assistant professor, associate professor, and other) accounting for approximately 20%. 83.7% of the authors hold a PhD degree and the working experience (defined as the difference between the year in which PhD was obtained and 2012) ranges from 0 to 52 years, with the average author having 12.9 years of experience. Most of the people in our sample are white (80%), followed by 11% who are East Asian, 6% South Asian, 1.5% of Middle-Eastern or North African appearance and 1% is black (race was coded based on appearance and other information available). As we do not always know the country of birth of the authors, we use the country in which they obtained their undergraduate degree as a proxy for country of origin. We use the World Bank classification to divide countries of origin into high income countries (78.5% of authors in our sample), upper and lower middle income (8.9% and 8.1%, respectively), and low income countries (4.5%). The summary statistics of all data are reported in Appendix B-1.

Besides basic information on the authors, we also rate the authors' attractiveness. To this effect, we circulated a number of online survey links to potential participants at Brunel University London and elsewhere, using direct communication, email and social networks. Each participant was required to complete the survey just once so that the survey link is disabled automatically after it was completed; however, participants can rate more than one survey. Each online survey collects basic background information on the assessor (gender, age, ethnicity, highest education, and student status) followed by 30 photos, with each picture placed on a separate page (we cannot distinguish assessors rating more than one survey from those who participated only once). In other words, each assessor rates up to 30 photos per survey (assessors can terminate the survey before seeing all 30 pictures, in which case the information already collected is retained) in order to diminish tiredness and boredom when completing the survey. In order to reduce answer bias, we randomise the order of pictures in the survey. In other words, the system generates different series of photos, thus, the orders of photo for each assessor are not the same. Each assessor is asked to rate the attractiveness of the person in the photo on an 11-point scale which ranged from 0 (unattractive) to 10 (very attractive). Assessors are not provided any information of the photographed individuals, thus their assessment are not affected by the socio-economic status of the person in the photo. Moreover, the assessors are asked whether they personally recognise the person in the picture or not before they move to the next photo. The beauty score of the person in the photo is excluded from the analysis if the assessor recognised the face. In addition, they are asked whether the photo is large and clear enough to rate or not. The beauty score of that photo is also excluded from the analysis if assessor is unable to see the person in the photo clearly. There were 1,860 assessors in total, with each picture rated by at least 20 separate assessors. 44.8% of our assessors are male while 55.2% are female. 58.3% of all assessors are between 25 and 34. East Asians forms the biggest proportion (50.9%) while white forms the second (31.3%) of all assessors. 45.2% of all assessors are students at the time of the survey. The proportion of participants who completed their master degree and bachelor degree are approximately the same, 32.6% and 32.5%, respectively, compared to 19.8% of participants with a PhD. The summary of assessors' information by category is shown in Appendix B-2 and the example of the online survey and is in Appendix B-3. Appendix B-11 shows three most attractive female and male authors.

Citation counts were collected from Scopus database and Google Scholar in March 2015 so as to provide enough time for article to be cited. The citation counts, journal rank and journal impact factor are all normalised to have a standard deviation equal to one. For journal ranking lists, there are several lists that are widely used to assess journal quality in business and economics. In this study, the Excellence in Research for Australia (ERA) lists 2010 and the Keele list 2006 from Keele University are applied to measure the impact of journals. The Journal Impact Factor (JIF) is a measure applied to journals and commonly refers to the average number of citations received during a given year for the articles published in that journal during the previous two years. The journal impact factor (JIF) provided by ISI *Journal Citation Reports (JCR*) is used in this study.

3.3.2 Variables

Dependent variable

The outcome of interest in this research is publication productivity. This can be measured in several ways depending on the context. In the context of research activity, measuring research productivity is a crucial part of any academic appraisal process such as academic hiring, tenure promotion, and funding proposal approval. The amount of publications per researcher seems to be the norm in bibliometrics as a measure of individual research productivity; however, the number of publications fails to reflect quality. There are various indicators and methods to evaluate the quality at an individual level and per publication output (e.g., H-Index, Citation Analysis, Journal Impact Factor (JIF), and Altmetrics). The h-index is an indicator that quantifies an individual's scientific research output using several databases such as Web of Science, Scopus, and Google Scholar. However, there are drawbacks to using the h-index as it does not adjust for some collaboration specific factors (Petersen *et al*., 2012). The citation analysis, instead, counts the number of times that article has been mentioned in other works. Various databases determine citations including Web of Science, Scopus, and Google Scholar. Citation index can be used as a measure of both the individual overall productivity and quality of specific publications. The journal impact factor, in turn, is a measure applied to journals and commonly refers to the average number of citations attained during a given year for articles published in that journal during the previous two years. However, impact factors identify the impact of a journal which is not the impact of individuals or articles. Altmetrics is an indicator of influence and impact of a particular work, and measures the quality and quantity of attention in which an article receives from various kinds of sources such as social media, researchers' websites, institutional repositories, journal websites, and article downloads.

The metrics mentioned above are all designed to reflect the ranking of and insight into quality of publications. However, each indicator has its own specific strengths and drawbacks. For example, any journal-based metric such as journal impact factor is not suitable for capturing the quality of an individual article or researchers and should not be used as a substitute for single-article measures or to appraise individual researchers (Campbell, 2008). The h-index is designed for measuring research quality at the individual level. However, the h-index fails to account for the number of co-authors and their contribution in the paper. Moreover, productivity is necessary to be carried out by field due to the intensity difference of publications across fields (Abramo and D'Angelo, 2014). Therefore, using a single bibliometric indicator as a sole measurement cannot give a full picture of collaboration, impact and productivity. Consequently, applying multiple indicators with complementary features brings about a more comprehensive measurement of publication quality (IEEE Board of Directors, 2013).

To this effect, various indices are used to measure the productivity of research (i.e., citation rates, credible journal rankings lists, and journal impact factor). In this study, the dependent variable is constructed using citation counts, journal rankings, and journal impact factor. Each of these indexes has different scales. For example, citation counts used in this study are collected from the Scopus and Google Scholar databases; and the citation rates from google scholar tend to be considerably higher than those from Scopus. The impact factor index, in turn, is lower than either citation rate. The journal rankings used in this study are based on two credible ranking lists in economics: the Keele list from Keele University and Excellence in Research for Australia (ERA). However, the ranking of journals from the Keele list range from 1 to 4 while the journals in the ERA list are ranked from C, B, A, and A*. To make them comparable, all of these indexes are normalised so as to eliminate the unit of measurement. The data are treated as vectors in multidimensional space, with each data vector transformed into a new vector whose norm or length is equal to one. We apply Min-Max normalisation, which is the simplest method to rescale the original values to the rage in [0,1]:

$$z_{\mathrm{i}} = \frac{x_{\mathrm{i}} - \min(x)}{\max(x) - \min(x)}$$

where $x = (x_1,\ldots,x_n)$ and z_i is the normalised value.

In this way, the citation rates from Scopus and Google Scholar, the journal ranking indexes from the Keele list and ERA, and the impact factor index are of the same norm, and range from 0 to 1. We then calculate the average of normalised citation rates from both databases and also calculate the average of normalised journal ranking indexes from both lists. We can then calculate the dependent variable from the average of normalised citations, the average of normalised journal rankings, and the normalised impact factors. We refer to this measure as the average productivity.

The average productivity assigns equal weights to our measures of citation counts, journal rank and impact factor. However, only the citation counts reflect the quality of an individual researcher or individual publication. We therefore use also a weighted productivity index and average normalised citation count. The weighted productivity, which we consider as our main dependent variable, combines normalised citations from Scopus and Google Scholar (together with a weight of 50%), normalised journal ranking from Excellence in Research for Australia (ERA) and the Keele list (together 30%), and normalised journal impact factor from Thomson Reuters Journal Citation Reports (20%). Hence, citations carry a weight of 50% rather than one third. Both weighted and average productivity measures give more weight to articles published in higher ranked or more renowned journals. The average normalised citation therefore uses citation counts as the only metric of research productivity.

Independent variables

Our main independent variable is the average attractiveness score obtained by means of surveys. The survey participants were recruited by means of personal contact among students and staff members at Brunel University London and residents in Uxbridge, London, as well as by circulating links to online surveys on by email and on social networks. The pictures were shown to assessors in random order and the participants were asked to rate it on an 11-point scale ranging from 0 (entirely unattractive) and 10 (very attractive). In total, 2,800 photos are assessed in the course of 2016 and each photo was rated by 20 assessors. The previous literature argues that attractiveness is a time-constant variable whose determinants are broadly agreed upon across different cultures and nationalities: “within the modern industrial world standards of beauty are both commonly agreed upon and stable over one’s working life” (Hamermesh and Biddle, 1994, p. 1177).

The rest of control variables belong to three sets of characteristics: author's personal background, author's occupational background, and article characteristics. The summary of variables is shown in Tables 3-1 and 3-2. The respondent's personal background includes gender, ethnicity, and nationality (to account for the level of development in country of origin). Gender information of authors is unavailable from their CV or personal websites; however, it is perceivable from their pictures. Similarly, ethnicity is determined based on the author's picture and name. We distinguish five categories: White, Black, South-Asian, East-Asian and people of Middle Eastern and North African (MENA) appearance. Whites refer to those who have white skin and European looks (e.g., White American, White Brazilian, White British, and White South African). South-Asian refers to people from the countries in South Asia such as Bangladesh, India, Nepal, Pakistan, and Sri Lanka. East-Asian in this study includes people from Central Asia (e.g., Kazakhstan, Tajikistan, and Uzbekistan), East Asia (e.g., China, Japan, and Mongolia), and South-East Asia (e.g., Cambodia, Malaysia, and Vietnam). Nationality information for defining a classification of countries by development is proxied by country in which the authors obtained their bachelor degree. To measure economic development, we rely on the classification used by the World Bank which divides countries into four income groupings; low, lower-middle, upper-middle, and high. This classification is based on gross national income (GNI) per capita, whereby the local currency is converted to U.S. dollars using the *World Bank Atlas methodology*, and the population size is estimated by World Bank demographers from a various sources, including the UN's biennial *World Population Prospects* (World Bank, 2017). Authors are allocated into these four groups according to their nationality (proxied by the country in which they completed their undergraduate degree). The level of development in the country of origin is likely to be correlated with the quality of education, which in turn can have an important effect on research productivity.

The respondent's occupational background includes academic rank and work experience. The academic ranks in this study are assistant professor, associate professor, full professor, and other occupations. Due to the fact that the ranking system is different in some countries (e.g., American vs British system), we assign people who are at an early stage of a teaching and research career into the assistant professor category while senior lecturers or readers are assigned into the associate professor group. The ‘other’ category mainly includes postdoctoral researchers and research fellows. Work experience is available directly from authors’ CVs, personal websites or institutional websites; therefore it is computed as the number of years since the author has received doctoral degree until the publication year (2012).

Table 3-1 Summary of variables

Variable	Definition
Dependent variables	
wprod	Weighted productivity
avgprod	Average productivity
avenormcite	Average normalised citation
Independent variables	
avebeauty	Average beauty score of individual author
workexp	Professional age* of all author in team
female	Dummy variable of female author
high	Dummy variable of high income countries
upmid	Dummy variable of upper middle income countries
lowmid	Dummy variable of lower middle income countries
low	Dummy variable of low income countries
prof	Dummy variable of professor
assoc	Dummy variable of associate professor
assist	Dummy variable of assistant professor
other	Dummy variable of other occupations
white	Dummy variable of white people
black	Dummy variable of black people
s_asian	Dummy variable of South Asians
e_asian	Dummy variable of East Asians
mena	Dummy variable of Middle Eastern and North Africans
teamsize	Number of author(s) in team
sa_ab	Interaction term of South Asians and average beauty score
ea_ab	Interaction term of East Asians and average beauty score
me_ab	Interaction term of MENAs and average beauty score
fe_ab	Interaction term of female author and average beauty score

Note: *professional age was derived from number of years since an individual has received a doctoral degree until the publication year (2012)

Table 3-2 Coding of dummy variables

Gender

Values	Codes	Percent	Frequency
Male	0	82.61	2,313
Female	1	17.39	487
		100	2,800

Ethnicity

Values	Codes	Percent	Frequency
White	1	80.07	2,242
Black	2	1.07	30
South Asian	3	5.93	166
East Asian	4	11.43	320
Middle Eastern	5	1.50	42
		100	2,800

Academic rank

Values	Codes	Percent	Frequency
Assistant professor	1	20.32	569
Associate professor	2	19.39	543
Professor	3	39.93	1,118
Others	4	19.43	544
N/A	5	0.93	26
		100	2,800

Classification of countries by development

Values	Codes	Percent	Frequency
Low income	1	3.57	100
Lower middle income	2	6.29	176
Upper middle income	3	6.93	194
High income	4	61.11	1,711
N/A	5	22.11	619
		100	2,800

The article characteristic is team size, indicating the number of authors of a particular article. Regarding the factors influencing citation rates, the number of authors has a generally positive impact on citations (Sooryamoorthy, 2009; Gazni and Didegah, 2011). Bornmann (2015) finds that each additional author or each additional page of an article is expected to yield 4% more citations. The information regarding a number of authors is collected from the journal websites. Table 3-1 describes summary of variables and Table 3-2 shows list of dummy variables and value codes. The base categories for dummy variables include male for gender; white for ethnicity; high income country for economic development; and professor for academic rank. Appendix B-1 shows the descriptive statistics.

3.3.3 Model specification

Estimates of the effect of physical attractiveness on labour market outcomes can be arrived using the different strategies. For example, the previous literature on the beauty premium in wages uses the earnings function (Harper, 2000; French, 2002; Fletcher, 2009). However, this study instead relies on the traditional productivity function, which is a method to capture the impact of physical attractiveness on research productivity. The concept of the production function explains the production process whereby a given set of inputs are used to produce a range of outputs. The literature in labour economics measures productivity change by relating it to human capital and other factors of production. Human capital theory relies on the investments in knowledge, skills, and abilities of people. When people invest in qualifications, their productivity increases. The process of the production function is the main inspiration and theoretical base for modification in the study in research productivity aspect (Levin and Stephan, 1991; Henderson and Cockburn, 1996). Therefore, the model used in this research is similar to any production function as it aims to examine the correlation between human capital aspects such as beauty and other characteristics (inputs) and research outcomes (outputs). In order to test the extent to which the attractiveness matters to research productivity, a modification of the standard production function is required by including the physical attractiveness and sets of control variables (i.e., respondent's personal background, respondent's occupational background, and article characteristics) to the model, to unravel to what extent physical attractiveness affects research productivity. With the aim to test whether the beauty premium is of more importance in some ethnicities than in others and have more effect on one gender than the other one, interaction terms involving attractiveness and ethnicity/gender are also included in the model. The specification of the research productivity equation is:

$$Productivity_i = \alpha + \beta_1 * Beauty_i + \beta_2 * Gender_i + \beta_3 * Ethnicity_i + \beta_4 * Country_i + \beta_5 * Rank_i + \beta_6 * TeamSize_i + \beta_7 * WorkExp_i + \beta_8 * WorkExp_i^2 + \beta_9 * Gender_i * Beauty_i + \beta_{10} * Ethnicity_i * Beauty_i + \varepsilon_i \quad (1)$$

where $Productivity_i$ denotes the research productivity, $Beauty_i$ is the average of the of beauty scores measured by assessors, $Gender_i$ equals 1 if the gender of author is female and 0 otherwise, $Ethnicity_i$ stands for a set of ethnicity dummies, $Country_i$ refers to dummies for country classification according to their level of development, $Rank_i$ si a set of dummies reflecting academic rank, $TeamSize_i$ captures the number of authors in the research team, $WorkExp_i$ denotes the accumulated years of work experience, $WorkExp_i^2$ is the square of years of work experience. $Gender_i * Beauty_i$ and $Ethnicity_i * Beauty_i$ indicate interaction terms to capture whether beauty has a different effect across genders and ethnic groups. α is the level of non-qualified research productivity.

Prior to analysing the correlation, the empirical distribution of research productivity is tested to identify whether parametric or non-parametric method is the suitable method. Both graphical and numerical tests are used to check the normality of distribution (i.e., histogram, quantile-quantile (Q-Q) plot, Shapiro–Wilk normality test, Shapiro–Francia normality test). The dependent variables (i.e., weighted productivity, average productivity, and average normalised citation) are found to be skewed with a long right tail (see Appendix B-4). Shapiro–Wilk normality test and Shapiro–Francia normality test imply a rejection of the assumption of the normality of the research productivity distribution. The standard regression estimates the means of a dependent variable conditional on the independent variables. It is a suitable technique when the regression assumptions are met, however, it does not work well when conditions are nonstandard particularly with the homoscedasticity assumption and normality assumption. For this reason, the estimation of the research productivity function using a least squares method would produce a coefficient estimates which are not being a proper representative of the entire model (Koenker and Bassett Jr., 1978; Dimelis and Louri, 2002; Hao and Naiman, 2007). Therefore, we employ a quantile regression technique which is a non-parametric method, as it is more appropriate to analyse the relationship. Quantile regression relaxes the regression assumptions and offers a comprehensive view of the impact of independent variables on the central and non-central location, shape, and scale of the distribution of the dependent variable. The estimations of this technique are robust to outliers, unlike the least squares technique, and it also allows us to test for the differences in the effects on productivity by explanatory variables in various quantiles. In other words, conditional quantile models provide the flexibility to choose positions and focus on these population sections which are tailored to researchers' specific inquiries (Koenker, 2005; Hao and Naiman, 2007). The explanation of the quantile regression technique is summarised in the next section and the report of the normality of distribution from graphical and numerical tests is illustrated in Appendix B-4.

Quantile regression

According to Baum (2013), standard linear regression techniques estimate the average correlation between the outcome variable and a set of explanatory variables based on the conditional mean function E (y|x). However, this technique presents only a partial view of the correlation and does not capture the correlation at other points of the conditional distribution of y. In this case, quantile regression can provide a broader view of the correlation. Comparable to the conditional mean function of linear regression, quantile regression summarises the correlation between the explanatory variables and the outcome using the different conditional median function, Qq (y|x), in which the median is the 50th percentile (i.e., quantile q) of the empirical distribution. The quantile $q \in (0, 1)$ means the data of y is divided into proportions q below, $F\ (yq) = q$; and $1 - q$ above, $yq = F -1\ (q)$ for the median (q = 0.5).

If ε_i is the model's prediction error, OLS minimises $\Sigma_i\ e^2_i$. Quantile regression minimises the sum that provides asymmetric penalties $q|\ e_i\ |$ for under-prediction and $(1-q)|\ e_i\ |$ for over-prediction. Even though the estimation of quantile regression requires linear programming methods, its estimator is asymptotically normally distributed. Quantile regression is more robust to outliers than OLS, and it avoids assumptions about the parametric distribution of the error process. Thus, assumptions of normality of distribution and constant variance are not required.

Quantile regression can also model conditional quantiles of the joint distribution of y and x. That is, $\hat{y}\ (x)$ is the predictor function; and $e(x) = y - \hat{y}\ (x)$ is the prediction error. Then, $L\ (e(x)) = L(y - \hat{y}\ (x))$ is the loss connected with the prediction errors. If $L\ (e) = e^2$, the squared error loss, and least squares is the best predictor.

If $L\ (e) = |e|$, the best predictor is the conditional median, med $(y|x)$, and the best predictor is that $\hat{\beta}$ which minimises $\Sigma_i \mid y_i - x'_i\, \beta|$.

Both the squared error loss function and absolute error loss function are symmetric so that the prediction error's sign is not relevant. The penalty is asymmetric if the quantile q differs from 0.5, with increasing asymmetry as q comes nearer 0 or 1. Benefits of quantile regression are: it is more robust to non-normal outliers and errors, that is, when the errors are highly non-normal, OLS can be biased. Quantile regression also provides a better characterisation of the data, in other words, it provides not only its conditional mean but also the impact of a covariate on the entire distribution of y. Moreover, quantile regression is stable to monotonic transformations (e.g., logarithm), thus, the quantiles of $h(y)$, a monotone transform of y, $h\ (Q_q(y))$, and the inverse transformation is applicable to translate the results back to y. This attribute is impractical for the mean as $E\ [h(y)] \neq h\ [E(y)]$. To implement the quantile regression, the estimator for quantile q minimises the objective function:

$$Q\left(\beta_q\right) = \sum_{i:\, y_i \geq x_i'\beta}^{N} q \left| y_i - x_i'\beta_q \right| + \sum_{i:\, y_i < x_i'\beta}^{N} (1-q) \left| y_i - x_i'\beta_q \right|$$

This non-differentiable function is minimised via the straightforward method, which is ensured to give a result in a finite number of iterations. Though the estimator is justified as being asymptotically normal with an analytical VCE, the bootstrap standard errors are preferable to analytical VCE.

We use STATA 14 to analyse our data. Various commands are applied for the different proposes. For example, the command "qreg" estimates a multivariate quantile regression with the default 0.5 quantile (median) and with analytic standard errors using an option "vce(robust)". The command "bsqreg", a bootstrapped quantile regression, estimates the model with bootstrap standard errors with the default 0.5 quantile (median) and the default time for bootstrap replications is 20. The option "quantile()" is to designate the different quantile of interest. The different bootstrap replications can be done with the option "reps()". The "qreg" and "bsqreg" maintains the assumption of independent errors whereas relax the identically distributed errors' assumption. Therefore, they are similar to robust standard errors in linear regression.

The command "iqreg", an interquantile range regression, estimates interquantile regression with the default, the quantiles (0.25, 0.75) and the default 20 replications of bootstrap standard errors are also produced. The option "quantile()" is used to estimate the interquantile range and the different bootstrap replications can be done with the option "reps()". The command "sqreg", a simultaneous-quantile regression, estimates quantile regression for various values of q at the same time and test differences between quantile regressions coefficients for different quantiles. Likewise, the default 20 replications of bootstrap standard errors are also produced. The option "quantile()" is to estimate several quantiles and the different bootstrap replications can be done with the option "reps()" (StataCorp, 2015). In OLS, the option "vce(bootstrap)" is used as it runs the regression with the default 50 replications of bootstrap standard errors, however, we are unable to change the time repetition. For this reason, we run regression using bootstrap data resampling with 50 repetitions for both quantile regression and OLS in this study.

3.4 Results

3.4.1 OLS and median regression results

To analyse the effect of attractiveness on research productivity, quantile regression which is robust to outliers is employed as the main regression, with the dependent variable (i.e., weighted productivity, average productivity, average normalised citation) taking values from 0 to 1. We also run OLS regression as a robustness check. The median-regression model, or the 0.5^{th} quantile, is the simplest quantile regression model to understand. It provides the conditional median of the dependent variable given the independent variables and constitutes a natural alternative to the linear-regression model that fits the conditional mean. It is natural to compare because they both endeavour to model the central location of the response distribution and the interpretation of the median-regression coefficient is similar to that of the linear-regression coefficient. In this study, we use bootstrapping approach for estimation of standard errors because the i.i.d. restricts to the assumption that expects no shapeshift of the response. Therefore, the more flexible approaches such as bootstrapping should be applied to estimate standard errors as it allows flexible errors and offers a numerical solution to the complex asymptotic method. Besides, the bootstrapped point estimates are analogous to the asymptotic approach, but they are likely to give smaller or larger standard errors than those from the asymptotic standard errors approach. In other words, the bootstrap reports a lower level of precision of the estimate at the 0.5^{th} quantile than the asymptotic estimate (Koenker, 2005; Hao and Naiman, 2007).

We report regressions' results comparing the effects by OLS and median regression using the weighted productivity as the dependent variable in Table 3-3. First, we only control for physical attractiveness, authors' characteristics (i.e., gender, ethnicity, country development, academic rank, work experience), and team size (columns 1 and 2). Adding a squared term of work experience (columns 3 and 4) changes the effect into a hump-shaped one but the quadratic term is not statistically significant. Finally, we add interaction terms of gender and average beauty score, and ethnicity and average beauty score (columns 5 and 6). In all specifications, the effect of attractiveness on the research productivity index is positive and highly significant. Considering columns 5 and 6, the coefficient of the average beauty score in the conditional-median model is 0.0389, which is slightly higher than the coefficient in the conditional-mean model. Therefore, an increase in attractiveness by one would translate into an increase in weighted productivity by 0.0389, or approximately 15% (the mean of the dependent variable is 0.260). Besides good looks, having co-authors has a positive impact on research productivity while the level of development of the home country and work experience shows a negative impact on research productivity, both with OLS and quantile regression at 0.5^{th} quantile. Each additional co-author increases weighted productivity by 0.0246, or 9.5%, while ten years of experience reduces productivity by 0.0157, or 6%.

The results obtained with average productivity and log average normalised citations, with the same independent variables as above, are reported in Tables 3-4 and 3-5.

Considering the average productivity as the dependent variable, the coefficient of the average beauty score from quantile regression at 0.5^{th} quantile is 0.0463, which is again higher than the OLS coefficient of 0.0371. Hence, a one-point increase in average attractiveness translates again into an increase of approximately 15% (on average productivity of 0.299). It is very similar to the effect obtained with weighted productivity as reported in Table 3-3.

Team size has a significantly positive impact on research productivity in both OLS and quantile regression at 0.5^{th} quantile while country development shows a negative impact on research productivity in both OLS and quantile regression at 0.5^{th} quantile. They are also in line with those reported in Table 3-3. However, work experience when considering average productivity as the dependent variable is not statistically significant in the conditional-median model while it is significant ($p<0.01$) with the negative effect on research productivity in the OLS model.

Table 3-3 Impact of beauty on weighted productivity, OLS and median regression

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)
Average beauty score	0.0270*** (0.0033)	0.0326*** (0.0053)	0.0274*** (0.0041)	0.0353*** (0.0036)	0.0302*** (0.0042)	0.0389*** (0.0066)
Female	-0.0230** (0.0076)	-0.0274 (0.0154)	-0.0239* (0.0104)	-0.0306* (0.0127)	0.0420 (0.0334)	0.0504 (0.0560)
Black	0.0191 (0.0429)	0.0358 (0.0555)	0.0207 (0.0465)	0.0339 (0.0461)	0.2230 (0.1911)	0.0961 (0.2714)
South Asian	0.0569*** (0.0154)	0.0692* (0.0343)	0.0559*** (0.0147)	0.0657* (0.0319)	0.0802 (0.0590)	0.0671 (0.0936)
East Asian	-0.0270* (0.0130)	-0.0436** (0.0136)	-0.0267** (0.0100)	-0.0377* (0.0183)	-0.0630* (0.0313)	-0.0316 (0.0392)
MENA	0.0057 (0.0232)	-0.0273 (0.0236)	0.0058 (0.0245)	-0.0189 (0.0374)	0.1360 (0.1600)	0.0852 (0.1970)
Low income country	-0.0745*** (0.0211)	-0.0878*** (0.0265)	-0.0741*** (0.0190)	-0.0876** (0.0286)	-0.0781*** (0.0204)	-0.0833** (0.0295)
Lower middle income country	-0.0503*** (0.0116)	-0.0699*** (0.0179)	-0.0497*** (0.0108)	-0.0764*** (0.0189)	-0.0518*** (0.0131)	-0.0699** (0.0213)
Upper middle income country	-0.0356** (0.0111)	-0.0641** (0.0196)	-0.0359** (0.0117)	-0.0710*** (0.0207)	-0.0354** (0.0108)	-0.0606*** (0.0170)
Assistant professor	-0.0225* (0.0108)	-0.0136 (0.0199)	-0.0152 (0.0127)	0.0012 (0.0201)	-0.0223* (0.0100)	-0.0099 (0.0137)
Associate professor	-0.0283** (0.0102)	-0.0156 (0.0162)	-0.0264* (0.0107)	-0.0146 (0.0197)	-0.0282** (0.0098)	-0.0171 (0.0141)
Other occupations	-0.0331** (0.0113)	-0.0266 (0.0203)	-0.0280 (0.0144)	-0.0145 (0.0204)	-0.0333** (0.0117)	-0.0230 (0.0196)
Teamsize	0.0234*** (0.0057)	0.0236** (0.0085)	0.0229*** (0.0053)	0.0240** (0.0079)	0.0232*** (0.0054)	0.0246*** (0.0067)
Work experience	-0.0015** (0.0005)	-0.0015 (0.0009)	0.0005 (0.0012)	0.0025 (0.0019)	-0.0015** (0.0005)	-0.0015* (0.0007)
Work experience squared			-0.0000 (0.0000)	-0.0001* (0.0001)		
Female*Average beauty score					-0.0145* (0.0073)	-0.0175 (0.0134)
Black*Average beauty score					-0.0629 (0.0531)	-0.0154 (0.0874)
South Asian*Average beauty score					-0.0059 (0.0169)	0.0009 (0.0268)
East Asian*Average beauty score					0.0099 (0.0083)	-0.0033 (0.0094)
MENA*Average beauty score					-0.0396 (0.0462)	-0.0307 (0.0558)
Constant	0.1620*** (0.0228)	0.1380*** (0.0413)	0.1460*** (0.0297)	0.0956** (0.0346)	0.1510*** (0.0260)	0.1090** (0.0413)
N	1926	1926	1926	1926	1926	1926

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Table 3-4 Impact of beauty on average productivity, OLS and median regression

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)
Average beauty score	0.0329***	0.0403***	0.0333***	0.0417***	0.0371***	0.0463***
	(0.0050)	(0.0060)	(0.0044)	(0.0047)	(0.0056)	(0.0068)
Female	-0.0270*	-0.0296	-0.0280**	-0.0351*	0.0581	0.0583
	(0.0123)	(0.0194)	(0.0094)	(0.0165)	(0.0388)	(0.0710)
Black	0.0334	0.0515	0.0352	0.0460	0.2910	0.1520
	(0.0640)	(0.0576)	(0.0552)	(0.0636)	(0.2605)	(0.2737)
South Asian	0.0731***	0.0982*	0.0721**	0.0920**	0.0906	-0.0043
	(0.0190)	(0.0405)	(0.0239)	(0.0290)	(0.0674)	(0.1235)
East Asian	-0.0299*	-0.0498*	-0.0296*	-0.0418*	-0.0733	-0.0358
	(0.0142)	(0.0241)	(0.0127)	(0.0199)	(0.0459)	(0.0532)
MENA	0.0126	-0.0362	0.0127	-0.0253	0.1810	0.0924
	(0.0310)	(0.0326)	(0.0298)	(0.0203)	(0.1704)	(0.2448)
Low income country	-0.0910**	-0.1150***	-0.0905***	-0.1160***	-0.0951***	-0.1160***
	(0.0277)	(0.0320)	(0.0250)	(0.0235)	(0.0278)	(0.0313)
Lower middle income country	-0.0617***	-0.0852**	-0.0610***	-0.0924***	-0.0634***	-0.0844***
	(0.0162)	(0.0262)	(0.0176)	(0.0182)	(0.0132)	(0.0200)
Upper middle income country	-0.0415**	-0.0834***	-0.0419**	-0.0909***	-0.0411**	-0.0772**
	(0.0151)	(0.0223)	(0.0143)	(0.0174)	(0.0155)	(0.0268)
Assistant professor	-0.0272	-0.0146	-0.0190	0.0075	-0.0269*	-0.0120
	(0.0152)	(0.0260)	(0.0148)	(0.0203)	(0.0136)	(0.0244)
Associate professor	-0.0326*	-0.0137	-0.0304**	-0.0104	-0.0323**	-0.0157
	(0.0129)	(0.0227)	(0.0106)	(0.0162)	(0.0124)	(0.0216)
Other occupations	-0.0399**	-0.0243	-0.0342**	-0.0122	-0.0401**	-0.0245
	(0.0153)	(0.0277)	(0.0129)	(0.0194)	(0.0142)	(0.0257)
Teamsize	0.0243***	0.0269**	0.0238***	0.0267**	0.0240***	0.0289***
	(0.0053)	(0.0088)	(0.0049)	(0.0083)	(0.0046)	(0.0073)
Work experience	-0.0017**	-0.0015	0.0005	0.0037	-0.0017**	-0.0016
	(0.0006)	(0.0011)	(0.0014)	(0.0023)	(0.0007)	(0.0012)
Work experience squared			-0.0000	-0.0001*		
			(0.0000)	(0.0001)		
Female*Average beauty score					-0.0190*	-0.0205
					(0.0085)	(0.0156)
Black*Average beauty score					-0.0793	-0.0249
					(0.0795)	(0.0901)
South Asian*Average beauty score					-0.0039	0.0290
					(0.0173)	(0.0343)
East Asian*Average beauty score					0.0120	-0.0029
					(0.0127)	(0.0123)
MENA*Average beauty score					-0.0513	-0.0350
					(0.0460)	(0.0694)
Constant	0.1870***	0.1440***	0.1690***	0.0988*	0.1720***	0.1150*
	(0.0307)	(0.0413)	(0.0278)	(0.0384)	(0.0288)	(0.0472)
N	1926	1926	1926	1926	1926	1926

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

We first run the regression on the full model and the reduced model from OLS and quantile regression at 0.5^{th} quantile using the average normalised citations and find that the constant of the most model is not statistically significant (See Appendix E). It might be the effect of the right-skewed response variable, i.e., the average normalised citations (See Appendix B-4) and we need to keep the constant in the model because it is fundamental for prediction to be included when reporting the regression. The intercept is essential as it applies to all types of modelling such as OLS, linear or nonlinear models. It is always significantly different from zero. If there is the case that the intercept is zero, it implies that the response function would be exactly zero when all the independent variables are set to zero. To deal with this issue, we apply a log transformation on the response variable, in this case, the average normalised citations. After taking log transformation, the skewness changes from 4.81 to -0.38 and the kurtosis changes from 33.61 to 3.14. Also, the constant of all models is statistically significant as presented in Table 5. Recall the usefulness of the log transformation; it is the appropriate method to apply to the right-skewed response variable because it helps the model assumptions at least close to being satisfied by allowing interpretation of predictors' effects in relative terms. On the other hand, dealing with left-skewed response variables by taking the square or some other power greater than one generates a new distribution which is more symmetric. These techniques are nonlinear, so-called monotonic transformations, generating the new distribution which provides a better fit to the data. However, modelling location shifts and shape shifts is associated with a change in a particular covariate, and it is better to analyse these shifts on a raw scale rather than the monotonically transformed scale. For this reason, retransforming log-scale coefficients to raw-scale coefficients is required for interpretation and understanding the potential effect of covariates on the response variable.

Considering the location shifts on the log scale, the method to model the central location of the dependent variable is to deal with the conditional-mean model (OLS) relating average beauty score to log average normalised citations. Table 3-5, model (5) presents that each additional score of the average beauty score increases the conditional-mean average normalised citations by a factor of $e^{0.167} = 1.1817$, which indicates a 18.17% increase. The corresponding fitted-median model at 0.5^{th}

quantile (See Table 3-5, model (6)) shows a coefficient of 0.13, which indicates that each additional score of the average beauty score increases the conditional-median average normalised citations by $e^{0.13} = 1.1388$, which indicates a 13.88% increase. Therefore, the effects of average beauty score on average normalised citations are similar in magnitude to those on weighted and average productivity as reported above.

For team size, one additional author in the research team increases the conditional-mean average normalised citations by a factor of $e^{0.281} = 1.3245$, which indicates a 32.45% increase. The corresponding fitted-median model at 0.5th quantile (See Table 3-5, model (6)) shows a coefficient of 0.318, which indicates that one additional author, increases the conditional-median average normalised citations by $e^{0.318} = 1.3744$, which indicates a 37.44% increase. Therefore, the effect of team size is stronger on the conditional median in relative terms (log transformation), whereas in absolute terms (See Appendix B-5), the effect of team size is stronger on the conditional mean.

The interpretation of work experience is slightly different as the coefficient is negative, i.e., -0.0152. The factor would be $e^{-0.0152} = 0.9849$, that is, a 1.5% decrease in average normalised citations for one additional year of work experience. The corresponding fitted-median model at 0.5th quantile (See Table 3-5, model (6)) shows a coefficient of -0.0113. The factor would be $e^{-0.0113} = 0.9888$, that is, a 1.12% decrease in average normalised citations for one additional year of work experience. In this case, the effect of work experience is slightly stronger on the conditional mean in relative terms (log transformation), whereas in absolute terms (See Appendix B-5), the effect of work experience is not found.

Table 3-5 Impact of beauty on log average normalised citations, OLS and median regression

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)
Average beauty score	0.1620*** (0.0390)	0.1280** (0.0450)	0.1640*** (0.0369)	0.1230** (0.0404)	0.1670*** (0.0485)	0.1300** (0.0483)
Female	-0.2290* (0.0937)	-0.1760 (0.1210)	-0.2310* (0.0994)	-0.1670 (0.1053)	-0.0909 (0.4172)	0.0665 (0.4831)
Black	-0.1300 (0.4399)	-0.0028 (0.5120)	-0.1260 (0.3349)	0.0029 (0.4325)	1.7720 (1.7550)	2.3220 (1.7451)
South Asian	0.3340 (0.1959)	0.4680* (0.2162)	0.3320* (0.1575)	0.4700* (0.2348)	0.3400 (0.6104)	0.5040 (0.5182)
East Asian	-0.3000* (0.1388)	-0.4250** (0.1485)	-0.2990** (0.1140)	-0.4400** (0.1475)	-0.6370 (0.4277)	-1.0290 (0.5515)
MENA	0.0454 (0.1864)	0.1670 (0.2433)	0.0445 (0.1951)	0.1650 (0.1905)	1.7330* (0.7867)	0.9650 (1.2706)
Low income country	-0.5650* (0.2636)	-0.8240** (0.2526)	-0.5640** (0.1868)	-0.8460*** (0.2449)	-0.6010** (0.2284)	-0.8920** (0.3113)
Lower middle income country	-0.1260 (0.1402)	-0.2350 (0.1700)	-0.1250 (0.1515)	-0.2510 (0.1531)	-0.1290 (0.1134)	-0.2710 (0.1609)
Upper middle income country	-0.3570** (0.1129)	-0.4540*** (0.1254)	-0.3570** (0.1127)	-0.4490*** (0.1341)	-0.3560** (0.1250)	-0.4160** (0.1331)
Assistant professor	-0.3220** (0.1099)	-0.2360 (0.1306)	-0.3040** (0.1135)	-0.2680 (0.1628)	-0.3230*** (0.0949)	-0.2480* (0.1178)
Associate professor	-0.2780** (0.0995)	-0.1380 (0.1128)	-0.2730** (0.0988)	-0.1650 (0.1114)	-0.2810** (0.0894)	-0.1540 (0.1127)
Other occupations	-0.1740 (0.1139)	-0.1380 (0.1523)	-0.1610 (0.1202)	-0.1760 (0.1528)	-0.1790 (0.0982)	-0.1390 (0.1578)
Teamsize	0.2820*** (0.0359)	0.3230*** (0.0518)	0.2810*** (0.0388)	0.3270*** (0.0493)	0.2810*** (0.0288)	0.3180*** (0.0439)
Work experience	-0.0151*** (0.0045)	-0.0109 (0.0058)	-0.0102 (0.0122)	-0.0172 (0.0128)	-0.0152*** (0.0041)	-0.0113* (0.0053)
Work experience squared			-0.0001 (0.0003)	0.0001 (0.0003)		
Female*Average beauty score					-0.0316 (0.0886)	-0.0442 (0.1024)
Black*Average beauty score					-0.5850 (0.5063)	-0.6790 (0.5727)
South Asian*Average beauty score					0.0054 (0.1628)	0.0031 (0.1561)
East Asian*Average beauty score					0.0921 (0.1094)	0.1820 (0.1468)
MENA*Average beauty score					-0.5100* (0.2516)	-0.2390 (0.3955)
Constant	-4.5090*** (0.2434)	-4.4180*** (0.2537)	-4.5490*** (0.2325)	-4.3470*** (0.2287)	-4.5190*** (0.2473)	-4.4020*** (0.2506)
N	1851	1851	1851	1851	1851	1851

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

To interpret a categorical independent variable in the log-transform model, the specification of a reference group should be aware due to the concept of a percent increase. When conducting log transformed for the response variable, keep in mind that interpreting the results of a dummy variable requires switching the reference category, changing the coefficient's sign, and transforming the percent change into its reciprocal (when the coefficient of log-term is negative). Regarding the country development variable in this study, the reference category is high-income country. Our fitted OLS model (Table 3-5, model (5)) shows that the coefficient of low-income country is -0.601. So we adopted the reverse code by changing low-income country as a reference category and high-income country as an interested category, the equivariance property of linear lease square model informs that the coefficient of high-income country should be 0.601. So the factor would be $e^{0.601} = 1.8239$ that indicates an 82.39% increase in average normalised citations. The value of the coefficient obviously becomes larger after using the reverse code. In other words, the average normalised citations of authors in high-income country are greater than those from low-income country by 82.39%. Applying the same technique for the corresponding fitted-median model at 0.5^{th} quantile (See Table 3-5, model (6)), the coefficient of low-income country is -0.892 and the factor would be $e^{0.892} = 2.44$, indicating a 144% increase in average normalised citations. In other words, the average normalised citations of authors in high-income country are greater than those from low-income country by 144%. Therefore, the effect from the conditional median model is much stronger than those from the conditional mean in relative terms (log transformation), whereas the effect from the conditional mean is stronger than the effect from the conditional median in absolute terms (See Appendix B-5).

Similarly, the coefficient for upper middle-income country from OLS model is -0.356 and the factor after reverse code would be $e^{0.356} = 1.4276$. That is, the average normalised citations of authors in high-income country are higher than those from upper middle-income country by 42.76%. The corresponding fitted-median model at 0.5^{th} quantile (See Table 3-5, model (6)) shows the upper middle-income country's coefficient of -0.416. The factor after reverse code would be $e^{0.416} =$ 1.5159, that is, the average normalised citations of authors who are in high-income country are higher than those from upper middle-income country by 51.59%. Thus, the effect from the conditional median model is stronger than those from the conditional mean in relative terms (log transformation) while the effect from the conditional mean model is not found in absolute terms (See Appendix B-5).

To interpret the academic rank dummy in which the reference category is the full professor and the coefficient of assistant professor is -0.323, we adopted the reverse code using assistant professor as a reference category and full professor as an interested category so the factor after reverse code would be $e^{0.323} = 1.3812$. That is, the average normalised citations of authors who are full professor are higher than those of assistant professor by 38.12%. The corresponding fitted-median model at 0.5^{th} quantile (See Table 3-5, model (6)) shows the assistant professor's coefficient of -0.248. The factor after reverse code would be $e^{0.248} = 1.2815$, that is, the average normalised citations of authors who are full professor are higher than those of assistant professor by 28.15%. In this case, the effect from the conditional mean model is stronger than those from the conditional median in relative terms (log transformation); whereas the effect is not found in absolute terms (See Appendix B-5).

3.4.2 Individual conditional quantiles

We are also interested in the other quantiles of distribution of productivity in addition to the median. For example, the advantageous of physical attractiveness may be more prominent among the most or least productive researchers. The quantile regression estimates for weighted productivity across quantiles are presented in Table 3-6. We can see that the impact of average beauty score on research productivity in the centre and right tail of the productivity distribution is more than those in the left tail, suggesting that the physical attractiveness matters little for relatively unproductive individuals while it is important for their highly productive peers.

Table 3-6 Quantile regression estimates for weighted productivity across quantiles

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
Average beauty score	0.0037 (0.0030)	0.0077** (0.0028)	0.0185*** (0.0041)	0.0382*** (0.0074)	0.0389*** (0.0066)	0.0331*** (0.0062)	0.0289*** (0.0059)	0.0314*** (0.0084)	0.0359*** (0.0087)
Female	0.0230 (0.0276)	0.0023 (0.0198)	0.0328 (0.0318)	0.1180* (0.0561)	0.0504 (0.0560)	0.0787 (0.0503)	0.0374 (0.0325)	0.0451 (0.0442)	0.0283 (0.0886)
Black	0.2680 (0.2751)	0.2480 (0.2024)	0.0977 (0.2602)	0.2770 (0.2835)	0.0961 (0.2714)	0.0943 (0.2934)	0.0017 (0.3693)	0.1710 (0.3662)	0.3380 (0.3802)
South Asian	0.0292 (0.0397)	0.0070 (0.0315)	0.0115 (0.0536)	0.0294 (0.0876)	0.0671 (0.0936)	0.0502 (0.0841)	0.0687 (0.0767)	0.0658 (0.0877)	0.1100 (0.0859)
East Asian	-0.0306 (0.0477)	0.0010 (0.0139)	-0.0065 (0.0295)	-0.0165 (0.0329)	-0.0316 (0.0392)	-0.0513 (0.0657)	-0.1110 (0.0621)	-0.1040 (0.0587)	-0.1010 (0.0850)
MENA	0.0209 (0.0993)	0.0458 (0.0860)	0.0978 (0.1057)	0.2250 (0.1490)	0.0852 (0.1970)	0.1660 (0.2433)	0.2830 (0.2279)	0.4310 (0.2348)	0.5810 (0.3308)
Low income country	-0.0307 (0.0224)	-0.0139 (0.0143)	-0.0233 (0.0293)	-0.0482 (0.0335)	-0.0833** (0.0295)	-0.0786** (0.0288)	-0.0834* (0.0385)	-0.0824 (0.0480)	-0.1020* (0.0436)
Lower middle income country	-0.0343* (0.0168)	-0.0088 (0.0056)	-0.0299** (0.0101)	-0.0456** (0.0167)	-0.0699** (0.0213)	-0.0835*** (0.0250)	-0.0755** (0.0233)	-0.0718** (0.0273)	-0.0622* (0.0261)
Upper middle income country	-0.0157 (0.0115)	-0.0133* (0.0059)	-0.0396*** (0.0088)	-0.0562** (0.0176)	-0.061*** (0.0170)	-0.0402 (0.0233)	-0.0110 (0.0151)	-0.0181 (0.0132)	-0.0141 (0.0180)
Assistant professor	-0.0200* (0.0097)	-0.0142 (0.0081)	-0.0193 (0.0117)	-0.0204 (0.0137)	-0.0099 (0.0137)	-0.0158 (0.0106)	-0.0230 (0.0150)	-0.0356 (0.0184)	-0.0247 (0.0214)
Associate professor	-0.0067 (0.0063)	-0.0082 (0.0050)	-0.0176* (0.0079)	-0.0190 (0.0103)	-0.0171 (0.0141)	-0.0228 (0.0122)	-0.0324** (0.0118)	-0.048*** (0.0136)	-0.0445** (0.0164)
Other occupations	-0.0289 (0.0225)	-0.0149 (0.0086)	-0.0283* (0.0114)	-0.0270* (0.0116)	-0.0230 (0.0196)	-0.0241 (0.0130)	-0.0369** (0.0123)	-0.0474* (0.0207)	-0.0132 (0.0272)
Teamsize	0.0023 (0.0031)	0.0035 (0.0021)	0.0069* (0.0034)	0.0146** (0.0054)	0.0246*** (0.0067)	0.0231*** (0.0058)	0.0298*** (0.0055)	0.0338*** (0.0055)	0.0429*** (0.0071)
Work experience	-0.0023*** (0.0007)	-0.0010** (0.0003)	-0.0018*** (0.0004)	-0.0021*** (0.0005)	-0.0015* (0.0007)	-0.0012** (0.0005)	-0.0013* (0.0005)	-0.0018* (0.0008)	-0.0010 (0.0009)
Female*Average beauty score	-0.0044 (0.0061)	-0.0013 (0.0051)	-0.0096 (0.0064)	-0.0357** (0.0133)	-0.0175 (0.0134)	-0.0207 (0.0108)	-0.0138 (0.0073)	-0.0192* (0.0097)	-0.0153 (0.0203)
Black*Average beauty score	-0.0934 (0.0874)	-0.0910 (0.0591)	-0.0375 (0.0805)	-0.0928 (0.0876)	-0.0154 (0.0874)	-0.0232 (0.0940)	0.0046 (0.1078)	-0.0445 (0.1015)	-0.0942 (0.1030)
South Asian* Average beauty score	0.0007 (0.0144)	0.0021 (0.0104)	0.0042 (0.0160)	0.0003 (0.0238)	0.0009 (0.0268)	0.0041 (0.0235)	-0.0024 (0.0199)	-0.0039 (0.0207)	-0.0135 (0.0201)
East Asian* Average beauty score	0.0072 (0.0111)	-0.0022 (0.0039)	-0.0037 (0.0088)	-0.0026 (0.0091)	-0.0033 (0.0094)	0.0011 (0.0178)	0.0251 (0.0164)	0.0210 (0.0146)	0.0190 (0.0230)
MENA*Average beauty score	0.0033 (0.0307)	-0.0118 (0.0255)	-0.0261 (0.0318)	-0.0656 (0.0449)	-0.0307 (0.0558)	-0.0630 (0.0675)	-0.0880 (0.0630)	-0.1360* (0.0618)	-0.1590 (0.0977)
Constant	0.1410*** (0.0174)	0.1280*** (0.0131)	0.1320*** (0.0230)	0.0896* (0.0358)	0.1090** (0.0413)	0.1710*** (0.0331)	0.2090*** (0.0281)	0.2560*** (0.0373)	0.2590*** (0.0428)
N	1926	1926	1926	1926	1926	1926	1926	1926	1926

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The coefficients of the quantile regression model for 9 quantiles in Table 3-6 can be used to examine the impacts of independent variables on various quantiles of the research productivity distribution. To simplify the interpretation, we group 9 quantiles into 3 groups; lower quantiles (i.e., below 0.3th quantile), middle quantiles (i.e., between 0.4th quantile and 0.6th quantile), and upper quantiles (i.e., 0.7th quantile and above). The results confirm the existence of the attractiveness effect across all quantiles except the 0.1th quantile, having a stronger positive effect on research productivity at the middle and the upper quantiles than the lower quantiles. With country development indicator, being in a low-income country has a negative effect at the middle and upper quantiles. Being in a lower middle-income country has a negative impact on research productivity across all quantiles and having a stronger effect particularly at the middle quantiles while being in an upper middle-income country has a negative effect in the lower and middle quantiles, with more substantial effect at the middle quantiles. For the associate professor, the existence of negative effects only appears at the upper quantiles. The size of the research team has an increasing effect across all quantiles except the 0.1th and 0.2th quantile, and the effect from OLS as shown in Table 3-3 (0.0232) is quite similar to the median estimate. It would imply that having more authors in the team improves the chance of producing high-quality publications. Work experience has a small negatively impact across all quantiles except the 0.9th quantile, that is, having more work experience slightly impedes the possibility to produce the high-quality publications.

The effect of covariates on the average productivity and the log average normalised citations are reported in Appendix B-7 and Appendix B-9 respectively. The results are largely in line with the results reported in Table 3-6, with the small difference in the effect and significance of covariates. In this section, we illustrate the location shift along the distribution of response variable because it is better to understand the lower or upper tails of distribution rather than in the central location. However, the information of location shifts only is not sufficient to demonstrate the effect of modifications. The shape of the shift (i.e., how large or small) and whether the shift is statistically significant are the issues of interest. The next section will describe the graphical view in which to provide some information of how the modifications of covariates generate shape shifts for a more comprehensive view.

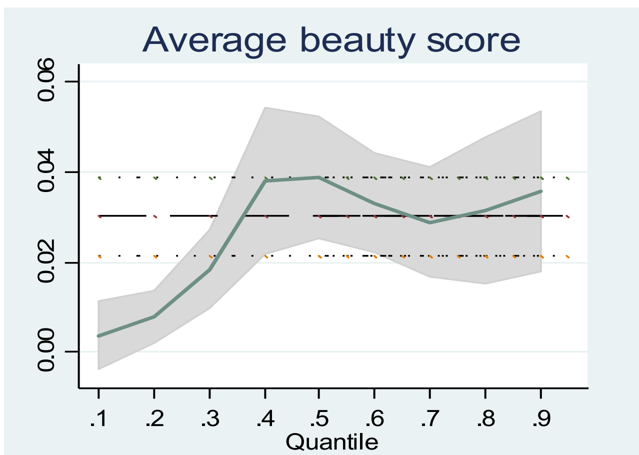
3.4.3 Graphical presentation of results

In social-science research, researchers who work on inequality research are not only focusing on location shifts but also on shape shifts. Because concentrating on the location alone overlooks the information about group difference. The shape effects analysis reveals more information than the location analysis alone and is conducted by using quantile regression estimates at multiple quantiles. It is considerably complicated because investigation for a long sequence of quantiles (e.g., 0.1, 0.2, …, 0.8, 0.9) is cumbersome; therefore, the graphical view facilitates the interpretation of quantile regression results for shape analysis. In other words, the graphical view does not only illustrate how the impacts of predictors vary across quantiles but also indicates the magnitude of the effects at various quantiles differing substantially from the OLS coefficient and even the confidence intervals around each coefficient (Baum, 2013).

In this section, we summarise the graphical patterns to determine the impact of predictors and how these predictors change the shape of the response distribution. The horizontal axis depicts the location shift by a one-unit increase in the predictor. Thus, arrays of these coefficients for a range of quantiles indicate the extent to which a one-unit increase in the independent variable impacts the shape of the dependent variable distribution. An upward-sloping curve shows an increase in the scale while a downward-sloping curve shows a decrease in the scale of the dependent variable distribution. Although the graphical view provides useful information on the extent to which modifications of the independent variables produce shape shifts, the indication of skewness shift is not sufficiently demonstrated by the graphical view. Figure 1a shows a graphical view of the weighted productivity at various quantiles as a function of average beauty score, fixing other covariates using the estimated coefficients (see Table 3-6). Author number and intercept are also described in this section; however, the full set of the graphical view for other covariates are illustrated in Appendix B-6.

We draw a graph of the impact of Average beauty score and the 95% confidence envelope based on bootstrap estimates with 50 repetitions data resampling. The effect of average beauty score can be explained by the change in a conditional-research productivity quantile generated by one additional score of average beauty score, fixing the other covariates. The confidence envelope (the thick horizontal line) never crosses the zero line means the attractiveness effect is positive and significant (except for the 0.1th quantile). Figure 3-1 depicts an upward-sloping curve at the beginning of the line signifying the impacts of attractiveness in which the effect of the additional score of average beauty score is positive across the lower quantiles and increasing until the 0.4th quantile. Then it levels off and stays flat until the median and then decreases slightly until the 0.7th quantile. The effect accelerates again after the 0.7th quantile. The slopes between the 0.2th quantile and 0.4th quantile are steeper than those in the upper quantiles.

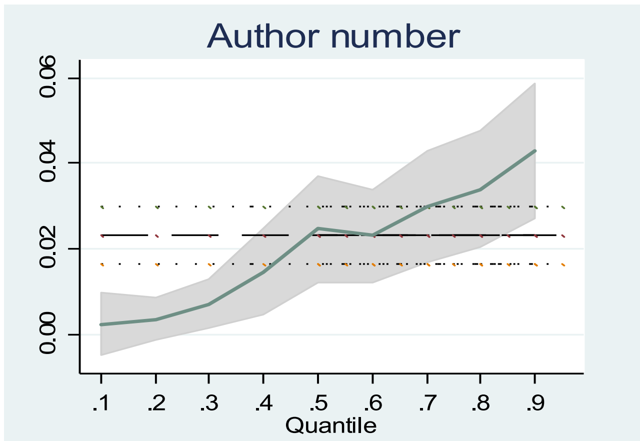
Figure 3-1 Quantile coefficients for weighted productivity



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

The impact of the number of co-authors can be defined as the change in the conditional research productivity quantile generated by one additional author in the research team, fixing the other covariates. The effect of the increasing the team size is significantly positive, as the confidence envelope is almost always above the zero line. Figure 3-2 illustrates a curve for the effect of author number on research productivity using weighted productivity as a measurement. It shows an upward-sloping curve along the quantiles, and a downward-sloping curve between the 0.5th quantile and the 0.6th quantile. The slopes between the 0.3th quantile and the 0.5th quantile and the slopes above the 0.6th quantile are steeper than those below the 0.3th quantiles. To sum up, the impact of one more in the research team is positive for almost all value of quantiles and steadily increasing with quantile. This increase accelerates more between the 0.3th quantile and the 0.5th quantile, and the slopes above the 0.8th quantile.

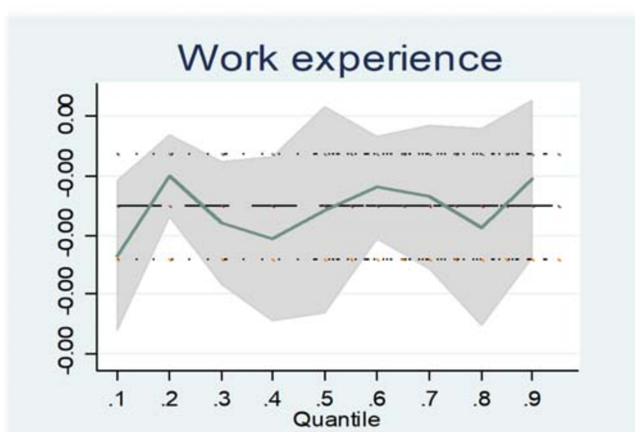
Figure 3-2 Quantile coefficients for weighted productivity



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Following the coefficients on different quantile of weighted productivity in the Figure 3-3, the author's work experience shows different impacts on the different level of research productivity as they fluctuate across all quantiles. There are 3 phases of the upward-sloping curves which are below the 0.2th quantile, between 0.4th and 0.6th quantile, and above 0.8th quantile. However, the steepest of the upward-sloping curves is the slopes at the first phase.

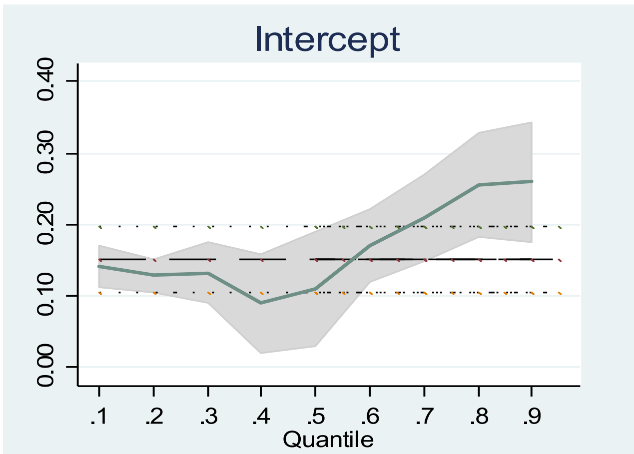
Figure 3-3 Quantile coefficients for weighted productivity



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Figure 3-4 illustrates the graph for the fitted Intercept. Since the covariates have been centred close to their means, the intercept depicts the fitted quantile function at the covariate mean, namely the "typical setting". Given the downward slopes below the 0.4th quantile, the steep upward slopes between the 0.5th quantile and the 0.8th quantile, and the slight upward-slopes above the 0.8th quantile, the conditional quantile function at the typical setting is right-skewed.

Figure 3-4 Quantile coefficients for weighted productivity



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

These graphs express additional patterns associated with the impacts of attractiveness and author number on research productivity. The full set of the graphical view for other covariates for the quantile regression model using weighted productivity is in Appendix B-6. In respect of the shifts in the response distribution; they are accountable for both location shifts and shape shifts. From our results, the graphs tell us that the average beauty score has a greater impact on research productivity at the middle quantiles of productivity distribution than the upper quantiles while author number has a progressively impact across all quantiles except those between the 0.5th and 0.6th quantile. That is to say, the change in average beauty score or author number changes the scale of the research productivity.

This section illustrates the graphical interpretations of quantile regression model estimates and quantitative measures of location shifts and shape shifts. We explain the contribution of covariates on research productivity using weighted productivity because it is considered the main response variable in this study.

However, the full sets of graphical view for the quantile regression model using average productivity and log average normalised citations, which are the benchmark for research productivity, are illustrated in Appendix B-8 and Appendix B-10 respectively.

3.4.4 Robustness

A plausible reason for the positive association between beauty and research productivity is that the assessors who rated the authors' pictures tend to rate relatively young authors as more attractive. If so, then the coefficient estimated for the average attractiveness score would effectively pick up the effect of authors' age. To allow for this possibility, we re-estimate our results for authors with up to 10 years of post-PhD work experience. We cannot observe the actual age for most authors, but given that most academics obtain their PhD around the age of 30 (or slightly before), this restriction should result in a sample with the vast majority of authors aged 40 or less. The results are presented in Tables 3-7 to 3-12.

Despite losing approximately half of the sample, the effect of beauty on research productivity is still very precisely estimated, and remarkably similar to that obtained in the whole sample. As before, physical attractiveness is associated with higher productivity, regardless of whether we measure quality of publications by weighted productivity, average productivity or (log of) normalised citations. The magnitude of the effect of beauty is also similar as when using the whole sample. When considering the individual quantiles, the effect is non-existent or weak for the bottom 30-40% of the sample and significant for the upper two thirds of the distribution.

Table 3-7 Impact of beauty on weighted productivity, OLS and median regression, authors with less than 10 years of working experience

	(1) **OLS**	(2) **QR(0.5)**	(3) **OLS**	(4) **QR(0.5)**	(5) **OLS**	(6) **QR(0.5)**
Average beauty score	0.0244*** (0.0038)	0.0264*** (0.0048)	0.0243*** (0.0048)	0.0257*** (0.0056)	0.0272*** (0.0047)	0.0272*** (0.0072)
Female	-0.0204 (0.0147)	-0.0109 (0.0184)	-0.0204 (0.0106)	-0.0103 (0.0155)	0.0697 (0.0435)	0.1050 (0.0748)
Black	-0.0162 (0.0370)	0.0330 (0.0523)	-0.0156 (0.0482)	0.0331 (0.0526)	0.2550 (0.1617)	0.2580 (0.2568)
South Asian	0.0489* (0.0194)	0.0337 (0.0296)	0.0485* (0.0216)	0.0350 (0.0300)	0.0066 (0.0523)	-0.0545 (0.0920)
East Asian	-0.0199 (0.0144)	-0.0428 (0.0220)	-0.0198 (0.0130)	-0.0418* (0.0198)	-0.0850* (0.0399)	-0.0929 (0.0643)
MENA	-0.0182 (0.0285)	-0.0357 (0.0299)	-0.0173 (0.0252)	-0.0362 (0.0432)	0.2420 (0.2725)	0.1220 (0.3253)
Low income country	-0.0823*** (0.0220)	-0.0972*** (0.0237)	-0.0825*** (0.0226)	-0.0991*** (0.0285)	-0.0862*** (0.0218)	-0.0973*** (0.0283)
Lower middle income country	-0.0481** (0.0150)	-0.0785*** (0.0179)	-0.0484** (0.0150)	-0.0780*** (0.0218)	-0.0491** (0.0151)	-0.0731*** (0.0196)
Upper middle income country	-0.0273 (0.0154)	-0.0488 (0.0307)	-0.0276 (0.0160)	-0.0497 (0.0350)	-0.0274* (0.0132)	-0.0566 (0.0347)
Assistant professor	-0.0119 (0.0150)	-0.0008 (0.0215)	-0.0128 (0.0146)	-0.0025 (0.0217)	-0.0130 (0.0174)	-0.0048 (0.0232)
Associate professor	-0.0173 (0.0156)	-0.0041 (0.0295)	-0.0173 (0.0161)	-0.0041 (0.0210)	-0.0174 (0.0188)	-0.0099 (0.0243)
Other occupations	-0.0518** (0.0197)	-0.0477 (0.0298)	-0.0515** (0.0175)	-0.0487 (0.0255)	-0.0544*** (0.0163)	-0.0612* (0.0282)
Teamsize	0.0227*** (0.0053)	0.0272** (0.0102)	0.0229*** (0.0056)	0.0267*** (0.0066)	0.0223*** (0.0061)	0.0266*** (0.0080)
Work experience	0.0013 (0.0016)	0.0014 (0.0024)	0.0041 (0.0071)	0.0020 (0.0080)	0.0008 (0.0020)	0.0008 (0.0026)
Work experience squared			-0.0002 (0.0007)	-0.0000 (0.0008)		
Female*Average beauty score					-0.0194* (0.0092)	-0.0236 (0.0153)
Black*Average beauty score					-0.0850 (0.0528)	-0.0966 (0.0836)
South Asian*Average beauty score					0.0135 (0.0137)	0.0206 (0.0277)
East Asian*Average beauty score					0.0169 (0.0100)	0.0132 (0.0153)
MENA*Average beauty score					-0.0769 (0.0848)	-0.0517 (0.0923)
Constant	0.1560*** (0.0264)	0.1340** (0.0480)	0.1500*** (0.0302)	0.1370** (0.0419)	0.1500*** (0.0298)	0.1410** (0.0501)
N	950	950	950	950	950	950

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Table 3-8 Impact of beauty on average productivity, OLS and median regression, authors with less than 10 years of working experience

	(1) **OLS**	(2) **QR(0.5)**	(3) **OLS**	(4) **QR(0.5)**	(5) **OLS**	(6) **QR(0.5)**
Average beauty score	0.0298*** (0.0045)	0.0309*** (0.0064)	0.0298*** (0.0050)	0.0307*** (0.0075)	0.0335*** (0.0044)	0.0351*** (0.0091)
Female	-0.0236 (0.0164)	-0.0098 (0.0276)	-0.0236 (0.0125)	-0.0082 (0.0257)	0.0889 (0.0503)	0.1350 (0.0831)
Black	-0.0096 (0.0482)	0.0465 (0.0681)	-0.0087 (0.0492)	0.0475 (0.0603)	0.3450 (0.6375)	0.3570 (0.2598)
South Asian	0.0627* (0.0248)	0.0579 (0.0355)	0.0621* (0.0297)	0.0575 (0.0360)	0.0022 (0.0703)	-0.0434 (0.1024)
East Asian	-0.0203 (0.0138)	-0.0462 (0.0255)	-0.0202 (0.0170)	-0.0464 (0.0276)	-0.0923 (0.0574)	-0.0883 (0.0711)
MENA	-0.0231 (0.0339)	-0.0393 (0.0496)	-0.0218 (0.0340)	-0.0384 (0.0471)	0.2920 (0.3815)	0.1690 (0.7408)
Low income country	-0.1020*** (0.0263)	-0.1310*** (0.0339)	-0.1020*** (0.0271)	-0.1300*** (0.0343)	-0.1070*** (0.0311)	-0.1270*** (0.0334)
Lower middle income country	-0.0607*** (0.0169)	-0.0947*** (0.0268)	-0.0611*** (0.0172)	-0.0863*** (0.0247)	-0.0618*** (0.0185)	-0.0880*** (0.0230)
Upper middle income country	-0.0320* (0.0128)	-0.0531 (0.0409)	-0.0323 (0.0176)	-0.0565 (0.0339)	-0.0319* (0.0149)	-0.0715 (0.0383)
Assistant professor	-0.0203 (0.0222)	-0.0039 (0.0336)	-0.0214 (0.0185)	-0.0029 (0.0353)	-0.0217 (0.0208)	0.0010 (0.0290)
Associate professor	-0.0263 (0.0231)	-0.0037 (0.0318)	-0.0263 (0.0187)	-0.0018 (0.0364)	-0.0265 (0.0221)	-0.0055 (0.0317)
Other occupations	-0.0671** (0.0227)	-0.0634 (0.0347)	-0.0668** (0.0228)	-0.0606 (0.0359)	-0.0704*** (0.0203)	-0.0600 (0.0407)
Teamsize	0.0244*** (0.0056)	0.0280** (0.0096)	0.0247*** (0.0062)	0.0285** (0.0106)	0.0240*** (0.0057)	0.0287** (0.0100)
Work experience	0.0020 (0.0022)	0.0019 (0.0026)	0.0057 (0.0056)	0.0036 (0.0110)	0.0014 (0.0023)	0.0014 (0.0035)
Work experience squared			-0.0003 (0.0005)	-0.0001 (0.0010)		
Female*Average beauty score					-0.0242* (0.0101)	-0.0297 (0.0184)
Black*Average beauty score					-0.1110 (0.2015)	-0.1270 (0.0847)
South Asian*Average beauty score					0.0192 (0.0201)	0.0230 (0.0314)
East Asian*Average beauty score					0.0187 (0.0158)	0.0108 (0.0184)
MENA*Average beauty score					-0.0929 (0.1204)	-0.0669 (0.2313)
Constant	0.1810*** (0.0289)	0.1570** (0.0574)	0.1740*** (0.0403)	0.1500* (0.0677)	0.1730*** (0.0329)	0.1400* (0.0607)
N	950	950	950	950	950	950

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 3-9 Impact of beauty on log average normalised citations, OLS and median regression, authors with less than 10 years of working experience

	(1) **OLS**	(2) **QR(0.5)**	(3) **OLS**	(4) **QR(0.5)**	(5) **OLS**	(6) **QR(0.5)**
Average beauty score	0.1560** (0.0482)	0.1470* (0.0641)	0.1550*** (0.0446)	0.1480** (0.0486)	0.1510*** (0.0422)	0.1310* (0.0614)
Female	-0.1920 (0.1333)	-0.1960 (0.1463)	-0.1920 (0.1180)	-0.1930 (0.1298)	0.0329 (0.5191)	0.0917 (0.4779)
Black	-0.3620 (0.4487)	-0.1520 (0.3463)	-0.3530 (0.5167)	-0.1480 (0.5746)	0.8530 (2.1536)	0.5560 (2.3104)
South Asian	0.3970 (0.3430)	0.4810 (0.2819)	0.3910 (0.3095)	0.4930* (0.2284)	0.5830 (0.9918)	0.6080 (0.9047)
East Asian	-0.3950** (0.1531)	-0.4400** (0.1613)	-0.3940** (0.1358)	-0.4330* (0.1942)	-1.0510* (0.4437)	-1.3180* (0.5623)
MENA	-0.1280 (0.3503)	-0.0837 (0.4465)	-0.1140 (0.3913)	-0.0813 (0.3602)	0.3170 (13.0127)	-0.8760 (5.4077)
Low income country	-0.3030 (0.3017)	-0.3570 (0.2994)	-0.3070 (0.3052)	-0.3530 (0.2875)	-0.3380 (0.3638)	-0.3170 (0.3709)
Lower middle income country	-0.0017 (0.1387)	-0.2220 (0.1964)	-0.0065 (0.1634)	-0.2230 (0.2032)	-0.0133 (0.1490)	-0.2750 (0.1968)
Upper middle income country	-0.2330 (0.1702)	-0.4410* (0.1904)	-0.2370 (0.1213)	-0.4560* (0.1923)	-0.2380 (0.1700)	-0.4400* (0.1804)
Assistant professor	-0.2850* (0.1271)	-0.1940 (0.1903)	-0.2980* (0.1394)	-0.2330 (0.2327)	-0.2800* (0.1382)	-0.1830 (0.1656)
Associate professor	-0.1850 (0.1488)	-0.0419 (0.1726)	-0.1850 (0.1388)	-0.0585 (0.1643)	-0.1820 (0.1493)	-0.0529 (0.1797)
Other occupations	-0.3350 (0.1786)	-0.3080 (0.2376)	-0.3330* (0.1421)	-0.3440 (0.1863)	-0.3370 (0.1726)	-0.2760 (0.1856)
Teamsize	0.3130*** (0.0506)	0.3480*** (0.0529)	0.3160*** (0.0514)	0.3490*** (0.0447)	0.3120*** (0.0409)	0.3440*** (0.0508)
Work experience	-0.0103 (0.0210)	-0.0022 (0.0262)	0.0307 (0.0660)	0.0057 (0.0789)	-0.0108 (0.0179)	0.0042 (0.0181)
Work experience squared			-0.0040 (0.0062)	-0.0012 (0.0074)		
Female*Average beauty score					-0.0478 (0.1025)	-0.0527 (0.1018)
Black*Average beauty score					-0.3830 (0.6972)	-0.1800 (0.7822)
South Asian*Average beauty score					-0.0500 (0.2579)	-0.0548 (0.2371)
East Asian*Average beauty score					0.1720 (0.1066)	0.2440 (0.1415)
MENA*Average beauty score					-0.1340 (3.2747)	0.1990 (1.7235)
Constant	-4.6140*** (0.3144)	-4.6290*** (0.3709)	-4.6880*** (0.3499)	-4.6120*** (0.2816)	-4.5860*** (0.2333)	-4.5860*** (0.3085)
N	923	923	923	923	923	923

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Table 3-10 Quantile regression estimates for weighted productivity across quantiles, authors with less than 10 years of working experience

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
Average beauty score	0.0034 (0.0031)	0.0097* (0.0043)	0.0147* (0.0065)	0.0306*** (0.0072)	0.0272*** (0.0062)	0.0250*** (0.0068)	0.0244** (0.0079)	0.0290** (0.0100)	0.0322** (0.0103)
Female	0.0230 (0.0534)	0.0153 (0.0440)	0.0117 (0.0447)	0.0847 (0.0749)	0.1050 (0.0908)	0.0783 (0.0763)	0.0969 (0.0648)	0.1290 (0.0905)	0.0894 (0.1224)
Black	0.2780 (0.1638)	0.2650 (0.1948)	0.1200 (0.1925)	0.1890 (0.2284)	0.2580 (0.2296)	0.0554 (0.2275)	0.1200 (0.2651)	0.2180 (0.3058)	0.4030 (0.3512)
South Asian	-0.0016 (0.0606)	0.0043 (0.0663)	-0.0124 (0.0718)	0.0035 (0.0962)	-0.0545 (0.1165)	-0.0932 (0.1080)	-0.0897 (0.0998)	-0.0290 (0.0996)	0.0774 (0.0968)
East Asian	-0.0190 (0.0611)	-0.0101 (0.0415)	-0.0824 (0.0430)	-0.1010* (0.0503)	-0.0929 (0.0820)	-0.0906 (0.0853)	-0.1150 (0.0975)	-0.0944 (0.0958)	-0.0516 (0.0966)
MENA	0.0371 (0.1970)	0.1190 (0.1776)	0.1940 (0.4643)	0.1730 (0.4513)	0.1220 (0.3649)	0.2190 (0.2937)	0.2340 (0.2824)	0.2070 (0.3094)	0.2870 (0.4314)
Low income country	-0.0416 (0.0339)	-0.0238 (0.0283)	-0.0471 (0.0251)	-0.0581 (0.0319)	-0.0973*** (0.0286)	-0.1170*** (0.0253)	-0.1170*** (0.0339)	-0.1130* (0.0443)	-0.0763 (0.0412)
Lower middle income country	-0.0081 (0.0134)	-0.0148 (0.0094)	-0.0302* (0.0146)	-0.0536** (0.0191)	-0.0731*** (0.0201)	-0.0886*** (0.0231)	-0.0843** (0.0277)	-0.0787* (0.0325)	-0.0494 (0.0337)
Upper middle income country	-0.0085 (0.0174)	-0.0194* (0.0095)	-0.0387** (0.0139)	-0.0613* (0.0255)	-0.0566 (0.0389)	-0.0229 (0.0314)	0.0035 (0.0226)	-0.0081 (0.0211)	-0.0136 (0.0213)
Assistant professor	-0.0168 (0.0131)	-0.0172 (0.0116)	0.0008 (0.0163)	0.0115 (0.0300)	-0.0048 (0.0258)	-0.0027 (0.0211)	-0.0309 (0.0285)	-0.0301 (0.0305)	-0.0329 (0.0300)
Associate professor	0.0041 (0.0145)	-0.0040 (0.0131)	0.0023 (0.0139)	-0.0064 (0.0313)	-0.0099 (0.0231)	-0.0105 (0.0199)	-0.0399 (0.0279)	-0.0408 (0.0300)	-0.0529* (0.0245)
Other occupations	-0.0244 (0.0236)	-0.0228 (0.0135)	-0.0229 (0.0199)	-0.0291 (0.0318)	-0.0612* (0.0299)	-0.0432 (0.0231)	-0.0602* (0.0248)	-0.0777** (0.0286)	-0.0879* (0.0360)
Teamsize	0.0053 (0.0052)	0.0022 (0.0045)	0.0072 (0.0049)	0.0147 (0.0077)	0.0266** (0.0083)	0.0237*** (0.0068)	0.0316*** (0.0047)	0.0326*** (0.0069)	0.0379*** (0.0097)
Work experience	-0.0032 (0.0025)	-0.0019 (0.0022)	-0.0000 (0.0023)	0.0039 (0.0039)	0.0008 (0.0031)	0.0006 (0.0023)	0.0014 (0.0027)	0.0001 (0.0028)	-0.0000 (0.0039)
Female* Ave rage beauty score	-0.0050 (0.0112)	-0.0032 (0.0092)	-0.0059 (0.0088)	-0.0279 (0.0144)	-0.0236 (0.0182)	-0.0193 (0.0148)	-0.0245 (0.0128)	-0.0330 (0.0188)	-0.0261 (0.0265)
Black*Average beauty score	-0.0960 (0.0543)	-0.0961 (0.0628)	-0.0433 (0.0633)	-0.0677 (0.0764)	-0.0966 (0.0737)	-0.0150 (0.0762)	-0.0351 (0.0922)	-0.0635 (0.1010)	-0.1240 (0.1149)
South Asian* Average beauty score	0.0097 (0.0156)	0.0050 (0.0172)	0.0112 (0.0216)	0.0071 (0.0276)	0.0206 (0.0353)	0.0446 (0.0331)	0.0418 (0.0289)	0.0245 (0.0236)	-0.0075 (0.0222)
East Asian* Average beauty score	0.0049 (0.0153)	0.0022 (0.0112)	0.0183 (0.0118)	0.0234 (0.0133)	0.0132 (0.0194)	0.0130 (0.0208)	0.0266 (0.0233)	0.0233 (0.0231)	0.0076 (0.0272)
MENA* Average beauty score	-0.0056 (0.0563)	-0.0286 (0.0488)	-0.0543 (0.1475)	-0.0564 (0.1406)	-0.0517 (0.1088)	-0.0781 (0.0835)	-0.0773 (0.0825)	-0.0788 (0.0935)	-0.1080 (0.1347)
Constant	0.133*** (0.0204)	0.133*** (0.0256)	0.127*** (0.0362)	0.0744 (0.0479)	0.141** (0.0479)	0.187*** (0.0393)	0.220*** (0.0457)	0.255*** (0.0530)	0.294*** (0.0685)
N	950	950	950	950	950	950	950	950	950

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Table 3-11 Quantile regression estimates for average productivity across quantiles, authors with less than 10 years of working experience

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
Average beauty score	0.0038 (0.0041)	0.0109 (0.0076)	0.0229* (0.0090)	0.0379*** (0.0087)	0.0351*** (0.0073)	0.0294** (0.0092)	0.0317** (0.0111)	0.0377** (0.0138)	0.0447* (0.0177)
Female	0.0278 (0.0503)	0.0218 (0.0569)	0.0411 (0.0591)	0.1120 (0.0943)	0.1350 (0.0928)	0.1240 (0.0863)	0.1360 (0.0828)	0.1710* (0.0848)	0.1110 (0.1463)
Black	0.2950 (0.2314)	0.3210 (0.2379)	0.2030 (0.2287)	0.2790 (0.2668)	0.3570 (0.2997)	0.1450 (0.3266)	0.1260 (0.3278)	0.3760 (0.4734)	0.8080 (0.5066)
South Asian	0.0058 (0.0982)	-0.0079 (0.0996)	0.0291 (0.1081)	0.0102 (0.1265)	-0.0434 (0.1129)	-0.1010 (0.0846)	-0.0889 (0.1014)	-0.0369 (0.1352)	0.1030 (0.1395)
East Asian	-0.0158 (0.0555)	-0.0044 (0.0440)	-0.0929 (0.0494)	-0.1050 (0.0589)	-0.0883 (0.0711)	-0.1190 (0.0961)	-0.1630 (0.1085)	-0.1180 (0.1099)	-0.1100 (0.1138)
MENA	0.0561 (2.1396)	0.1250 (2.1971)	0.2120 (2.1752)	0.2400 (2.0285)	0.1690 (1.8091)	0.3260 (1.8592)	0.2770 (1.7053)	0.2820 (1.6394)	0.3500 (1.6205)
Low income country	-0.0357 (0.0449)	-0.0302 (0.0368)	-0.0660 (0.0412)	-0.0766 (0.0392)	-0.127*** (0.0359)	-0.155*** (0.0428)	-0.1330* (0.0551)	-0.1200 (0.0710)	-0.0681 (0.0463)
Lower middle income country	-0.0051 (0.0114)	-0.0142 (0.0122)	-0.0524** (0.0180)	-0.0657** (0.0233)	-0.088*** (0.0208)	-0.119*** (0.0266)	-0.113*** (0.0302)	-0.0880** (0.0340)	-0.0398 (0.0463)
Upper middle income country	-0.0072 (0.0130)	-0.0179 (0.0127)	-0.0538** (0.0199)	-0.0693** (0.0228)	-0.0715 (0.0378)	-0.0351 (0.0361)	0.0061 (0.0231)	0.0002 (0.0210)	-0.0326 (0.0211)
Assistant professor	-0.0134 (0.0125)	-0.0281 (0.0181)	0.0065 (0.0216)	0.0170 (0.0330)	0.0010 (0.0245)	0.0032 (0.0256)	-0.0334 (0.0331)	-0.0367 (0.0337)	-0.0437 (0.0491)
Associate professor	0.0061 (0.0110)	-0.0120 (0.0143)	0.0023 (0.0193)	-0.0026 (0.0300)	-0.0055 (0.0242)	-0.0019 (0.0263)	-0.0531 (0.0335)	-0.0631 (0.0345)	-0.0688 (0.0459)
Other occupations	-0.0236 (0.0277)	-0.0329* (0.0140)	-0.0236 (0.0252)	-0.0283 (0.0383)	-0.0600 (0.0367)	-0.0540 (0.0378)	-0.0781* (0.0371)	-0.0987** (0.0375)	-0.1110 (0.0653)
Teamsize	0.0046 (0.0036)	0.0021 (0.0044)	0.0069 (0.0055)	0.0185* (0.0092)	0.0287** (0.0101)	0.0261** (0.0095)	0.0341*** (0.0062)	0.0346*** (0.0087)	0.0389*** (0.0116)
Work experience	-0.0029 (0.0027)	-0.0022 (0.0027)	0.0001 (0.0026)	0.0041 (0.0046)	0.0014 (0.0037)	0.0001 (0.0030)	0.0023 (0.0032)	0.00197 (0.0042)	0.0026 (0.0053)
Female*Average beauty score	-0.0057 (0.0103)	-0.0041 (0.0129)	-0.0135 (0.0125)	-0.0343 (0.0187)	-0.0297 (0.0203)	-0.0286 (0.0178)	-0.0326* (0.0159)	-0.0434* (0.0182)	-0.0349 (0.0319)
Black*Average beauty score	-0.1050 (0.0710)	-0.114 (0.0754)	-0.0686 (0.0769)	-0.0935 (0.0905)	-0.127 (0.0960)	-0.0378 (0.1022)	-0.0389 (0.0991)	-0.1110 (0.1464)	-0.2400 (0.1623)
South Asian* Average beauty score	0.0066 (0.0249)	0.0103 (0.0264)	0.0005 (0.0322)	0.0107 (0.0361)	0.0230 (0.0338)	0.0514 (0.0271)	0.0467 (0.0270)	0.0312 (0.0335)	-0.0116 (0.0333)
East Asian* Average beauty score	0.0040 (0.0132)	0.0011 (0.0125)	0.0237 (0.0134)	0.0231 (0.0136)	0.0108 (0.0164)	0.0204 (0.0237)	0.0400 (0.0266)	0.0298 (0.0268)	0.0219 (0.0282)
MENA*Average beauty score	-0.0116 (0.7138)	-0.0307 (0.7330)	-0.0596 (0.7251)	-0.0752 (0.6764)	-0.0669 (0.6035)	-0.1080 (0.6197)	-0.0943 (0.5711)	-0.1020 (0.5502)	-0.1300 (0.5402)
Constant	0.1430*** (0.0138)	0.1520*** (0.0260)	0.1240** (0.0430)	0.0660 (0.0487)	0.1400** (0.0443)	0.2200*** (0.0395)	0.2520*** (0.0486)	0.2860*** (0.0630)	0.3310** (0.1132)
N	950	950	950	950	950	950	950	950	950

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Table 3-12 Quantile regression estimates for log average normalised citations across quantiles, authors with less than 10 years of working experience

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
Average beauty score	0.2650* (0.1157)	0.1630* (0.0810)	0.0794 (0.0713)	0.0755 (0.0735)	0.1310* (0.0664)	0.0759 (0.0685)	0.1210* (0.0576)	0.1530** (0.0557)	0.1380* (0.0586)
Female	-0.4810 (1.1743)	0.1230 (0.6956)	0.0535 (0.8946)	0.1280 (0.7296)	0.0917 (0.5973)	-0.2260 (0.5358)	-0.2260 (0.4884)	0.0767 (0.8381)	0.4230 (0.8464)
Black	3.5850 (9.9420)	5.6200 (5.6726)	5.2930 (5.2925)	3.0580 (3.6450)	0.5560 (3.0516)	-0.0645 (2.3836)	1.0350 (1.8904)	0.7620 (1.9492)	-1.8610 (2.1088)
South Asian	0.4950 (3.0319)	0.9940 (2.3618)	0.2570 (1.6451)	0.5100 (1.1235)	0.6080 (0.8162)	0.8060 (0.7286)	0.6810 (0.7325)	0.0834 (0.9146)	0.5810 (1.1076)
East Asian	-0.0139 (0.8267)	-0.6950 (0.5942)	-0.9390 (0.6074)	-1.1780* (0.5780)	-1.3180* (0.5236)	-1.7250** (0.5457)	-1.2740 (0.7189)	-0.9820* (0.4940)	-1.8450** (0.7066)
MENA	12.2700* (5.1528)	7.8950 (5.1890)	-0.8770 (5.5655)	-1.2420 (4.4095)	-0.8760 (4.6557)	-2.0920 (4.1990)	-1.4710 (4.6402)	-0.3100 (6.0843)	-0.4470 (7.6442)
Low income country	-0.6790 (0.9187)	-0.7400 (0.6959)	-0.6070 (0.6276)	-0.3550 (0.5455)	-0.3170 (0.3376)	-0.4220 (0.3135)	-0.3300 (0.3119)	-0.1910 (0.3269)	-0.0988 (0.3890)
Lower middle income country	0.5410 (0.2961)	0.2320 (0.2310)	0.0141 (0.2011)	-0.1590 (0.1950)	-0.2750 (0.1818)	-0.1880 (0.1670)	-0.2430 (0.1589)	-0.1310 (0.2508)	0.0145 (0.3695)
Upper middle income country	-0.7150 (0.5229)	-0.0087 (0.2138)	-0.2000 (0.1216)	-0.3490* (0.1481)	-0.4400** (0.1678)	-0.3350* (0.1679)	-0.2320 (0.1939)	-0.2300 (0.2311)	-0.1470 (0.1699)
Assistant professor	-0.6800* (0.2865)	-0.7540** (0.2327)	-0.523*** (0.1559)	-0.4830* (0.2053)	-0.1830 (0.1887)	-0.1430 (0.1905)	-0.0355 (0.1770)	0.0793 (0.1842)	0.3290 (0.2510)
Associate professor	-0.1110 (0.3028)	-0.1740 (0.2184)	-0.0207 (0.1205)	-0.1160 (0.1820)	-0.0529 (0.1551)	-0.1310 (0.1714)	-0.0477 (0.1531)	-0.1830 (0.1694)	-0.1240 (0.2219)
Other occupations	-0.5340 (0.3679)	-0.7150** (0.2234)	-0.3820* (0.1793)	-0.3980* (0.1987)	-0.2760 (0.2229)	-0.2250 (0.2015)	-0.1640 (0.1661)	-0.0300 (0.1539)	-0.0015 (0.2455)
Teamsize	0.4140*** (0.0949)	0.3230*** (0.0587)	0.2930*** (0.0488)	0.3650*** (0.0534)	0.3440*** (0.0419)	0.3440*** (0.0537)	0.3240*** (0.0594)	0.3400*** (0.0662)	0.2570** (0.0802)
Work experience	-0.0629 (0.0430)	-0.0554 (0.0291)	-0.0362 (0.0233)	-0.0269 (0.0245)	0.0042 (0.0259)	0.0104 (0.0216)	0.0138 (0.0214)	0.0167 (0.0248)	0.0302 (0.0361)
Female*Average beauty score	0.0382 (0.2415)	-0.0297 (0.1301)	-0.0231 (0.1618)	-0.0274 (0.1482)	-0.0527 (0.1254)	0.0281 (0.1230)	0.0013 (0.1069)	-0.0855 (0.1640)	-0.1040 (0.1690)
Black*Average beauty score	-0.8890 (3.2542)	-1.8240 (1.7904)	-1.8110 (1.7484)	-1.1980 (1.2487)	-0.1800 (1.0582)	-0.0687 (0.8613)	-0.4180 (0.6901)	-0.4510 (0.7342)	0.4040 (0.7863)
South Asian* Aver beauty score	0.3110 (0.7793)	0.0386 (0.6173)	0.1200 (0.4153)	-0.0274 (0.2791)	-0.0548 (0.2095)	-0.1330 (0.1924)	-0.0756 (0.2033)	0.0505 (0.2528)	-0.1170 (0.2966)
East Asian* Average beauty score	-0.0874 (0.2040)	0.0613 (0.1582)	0.1340 (0.1670)	0.2190 (0.1532)	0.2440 (0.1382)	0.3010* (0.1301)	0.2340 (0.1671)	0.1710 (0.1380)	0.3740* (0.1782)
MENA*Average beauty score	-3.4560* (1.6817)	-2.4950 (1.7075)	0.3280 (1.8150)	0.3730 (1.4496)	0.1990 (1.4854)	0.6240 (1.3003)	0.4490 (1.4178)	0.0847 (1.8615)	-0.0412 (2.3459)
Constant	-6.620*** (0.6715)	-5.238*** (0.4623)	-4.642*** (0.3729)	-4.486*** (0.4137)	-4.586*** (0.3325)	-4.092*** (0.4040)	-4.080*** (0.3630)	-3.951*** (0.3156)	-3.367*** (0.4649)
N	923	923	923	923	923	923	923	923	923

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

3.5 Conclusions

Investigating the role of physical attractiveness in the labour market is not new; indeed there are many studies on this topic. This study extends this research by investigating the role of physical attractiveness in shaping publication productivity in academic publishing. This is a context in which physical attractiveness should play no or very limited role: the peer-review process is, as a rule, free of face-to-face interactions. We collect detailed information together with photos of authors who published their papers in 2012 in 16 economics journals listed in Association of Business Schools (ABS) Journal Quality Guide (2010). We had these photos rated for the authors' attractiveness by survey participants, with 20 assessors rating each photo. We examine the extent to which physical attractiveness correlates with research productivity using weighted productivity, average productivity and average normalised citations as outcome measures.

Based on the sample used in this study, the results strongly suggest that being more attractive increases the probability to produce high-quality publications. In other words, the attractiveness of author appears to be a productive factor. This result is obtained with quantile regression with OLS alike. The results show a stronger positive effect on research productivity for the middle and upper quantiles than in the lower quantiles. All in all, the attractiveness of authors has a significantly positive effect, which is stronger for the authors of better ranked and more often cited articles. Another strong predictor is team size which also has a significantly positive effect on productivity in all models and measurements, that is, increasing in team size increases the possibility to produce the higher quality of the publication.

This study corresponds with the previous literature in which beauty plays a significant role in determining labour-market outcomes and provides evidence to confirm the existence of beauty effect on productivity even in the area of the low degree of exposure such as publication activities. We can conclude that beauty can be a plausible factor for productive research production based on our results. However, our findings present correlation rather than causality, so we are unable to indicate what mechanism brings about our findings. One possible explanation is beauty is indeed a proxy for intelligence as suggested by the previous studies

(Langlois *et al*., 2000; Zebrowitz *et al*., 2002; Kanazawa and Kovar, 2004). The publication productivity should mainly reflect the merit of the research (and of its authors). Therefore, our findings are consistent with positive association between perceived beauty and intelligence. An alternative explanation would be one of discrimination. For instance, attractive researchers may get paired up with more productive co-authors, have better access to research funding, or get the best PhD supervisors and mentors. Manuscripts written by good looking academics may also receive better treatment from journal editors and referees, although this is less likely, given the no-face-to-face nature of the interaction in peer review and the fact that many journals rely on double-blind refereeing. It is, however, more difficult to imagine how beauty translates into more citations. Therefore, further research is required to shed more light on the relationship between physical attractiveness and productivity.

Appendix B

Appendix B – 1 Summary statistics

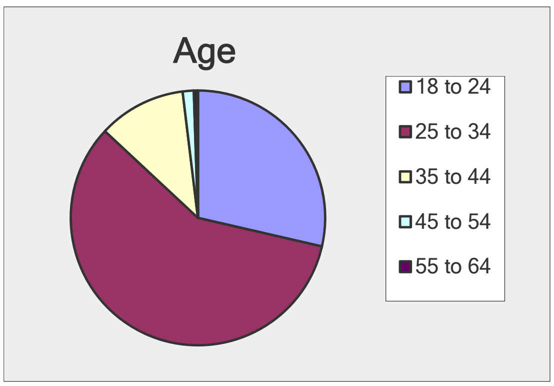
Economists	N	Mean	Std.Dev.	Min	Max
teamsize	2,800	2.535	1.002	1	8
cite_scopus	2,800	5.676	9.579	0	94
norma_scopus	2,800	0.060	0.102	0	1
cite_gscholar	2,800	29.21	58.09	0	616
norma_gscholar	2,800	0.047	0.094	0	1
avenormcite	2,800	0.053	0.095	0	0.968
female	2,800	0.174	0.379	0	1
countrydevelopment	2,181	3.612	0.821	1	4
ugyear	1,953	1992	10.24	1956	2012
phdyear	2,343	1999	9.945	1960	2017
workexp	2,322	12.94	9.936	0	52
rank	2,774	2.590	1.022	1	4
race	2,800	1.532	1.111	1	5
keele_rank	2,800	2.796	0.840	1	4
norma_keele	2,800	0.599	0.280	0	1
era_rank_number	2,800	3.379	0.615	2	4
norma_era	2,800	0.689	0.308	0	1
avenormrank	2,800	0.644	0.280	0	1
jif	2,800	1.368	1.087	0.404	5.278
norma_jif	2,800	0.198	0.223	0	1
weighted_productivity	2,800	0.260	0.148	0	0.886
average_productivity	2,800	0.299	0.173	0	0.924
logavenormcite	2,668	-3.739	1.417	-7.116	-0.032
minbeauty	2,800	0.494	0.953	0	5
spanbeauty	2,800	6.773	1.327	3	10
maxbeauty	2,800	7.266	1.278	4	10
avebeauty	2,800	3.885	1.041	1.100	7.550
assistant_professor	2,774	0.205	0.404	0	1
associate_professor	2,774	0.196	0.397	0	1
professor	2,774	0.403	0.491	0	1
other	2,774	0.196	0.397	0	1
white	2,800	0.801	0.400	0	1
black	2,800	0.010	0.103	0	1
south_asian	2,800	0.059	0.236	0	1
east_asian	2,800	0.114	0.318	0	1
mena	2,800	0.015	0.122	0	1
low	2,181	0.045	0.209	0	1
lowmid	2,181	0.080	0.272	0	1
upmid	2,181	0.089	0.285	0	1
high	2,181	0.785	0.411	0	1
sa*avebeauty	2,800	0.188	0.786	0	6.300
ea*avebeauty	2,800	0.411	1.185	0	7.350
me*avebeauty	2,800	0.049	0.413	0	4.950
female*avebeauty	2,800	0.816	1.838	0	7.550

Appendix B - 1 (Continued) The summary statistics

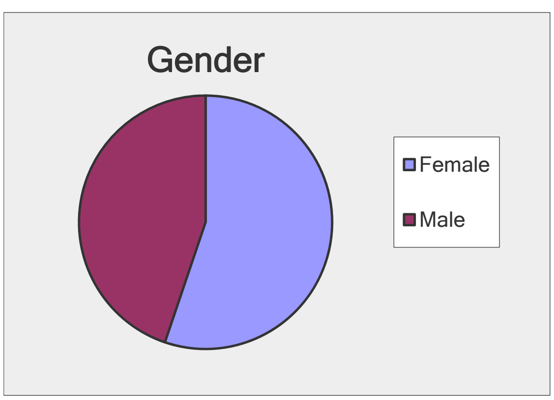
Assessors	**N**	**Mean**	**Std.Dev.**	**Min**	**Max**
age	1,860	1.870	0.702	1	6
female	1,860	0.552	0.497	0	1
race	1,860	2.988	1.459	1	6
education	1,860	3.595	1.007	1	6
student	1,860	0.452	0.498	0	1

Appendix B – 2 Summary of assessors' information by category

Age	Response Percent	Response Count
18 to 24	28.6%	532
25 to 34	58.3%	1085
35 to 44	11.1%	207
45 to 54	1.4%	26
55 to 64	0.4%	8
65 to 74	0.1%	2
75 or older	0.0%	0
	100.0%	**1860**

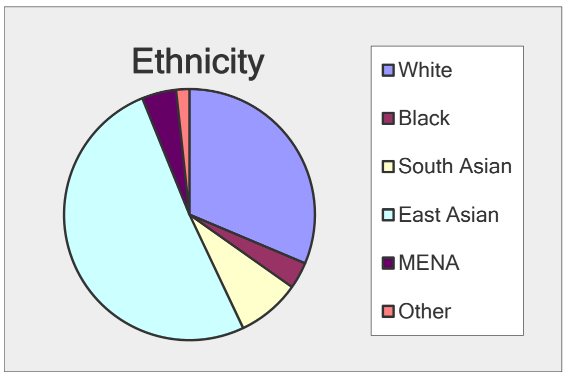


Gender	Response Percent	Response Count
Female	55.2%	1027
Male	44.8%	833
	100.0%	**1860**

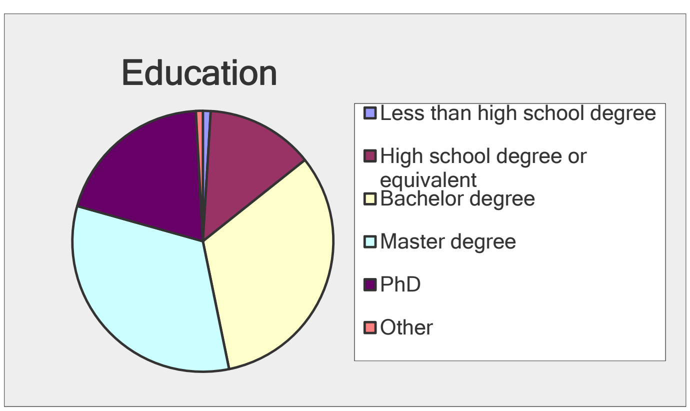


Appendix B - 2 (Continued) Summary of assessors' information by category

Ethnicity	**Response Percent**	**Response Count**
White	31.3%	583
Black	3.4%	64
South Asian	8.2%	152
East Asian	50.9%	947
MENA	4.4%	82
Other	1.7%	32
	100.0%	**1860**

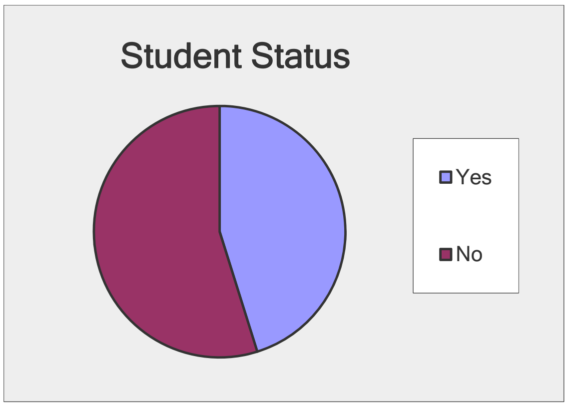


Education	**Response Percent**	**Response Count**
Less than high school degree	1.0%	18
High school degree or equivalent	13.3%	248
Bachelor degree	32.5%	604
Master degree	32.6%	606
PhD	19.8%	368
Other	0.9%	16
	100.0%	**1860**



Appendix B - 2 (Continued) Summary of assessors' information by category

Student Status	**Response Percent**	**Response Count**
Yes	45.2%	840
No	54.8%	1020
	100.0%	**1860**



Appendix B – 3 Example of the online survey

Beauty Survey 1

Personal information

We would like to thank you for agreeing to take part in this survey. This project is a part of PhD thesis in order to determine how people perceive others and especially how they form opinions about other people's attractiveness. It is for a study on discrimination based on visual appearance and your response will be kept strictly confidential. The survey should take no more than 10 minutes to complete. Thank you very much once again in advance.

What is your age?

- ◯ 18 to 24
- ◯ 25 to 34
- ◯ 35 to 44
- ◯ 45 to 54
- ◯ 55 to 64
- ◯ 65 to 74
- ◯ 75 or older

What is your gender?

- ◯ Female
- ◯ Male

Which race/ethnicity best describes you? (Please choose only one.)

- ◯ White
- ◯ Black / African American
- ◯ South Asian (e.g., India, Pakistan, Bangladesh)
- ◯ East Asian / Southeast Asian (e.g., Chinese, Japanese, Thai, Malaysian)
- ◯ Middle Eastern
- ◯ Multiple ethnicity / Other (please specify)

What is the highest level of school you have completed or the highest degree you have received?

- ◯ Less than high school degree
- ◯ High school degree or equivalent (e.g., GED)
- ◯ Bachelor degree
- ◯ Master degree
- ◯ PhD
- ◯ Other

Are you currently enrolled as a student?

- ◯ Yes
- ◯ No

Please take a few minutes and rate the following pictures according to the person's physical attractiveness on a 10-point scale, which range from unattractive or homely (0 point) to strikingly beautiful/handsome (10 points).

Next

Appendix B – 3 (Continued) Example of the online survey

Beauty Survey 1

Please rate the following pictures on a scale of 0 (Unattractive) to 10 (Strikingly attractive).

Please rate the above picture.

	Unattractive 0	1	2	3	4	5	6	7	8	9	Strikingly attractive 10
Your score:	○	○	○	○	○	○	○	○	○	○	○

Do you know this person? (If you don't know this person, please ignore this question)

○ Yes

Click here if the picture is unavailable. (If the picture is available, please ignore this question)

○ I can't see this picture.

Previous   Next

Powered by

SurveyMonkey

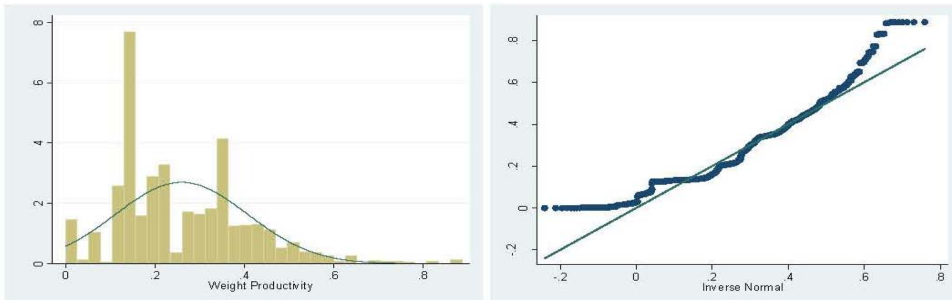
See how easy it is to create a survey.

Note: Photo has been anonymised due to privacy issues

Appendix B – 4 Normality of distribution by variable

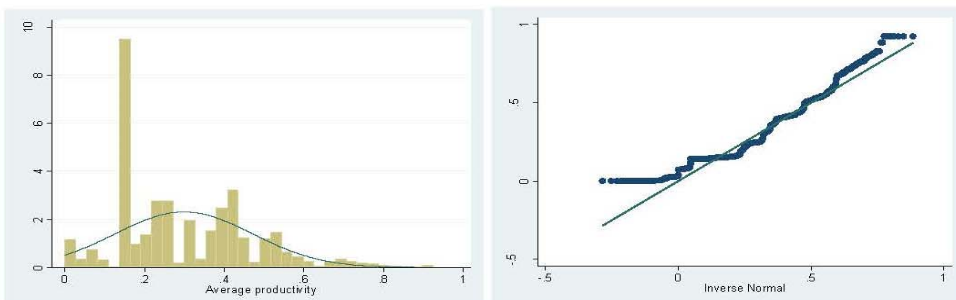
Weight productivity (wprod)

Skewness: 0.8650315, Kurtosis: 4.087823



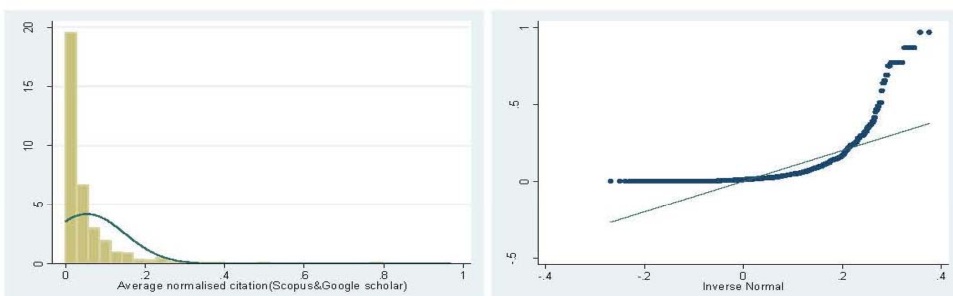
Average productivity (aveprod)

Skewness: 0.7108023, Kurtosis: 3.187089



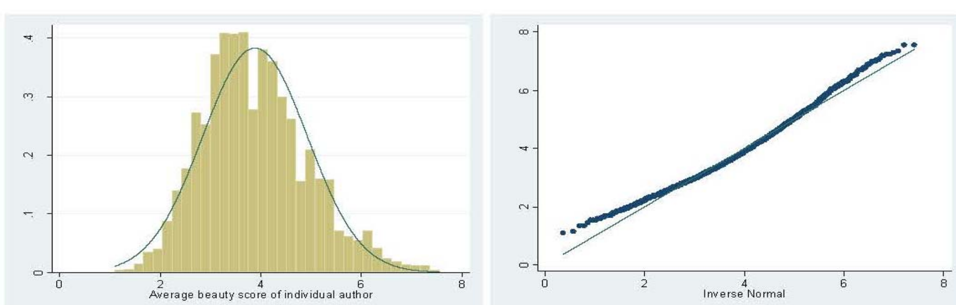
Average normalised citations (avenormcite)

Skewness: 4.810407, Kurtosis: 33.61025



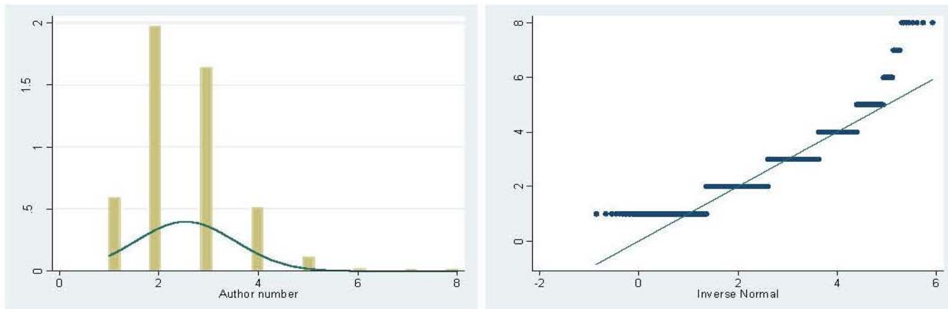
Average beauty score of individuals (avebeauty)

Skewness: 0.4790202, Kurtosis: 3.089837

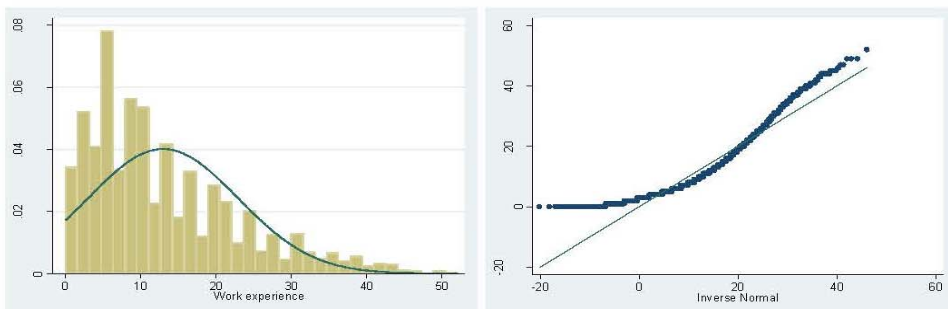


Appendix B – 4 (Continued) Normality of distribution by variable

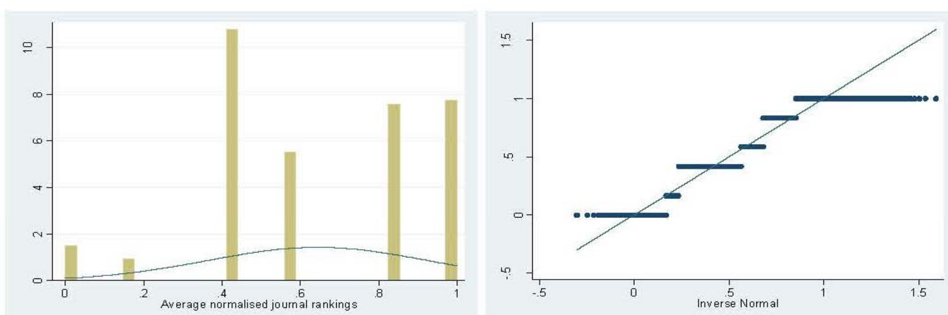
Author number (teamsize) Skewness: 0.9778917, Kurtosis: 5.788467



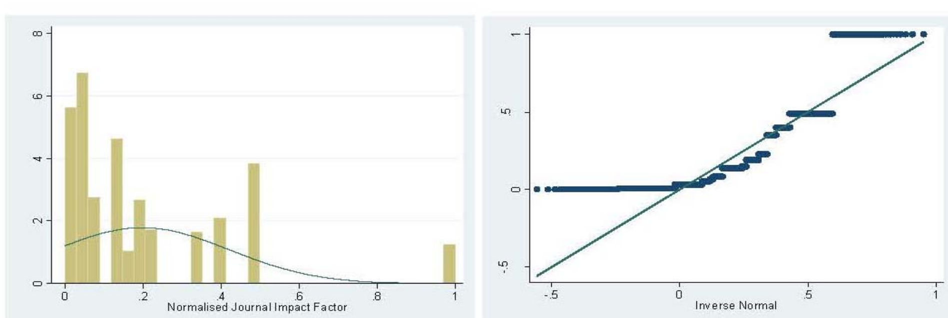
Work experience (workexp) Skewness: 1.077584, Kurtosis: 3.69367



Average normalised journal rankings (avenormrank) Skewness: -0.3061057, Kurtosis: 2.248191



Normalised Journal Impact Factor (norma_jif) Skewness: 1.814065, Kurtosis: 6.631405



Appendix B – 4 (Continued) Normality of distribution by variable

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
wprod	2,800	0.9397	97.0400	11.7780	0.00000
aveprod	2,800	0.9427	92.1230	11.6440	0.00000
avenormcite	2,800	0.5236	766.6700	17.0990	0.00000
avebeauty	2,800	0.9853	23.5990	8.1380	0.00000
teamsize	2,800	0.9701	47.9780	9.9650	0.00000
workexp	2,322	0.9132	117.8320	12.1980	0.00000
avenormrank	2,800	0.9852	23.6750	8.1470	0.00000
norma_jif	2,800	0.7946	330.4840	14.9330	0.00000

Note: The normal approximation to the sampling distribution of W is valid for 4<=n<=2000.

Shapiro-Francia W' test for normal data

Variable	Obs	W'	V'	z	Prob>z
wprod	2,800	0.9397	103.0760	11.3320	0.00001
aveprod	2,800	0.9428	97.6560	11.2000	0.00001
avenormcite	2,800	0.5249	812.0380	16.3780	0.00001
avebeauty	2,800	0.9854	24.9170	7.8610	0.00001
teamsize	2,800	0.9722	47.5250	9.4390	0.00001
workexp	2,322	0.9158	121.1290	11.5920	0.00001
avenormrank	2,800	0.9858	24.2210	7.7920	0.00001
norma_jif	2,800	0.7943	351.5240	14.3310	0.00001

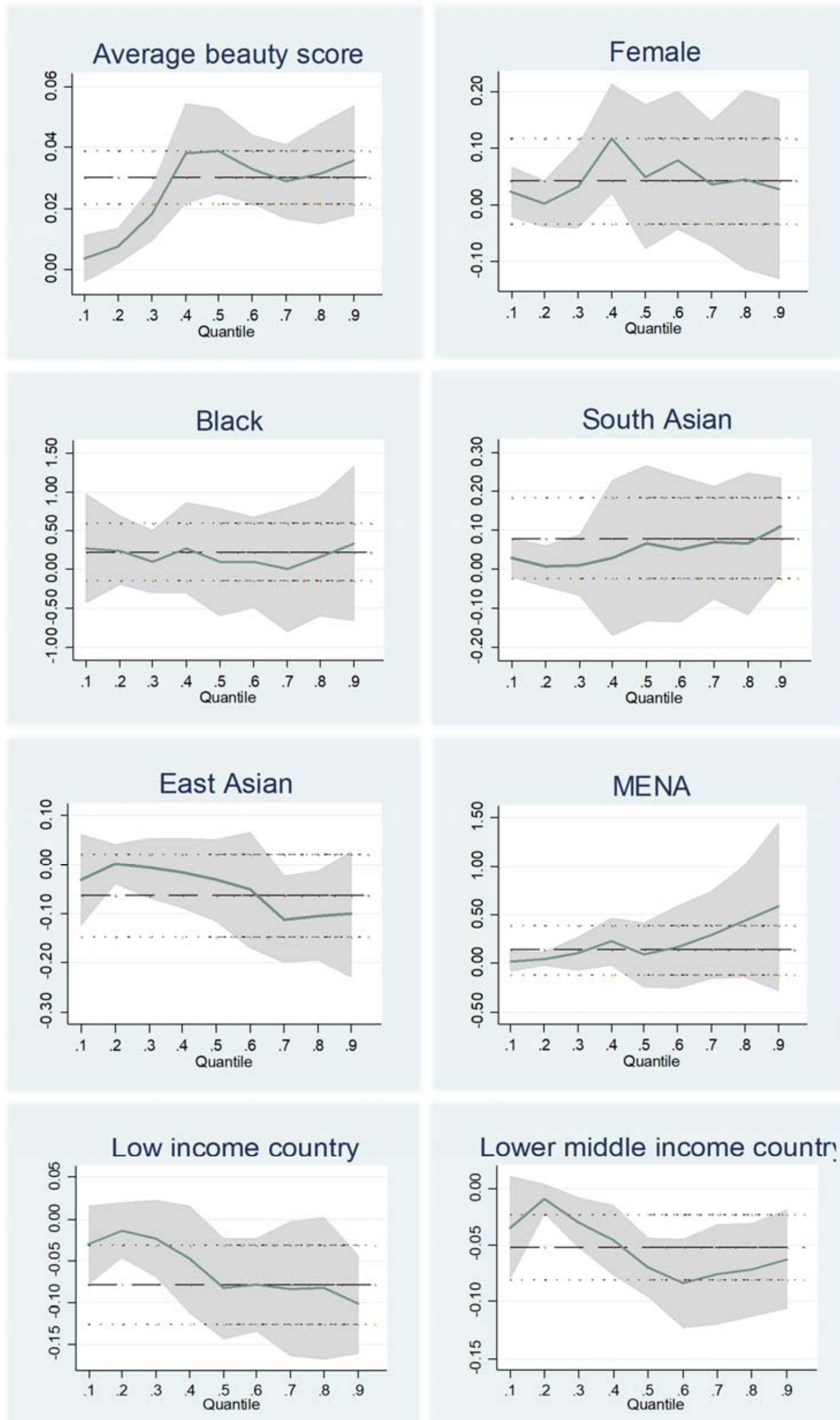
Note: The normal approximation to the sampling distribution of W' is valid for 10<=n<=5000.

Appendix B - 5 Impact of beauty on average normalised citations, OLS and 0.50th quantile

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)
Average beauty score	0.0104*** (0.00249)	0.0039*** (0.00118)	0.0106*** (0.00258)	0.0040** (0.00125)	0.0107** (0.00327)	0.0041** (0.00158)
Female	-0.0127* (0.00632)	-0.0059* (0.00280)	-0.0131* (0.00626)	-0.0060* (0.00255)	-0.0116 (0.02174)	0.0012 (0.01283)
Black	0.0070 (0.01827)	0.0062 (0.00988)	0.0078 (0.01817)	0.0049 (0.01051)	0.0904 (0.07057)	0.0576 (0.04095)
South Asian	0.0156* (0.00774)	0.0123 (0.00789)	0.0152 (0.00855)	0.0134 (0.00845)	0.0298 (0.02821)	0.0154 (0.01975)
East Asian	-0.0178*** (0.00461)	-0.0091*** (0.00276)	-0.0177*** (0.00497)	-0.0087** (0.00289)	-0.0224 (0.01986)	-0.0193 (0.01204)
MENA	-0.0148* (0.00643)	0.0028 (0.00480)	-0.0147* (0.00689)	0.0030 (0.00424)	0.0161 (0.03405)	0.0138 (0.02989)
Low income country	-0.0298*** (0.00743)	-0.0206* (0.00911)	-0.0296*** (0.00738)	-0.0204* (0.00848)	-0.0321*** (0.00949)	-0.0226* (0.00891)
Lower middle income country	-0.0129* (0.00552)	-0.0063 (0.00359)	-0.0126 (0.00733)	-0.0063 (0.00350)	-0.0132* (0.00612)	-0.0073* (0.00377)
Upper middle income country	-0.0139 (0.00711)	-0.0097*** (0.00292)	-0.0141 (0.00860)	-0.0097** (0.00302)	-0.0140 (0.00737)	-0.0097*** (0.00295)
Assistant professor	-0.0070 (0.00798)	-0.0047 (0.00389)	-0.0036 (0.00771)	-0.0062 (0.00449)	-0.0072 (0.00883)	-0.0049 (0.00463)
Associate professor	-0.0191*** (0.00545)	-0.0015 (0.00368)	-0.0182** (0.00574)	-0.0023 (0.00364)	-0.0194** (0.00660)	-0.0024 (0.00355)
Other occupations	-0.0079 (0.00729)	-0.0038 (0.00496)	-0.0055 (0.01005)	-0.0040 (0.00449)	-0.0080 (0.00881)	-0.0043 (0.00303)
Teamsize	0.0241*** (0.00473)	0.0088*** (0.00178)	0.0239*** (0.00396)	0.0091*** (0.00175)	0.0240*** (0.00474)	0.0093*** (0.00149)
Work experience	-0.0004 (0.00029)	-0.0002 (0.00016)	0.0004 (0.00108)	-0.0005 (0.00039)	-0.0005 (0.00031)	-0.0003* (0.00017)
Work experience squared			-0.0000 (0.00002)	0.0000 (0.00001)		
Female*Average beauty score					-0.0002 (0.00527)	-0.0016 (0.00281)
Black*Average beauty score					-0.0254 (0.01985)	-0.0153 (0.01120)
South Asian*Average beauty score					-0.0038 (0.00907)	-0.0002 (0.00532)
East Asian*Average beauty score					0.0013 (0.00523)	0.0031 (0.00337)
MENA*Average beauty score					-0.0094 (0.01013)	-0.0025 (0.00974)
Constant	-0.0207 (0.01751)	0.0020 (0.00779)	-0.0284* (0.01399)	0.0037 (0.00775)	-0.0216 (0.02126)	0.0012 (0.00732)
N	1926	1926	1926	1926	1926	1926

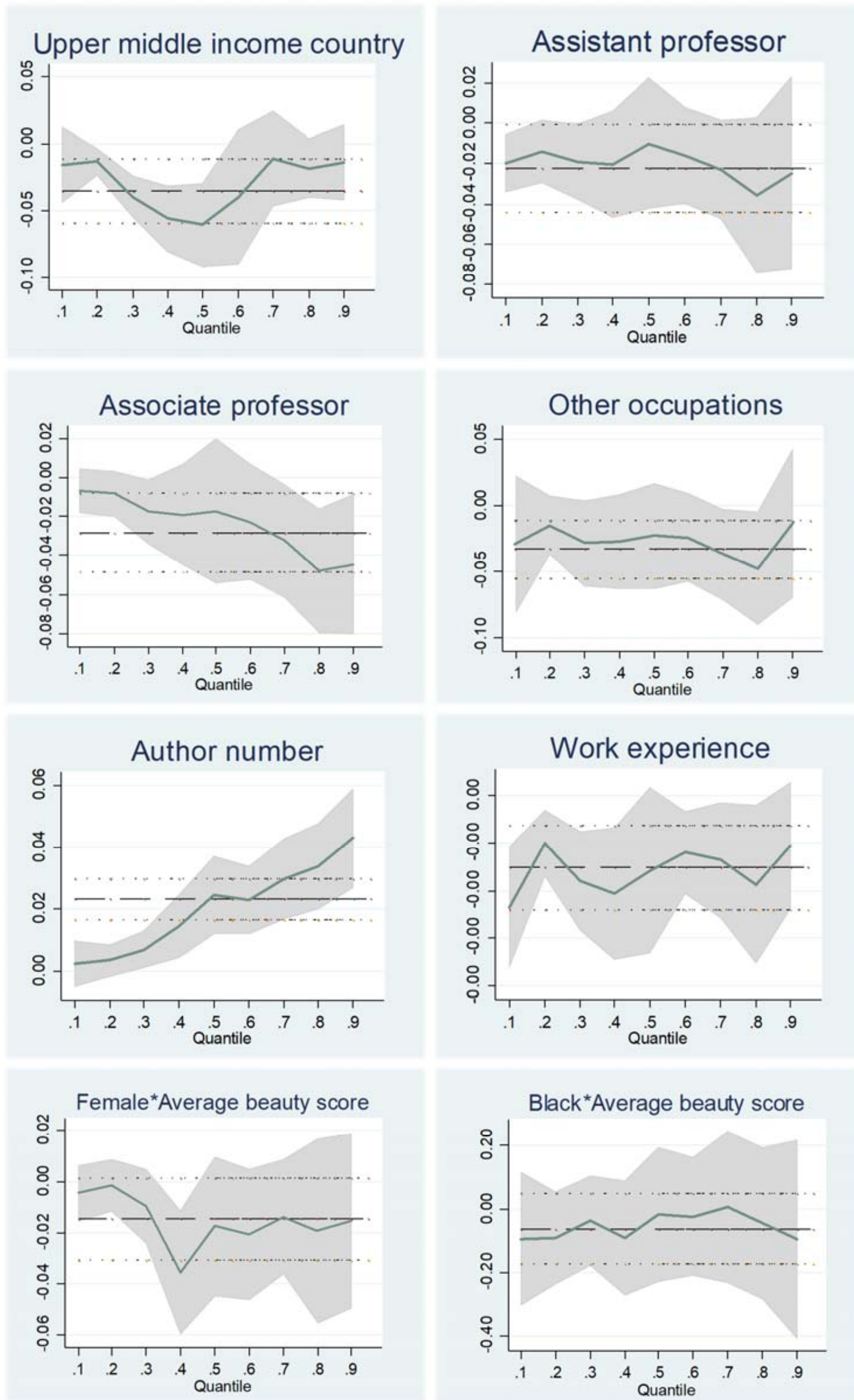
Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Appendix B – 6 Quantile coefficients for weighted productivity



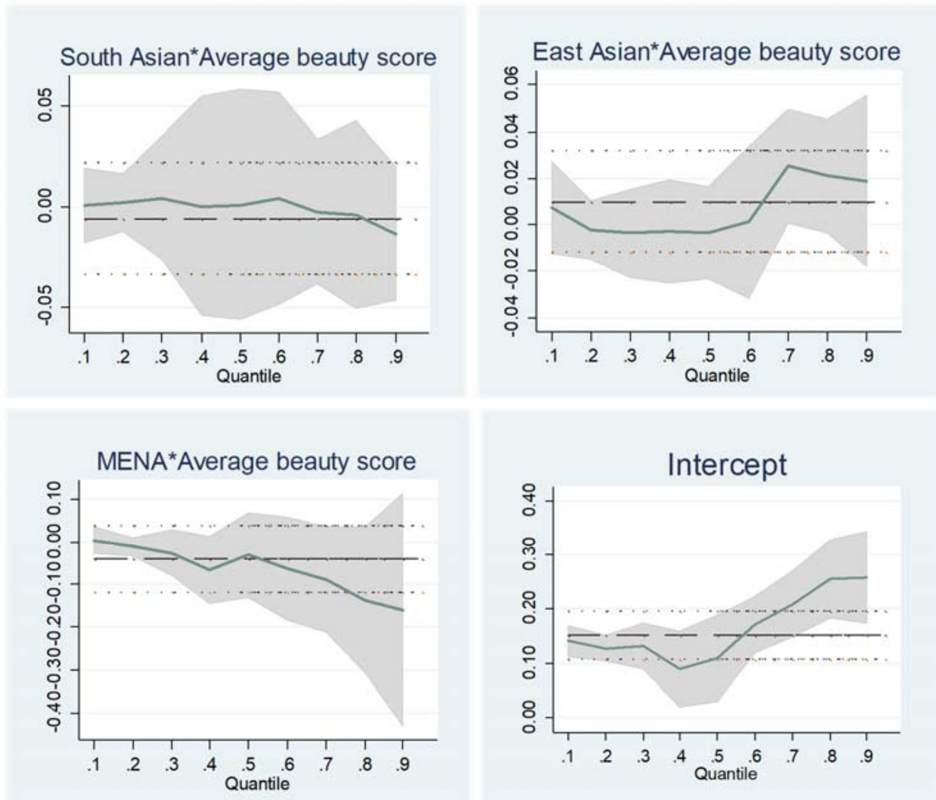
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Appendix B – 6 (Continued) Quantile coefficients for weighted productivity



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Appendix B – 6 (Continued) Quantile coefficients for weighted productivity



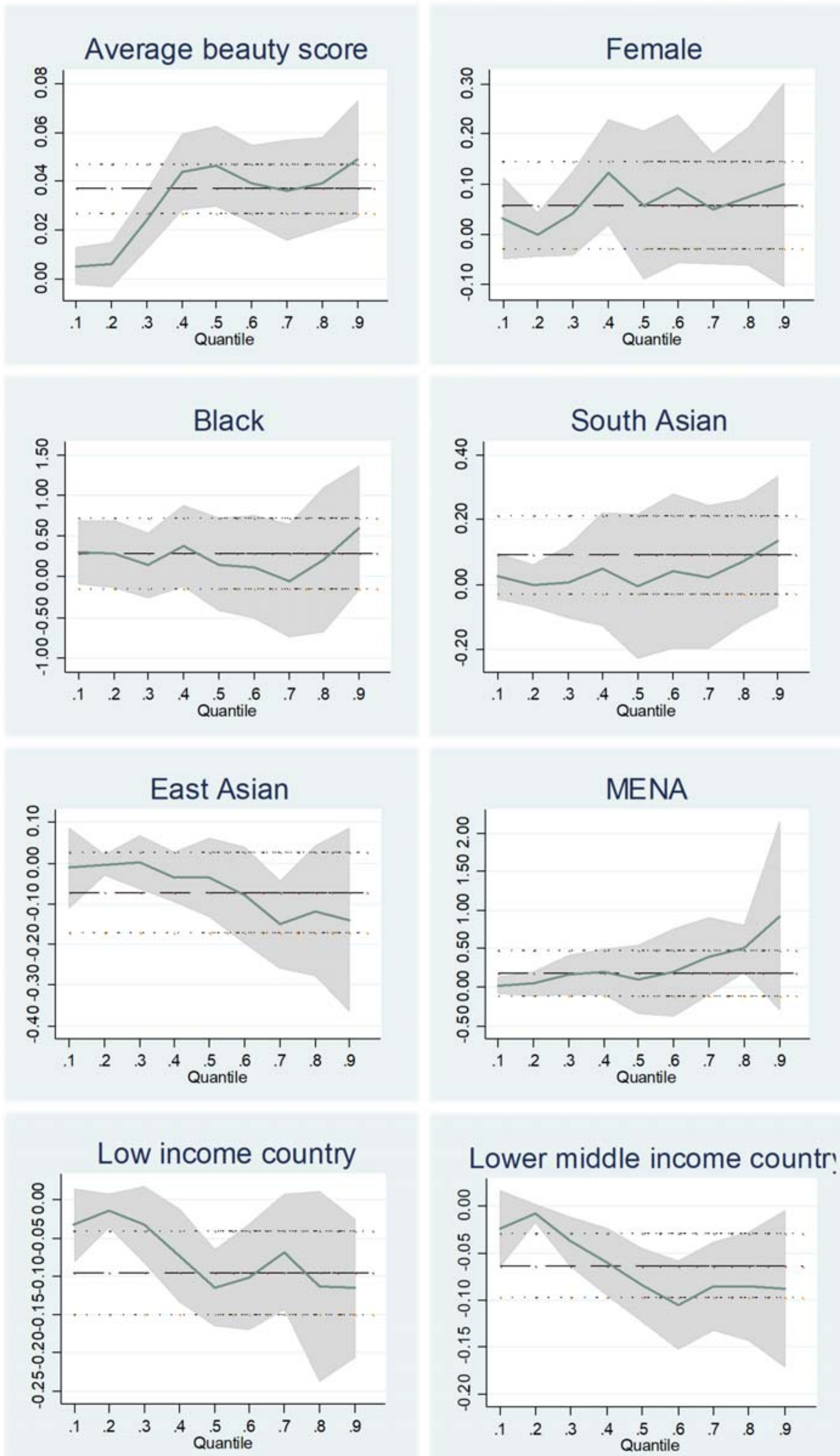
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Appendix B – 7 Quantile regression estimates for average productivity across quantiles

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
Average beauty score	0.0053 (0.0044)	0.0060 (0.0041)	0.0243*** (0.0058)	0.0437*** (0.0102)	0.0463*** (0.0068)	0.0392*** (0.0074)	0.0364*** (0.0083)	0.0392*** (0.0094)	0.0490*** (0.0103)
Female	0.0322 (0.0273)	-0.0006 (0.0222)	0.0418 (0.0436)	0.1240* (0.0606)	0.0583 (0.0710)	0.0922 (0.0632)	0.0506 (0.0541)	0.0758 (0.0664)	0.0991 (0.0879)
Black	0.3060 (0.2298)	0.2800 (0.1947)	0.1450 (0.1766)	0.3810 (0.2493)	0.1520 (0.2737)	0.1220 (0.3895)	-0.0522 (0.5141)	0.2070 (0.5438)	0.5950 (0.5393)
South Asian	0.0243 (0.0486)	-0.0027 (0.0315)	0.0083 (0.0500)	0.0482 (0.0824)	-0.0043 (0.1235)	0.0408 (0.1161)	0.0225 (0.0948)	0.0714 (0.1196)	0.1330 (0.0999)
East Asian	-0.0119 (0.0397)	-0.0042 (0.0156)	0.0026 (0.0355)	-0.0346 (0.0392)	-0.0358 (0.0532)	-0.0782 (0.0715)	-0.1510* (0.0687)	-0.1180* (0.0563)	-0.1400 (0.0845)
MENA	0.0218 (0.1260)	0.0421 (0.1220)	0.1610 (0.1353)	0.2020 (0.2209)	0.0924 (0.2448)	0.1900 (0.2617)	0.3960 (0.2554)	0.5010 (0.3579)	0.9230 (0.5108)
Low income country	-0.0329 (0.0287)	-0.0139 (0.0152)	-0.0324 (0.0198)	-0.0729* (0.0353)	-0.1160*** (0.0313)	-0.1020** (0.0371)	-0.0682 (0.0480)	-0.1130 (0.0667)	-0.1150* (0.0471)
Lower middle income country	-0.0236 (0.0184)	-0.0074 (0.0055)	-0.0377** (0.0121)	-0.0593** (0.0205)	-0.0844*** (0.0200)	-0.105*** (0.0293)	-0.0858** (0.0291)	-0.0851** (0.0289)	-0.0882* (0.0423)
Upper middle income country	-0.0110 (0.0116)	-0.0107 (0.0071)	-0.0468*** (0.0121)	-0.0688** (0.0220)	-0.0772** (0.0268)	-0.0593 (0.0417)	-0.0076 (0.0285)	-0.0088 (0.0229)	-0.0312 (0.0212)
Assistant professor	-0.0206* (0.0102)	-0.0117 (0.0068)	-0.0221 (0.0124)	-0.0241 (0.0170)	-0.0120 (0.0244)	-0.0043 (0.0213)	-0.0213 (0.0225)	-0.0354 (0.0230)	-0.0261 (0.0302)
Associate professor	-0.0049 (0.0074)	-0.0061 (0.0057)	-0.0219* (0.0109)	-0.0233 (0.0126)	-0.0157 (0.0216)	-0.0173 (0.0191)	-0.0318 (0.0164)	-0.0557*** (0.0162)	-0.0572* (0.0227)
Other occupations	-0.0299 (0.0257)	-0.0118 (0.0093)	-0.0326* (0.0155)	-0.0298 (0.0202)	-0.0245 (0.0257)	-0.0216 (0.0210)	-0.0433* (0.0204)	-0.0549* (0.0222)	-0.0375 (0.0345)
Teamsize	0.0024 (0.0033)	0.0022 (0.0028)	0.0070 (0.0046)	0.0160** (0.0059)	0.0289*** (0.0073)	0.0248*** (0.0070)	0.0312*** (0.0084)	0.0374*** (0.0081)	0.0470*** (0.0075)
Work experience	-0.0026*** (0.0007)	-0.0008 (0.0004)	-0.0020*** (0.0005)	-0.0024** (0.0008)	-0.0016 (0.0012)	-0.0011 (0.0008)	-0.0014 (0.0008)	-0.0021* (0.0010)	-0.0014 (0.0011)
Female* Average beauty score	-0.0063 (0.0057)	-0.0003 (0.0055)	-0.0121 (0.0094)	-0.0376* (0.0146)	-0.0205 (0.0156)	-0.0244 (0.0126)	-0.0177 (0.0116)	-0.0260 (0.0144)	-0.0347 (0.0189)
Black*Average beauty score	-0.1070 (0.0756)	-0.1030 (0.0677)	-0.0531 (0.0637)	-0.1230 (0.0853)	-0.0249 (0.0901)	-0.0315 (0.1239)	0.0136 (0.1568)	-0.0476 (0.1644)	-0.1530 (0.1597)
South Asian* Average beauty score	0.0016 (0.0159)	0.0056 (0.0132)	0.0062 (0.0194)	0.0024 (0.0262)	0.0290 (0.0343)	0.0113 (0.0328)	0.0093 (0.0236)	0.0060 (0.0290)	-0.0132 (0.0237)
East Asian* Average beauty score	0.0030 (0.0093)	-0.0003 (0.0045)	-0.0072 (0.0094)	0.0024 (0.0113)	-0.0029 (0.0123)	0.0063 (0.0173)	0.0325 (0.0171)	0.0256 (0.0132)	0.0267 (0.0227)
MENA*Average beauty score	0.0004 (0.0381)	-0.0107 (0.0376)	-0.0452 (0.0388)	-0.0578 (0.0632)	-0.0350 (0.0694)	-0.0753 (0.0739)	-0.1250 (0.0696)	-0.1630 (0.0947)	-0.2420 (0.1474)
Constant	0.149*** (0.0189)	0.146*** (0.0134)	0.141*** (0.0285)	0.103** (0.0379)	0.115* (0.0472)	0.194*** (0.0334)	0.240*** (0.0395)	0.292*** (0.0435)	0.299*** (0.0388)
N	1926	1926	1926	1926	1926	1926	1926	1926	1926

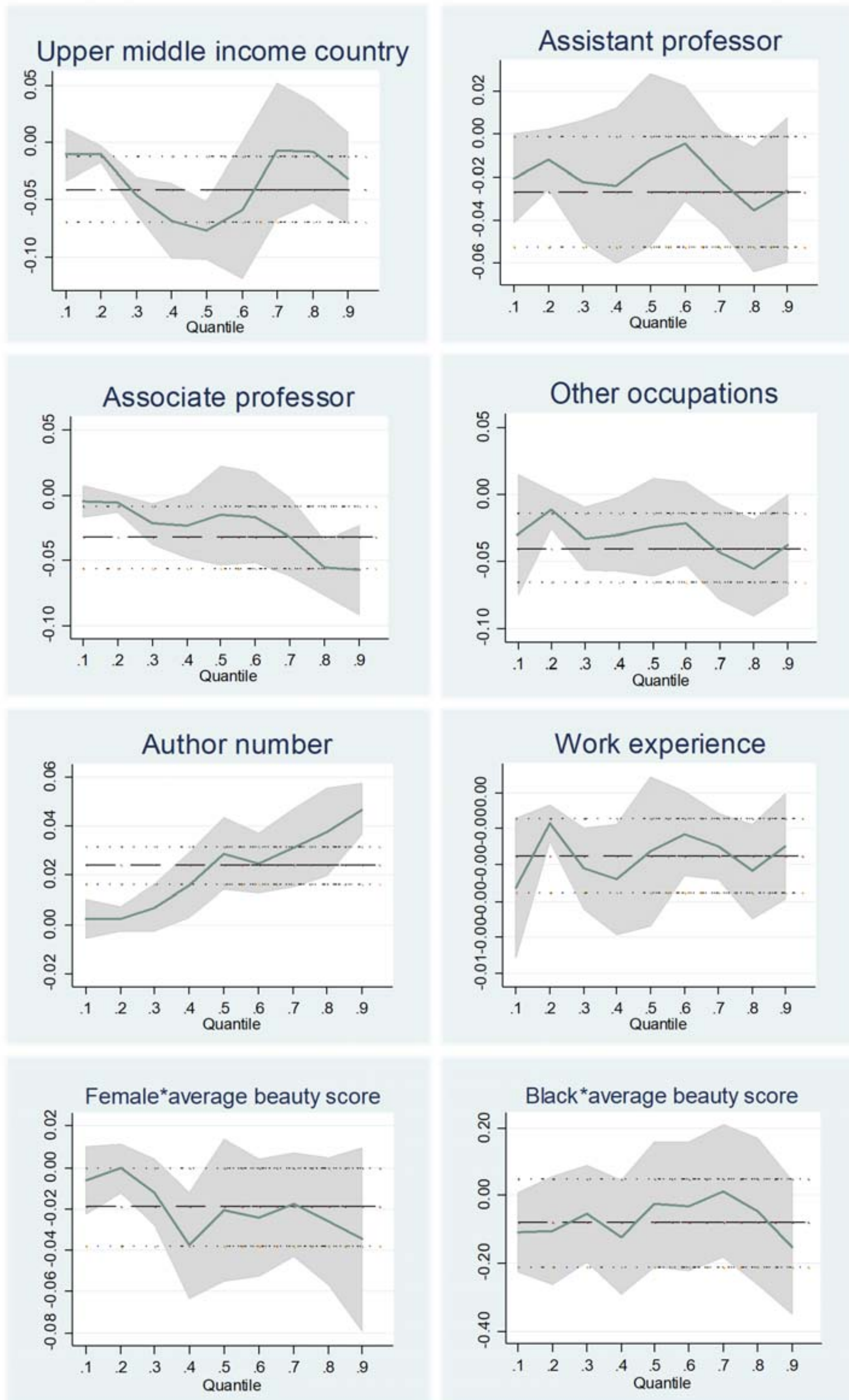
Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Appendix B – 8 Quantile coefficients for average productivity



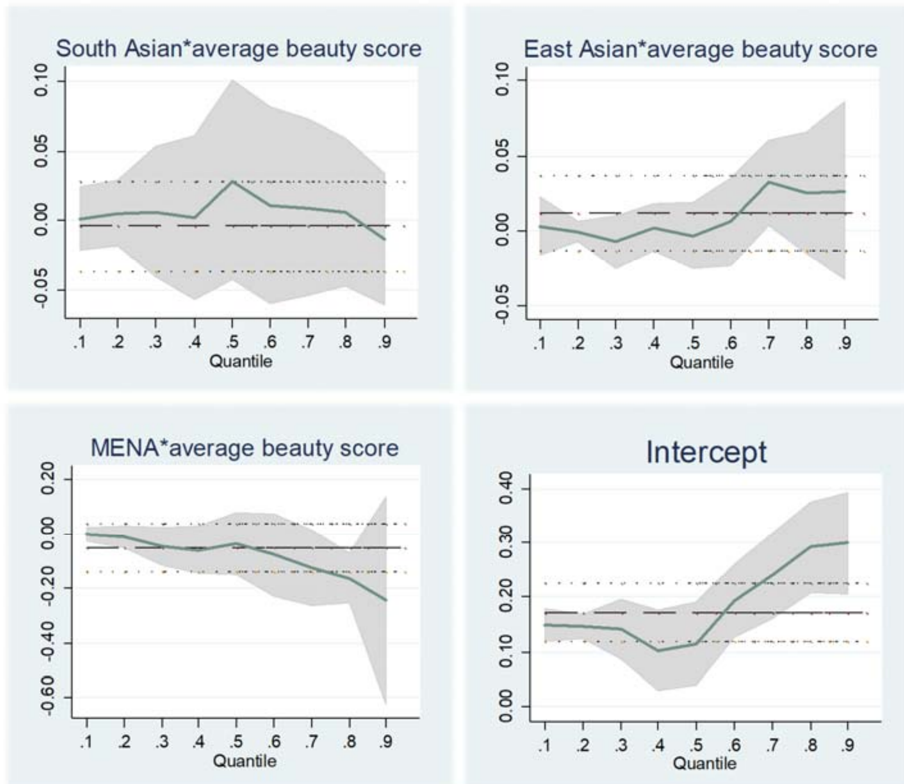
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

Appendix B – 8 (Continued) Quantile coefficients for average productivity



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

Appendix B – 8 (Continued) Quantile coefficients for average productivity



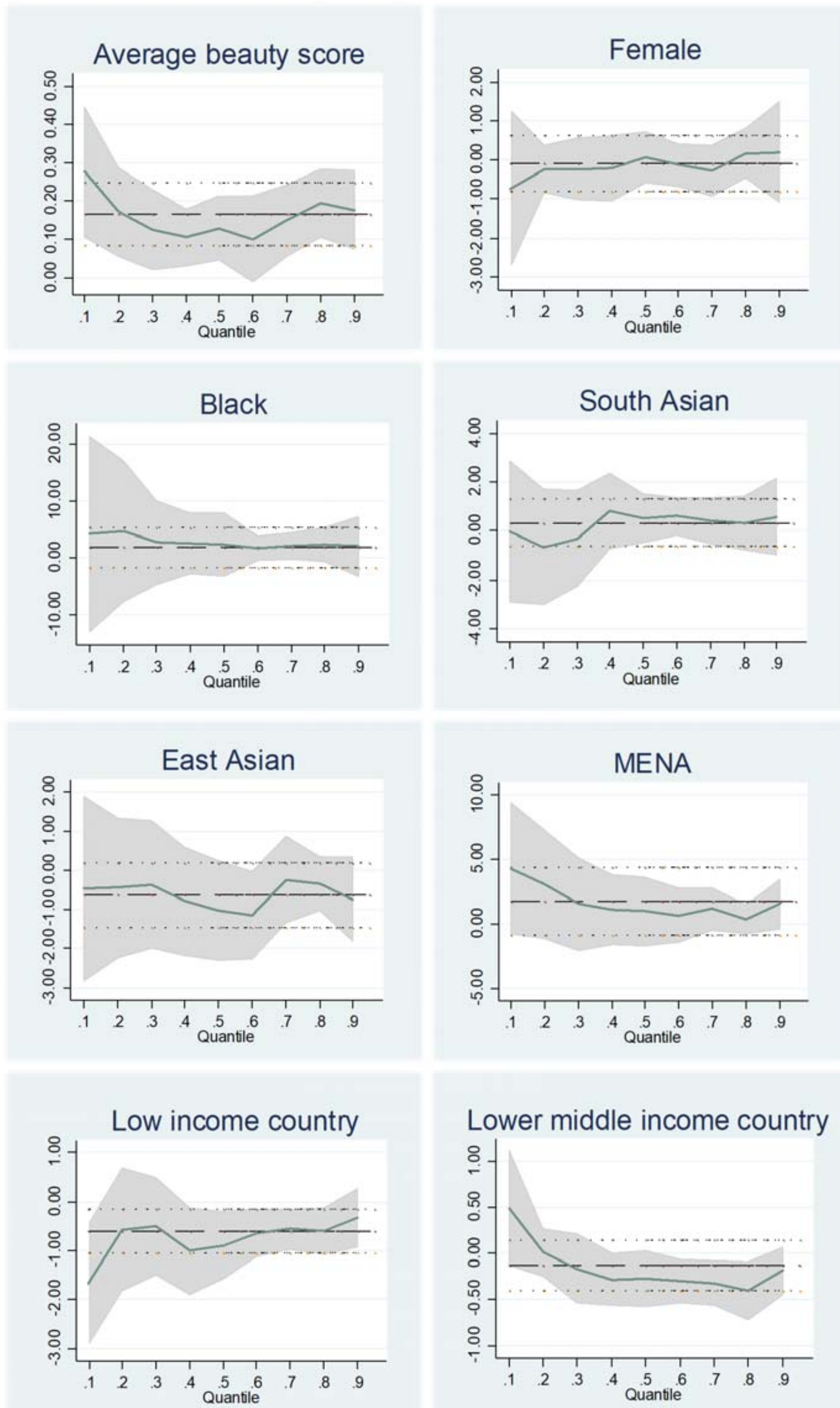
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

Appendix B – 9 Quantile regression estimates for log average normalised citations across quantiles

	(1) **Q(0.10)**	(2) **Q(0.20)**	(3) **Q(0.30)**	(4) **Q(0.40)**	(5) **Q(0.50)**	(6) **Q(0.60)**	(7) **Q(0.70)**	(8) **Q(0.80)**	(9) **Q(0.90)**
Average beauty score	0.2760** (0.1067)	0.1720** (0.0553)	0.1260* (0.0616)	0.1050* (0.0519)	0.1300** (0.0483)	0.1010 (0.0538)	0.1500*** (0.0434)	0.1950*** (0.0396)	0.1770* (0.0782)
Female	-0.7300 (1.3522)	-0.2290 (0.4508)	-0.2290 (0.5073)	-0.1960 (0.5750)	0.0665 (0.4831)	-0.1190 (0.3803)	-0.2620 (0.4475)	0.1770 (0.5350)	0.2090 (0.6031)
Black	4.1060 (7.0096)	4.5940 (4.7612)	2.5940 (3.1493)	2.4830 (2.3442)	2.3220 (1.7451)	1.5890 (1.5171)	1.9740 (1.5214)	2.3320 (2.0779)	1.9580 (3.3030)
South Asian	-0.0331 (2.0805)	-0.6640 (1.2412)	-0.3050 (0.9664)	0.8060 (0.8199)	0.5040 (0.5182)	0.5940 (0.4166)	0.4060 (0.4707)	0.3220 (0.6047)	0.5900 (1.1083)
East Asian	-0.4800 (0.9503)	-0.4540 (0.5413)	-0.3660 (0.6509)	-0.7940 (0.5517)	-1.0290 (0.5515)	-1.1460 (0.6108)	-0.2460 (0.6370)	-0.3450 (0.5544)	-0.7370 (0.6898)
MENA	4.3040* (2.0777)	3.0910 (1.6641)	1.5220 (1.2823)	1.1380 (1.2323)	0.9650 (1.2706)	0.6780 (1.0177)	1.1780 (1.0859)	0.3900 (0.7904)	1.5240 (1.0826)
Low income country	-1.6630* (0.7380)	-0.5690 (0.6324)	-0.5110 (0.4609)	-1.0100** (0.3867)	-0.8920** (0.3113)	-0.6450* (0.2507)	-0.5630* (0.2566)	-0.6060** (0.2264)	-0.3340 (0.3061)
Lower middle income country	0.4930 (0.2926)	0.0124 (0.1903)	-0.1620 (0.1924)	-0.2850 (0.1573)	-0.2710 (0.1609)	-0.3010* (0.1225)	-0.3190* (0.1274)	-0.3990** (0.1428)	-0.1870 (0.1599)
Upper middle income country	-0.6750 (0.4010)	-0.2700 (0.2269)	-0.3080* (0.1416)	-0.4260** (0.1317)	-0.4160** (0.1331)	-0.4400*** (0.1125)	-0.4570*** (0.1126)	-0.4420*** (0.1217)	-0.3470 (0.2190)
Assistant professor	-0.7160** (0.2712)	-0.6520*** (0.1971)	-0.4540*** (0.1309)	-0.3690** (0.1340)	-0.2480* (0.1178)	-0.2130 (0.1114)	-0.2160 (0.1404)	-0.2380* (0.1169)	0.0175 (0.1940)
Associate professor	-0.3090 (0.2867)	-0.2210 (0.1187)	-0.1680 (0.1306)	-0.1460 (0.1367)	-0.1540 (0.1127)	-0.2120* (0.0969)	-0.2470* (0.1069)	-0.4470*** (0.0888)	-0.4400** (0.1434)
Other occupations	-0.2930 (0.2847)	-0.2500 (0.1593)	-0.1830 (0.1432)	-0.2280 (0.1474)	-0.1390 (0.1578)	-0.1470 (0.1130)	-0.2220 (0.1219)	-0.2980* (0.1226)	0.0975 (0.1645)
Teamsize	0.3220*** (0.0873)	0.3230*** (0.0605)	0.2830*** (0.0521)	0.3030*** (0.0520)	0.3180*** (0.0439)	0.3060*** (0.0368)	0.2940*** (0.0472)	0.3120*** (0.0359)	0.2460*** (0.0318)
Work experience	-0.0315* (0.0126)	-0.0222** (0.0074)	-0.0171** (0.0059)	-0.0138** (0.0052)	-0.0113* (0.0053)	-0.0122*** (0.0036)	-0.0108** (0.0036)	-0.0171*** (0.0046)	-0.0068 (0.0074)
Female* Average beauty score	0.0704 (0.2905)	0.0092 (0.1028)	0.0015 (0.1057)	0.0280 (0.1188)	-0.0442 (0.1024)	-0.0062 (0.0830)	0.0061 (0.0914)	-0.1100 (0.1180)	-0.0486 (0.1249)
Black*Average beauty score	-1.0100 (2.0468)	-1.4630 (1.5156)	-0.9130 (0.9490)	-0.6300 (0.7590)	-0.6790 (0.5727)	-0.5460 (0.5095)	-0.6670 (0.4440)	-0.8610 (0.6217)	-0.5520 (0.9447)
South Asian* Average beauty score	0.3260 (0.5994)	0.3510 (0.3380)	0.1980 (0.2239)	0.0056 (0.1868)	0.0031 (0.1561)	-0.0762 (0.1248)	-0.0010 (0.1443)	0.0111 (0.1691)	-0.0861 (0.3093)
East Asian* Average beauty score	0.0445 (0.2337)	0.0147 (0.1586)	0.0325 (0.1761)	0.1580 (0.1523)	0.1820 (0.1468)	0.1880 (0.1530)	-0.0046 (0.1540)	0.0508 (0.1443)	0.1160 (0.1815)
MENA*Average beauty score	-1.0960 (0.6981)	-0.8470 (0.5656)	-0.4330 (0.4144)	-0.2460 (0.3764)	-0.2390 (0.3955)	-0.2240 (0.3079)	-0.3730 (0.3407)	-0.1410 (0.2582)	-0.5900 (0.3326)
Constant	-6.577*** (0.5972)	-5.498*** (0.3330)	-4.908*** (0.3008)	-4.599*** (0.2836)	-4.402*** (0.2506)	-3.949*** (0.2492)	-3.804*** (0.2120)	-3.532*** (0.2165)	-3.098*** (0.3288)
N	1851	1851	1851	1851	1851	1851	1851	1851	1851

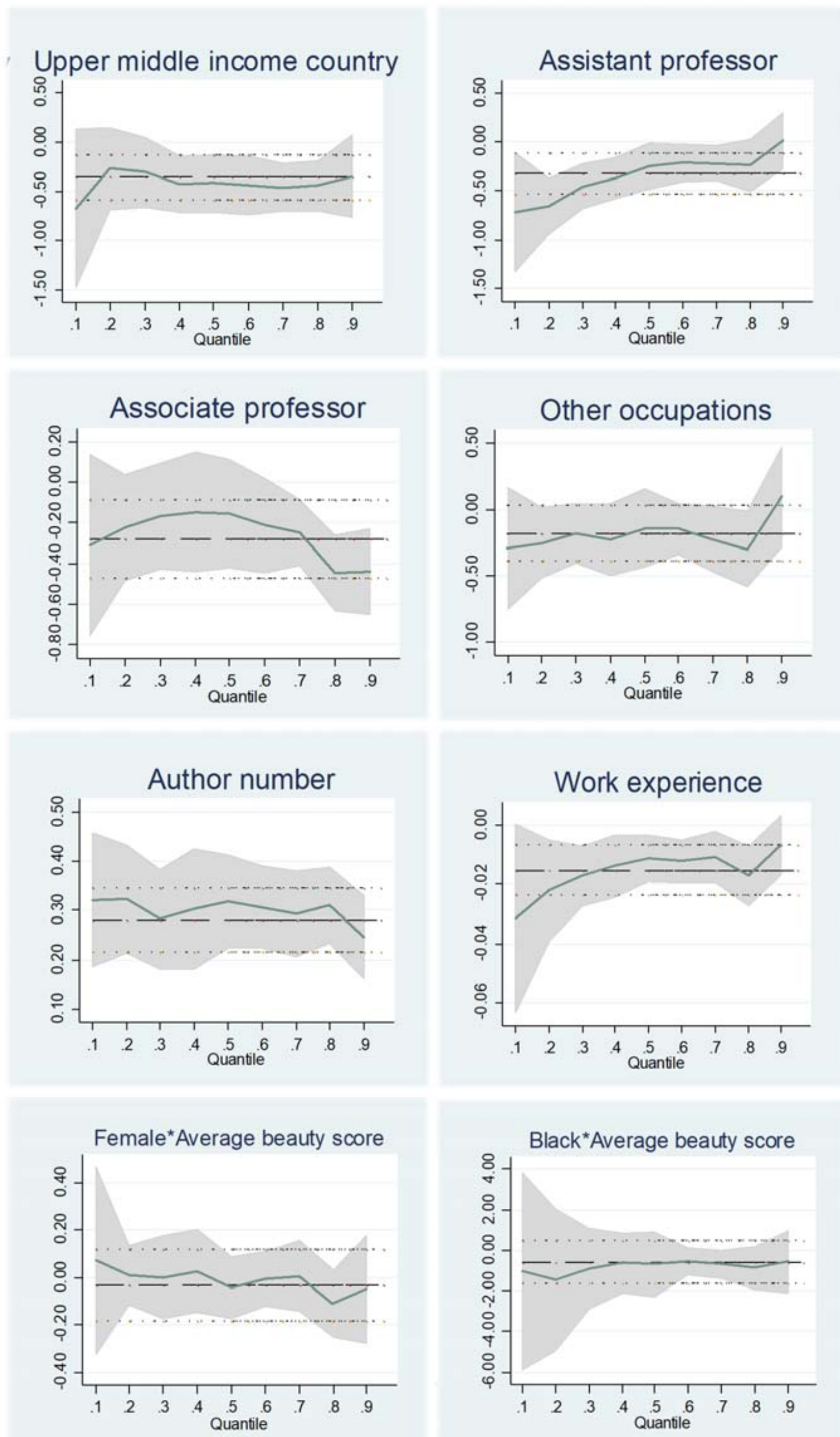
Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Appendix B – 10 Quantile coefficients for log average normalised citation



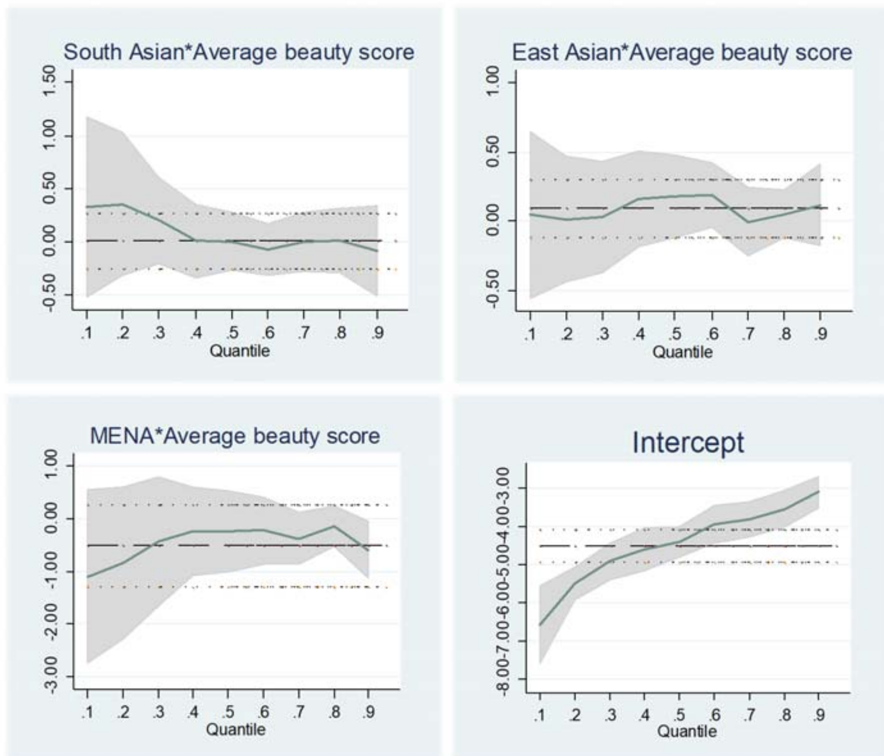
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

Appendix B – 10 (Continued) Quantile coefficients for log average normalised citation



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

Appendix B – 10 (Continued) Quantile coefficients for log average normalised citation



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

Appendix B – 11 Three most attractive authors by gender

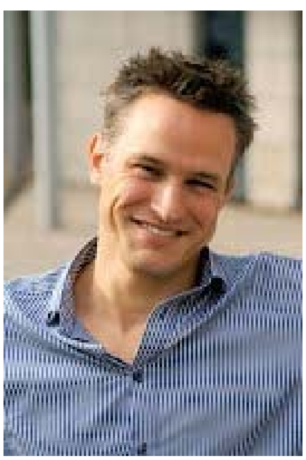
<u>Three most attractive female authors</u>

Guerrieri Veronica, Professor (7.55, American Economic Review)

Name and picture withheld at the request of the author in question (7.35, American Economic Review)

Name and picture withheld at the request of the author in question (7.3, European Economic Review)

<u>Three most attractive male authors</u>



Salvatori Andrea, Economist (7.55, Labour Economics)

Sheremeta Roman M., Assistant Professor (6.95, European Economic Review)

Gabaix Xavier, Professor (6.85, Quarterly Journal of Economics)

CHAPTER FOUR

BEAUTIFUL MINDS:
NOBEL BEAUTY

4.1 Introduction

Physical attractiveness has an important effect on one's well-being: attractive people tend to be happier and more content than their less fortunate peers. Attractiveness and beauty is also an important factor of success in the marriage market. Not surprisingly, both men and women the world over spend vast resources on cosmetics; beauty products and cosmetic surgery (Lee, 2015).

What is less obvious is the effect physical attractiveness has on economic outcomes. Such effects are non-negligible, and there is plenty of evidence to back this up. The seminal contribution by Hammermesh and Biddle (1994) finds that plain looking people suffer a wage penalty, while attractive people earn more than those with average looks (height also has a positive effect on earnings, see Persico, Postlewaite, and Silverman, 2004). Johnston (2010) complements this finding by showing that blonde women earn substantially higher wages than women whose hair is another colour. According to Price (2008), the preference for blondes extends beyond the labour market: he finds that blonde fund raisers receive more generous donations for charitable causes than brunettes. Patacchini, Ragusa and Zenou (2012) show that attractive women are at an advantage when applying for jobs: in an experiment with fake CVs accompanied by pictures, they found higher call-back rates for attractive low-skilled women but little difference for high-skilled ones. Sala et al. (2013) argue that facial beauty has a significant return with respect to labour market outcomes and for one's occupational prestige.

The benefits of beauty are not limited to the labour market. Hammermesh (2006) finds that attractive-looking economists are more likely to be elected as officers of the American Economic Association. Berggren, Jordahl, and Poutvaara (2010), in turn, find that attractive politicians do better in local elections. According to Belot, Bhaskar and van de Ven (2012), attractive contestants are less likely to be voted out of the game by other contestants (in the Weakest Link TV show), even when keeping them in the game is costly to the other contestants. Deryugina and Shurchkov (2015) find that attractive female undergraduate students do better in college. This last result is confirmed by the findings of Hernández-Julián and Peters (2015) who also find that pretty female students do better. Important, this result only applies to students to attend classes in person. Students who participate in online courses do not benefit from being attractive. This suggests that the gain from attractiveness is driven by the behaviour of teachers who either favour attractive students or give them more help and attention.

The aforementioned literature, nevertheless, largely fails to shed light on the mechanism behind these effects, which could be either due to discriminatory behaviour, or due to the fact that attractive people are intrinsically more productive. The latter could be the case if, for instance, healthy people are generally considered to be more beautiful.

In this paper, we add additional evidence to the literature on the effect of physical attractiveness. Due to the significantly positive effect of the physical attractiveness of authors on research productivity, as found in chapter 3, which is observed among regular academics, the beauty-effect on top scientists is of interest in order to confirm the effect of beauty on academic activities. This chapter re-examines the role of physical attractiveness on the probability of winning the Nobel Prize, i.e. looking at the top tier of the distribution of academics to confirm the existence of appearance-based discrimination in academia. Specifically, we consider scientists who were predicted to win the Nobel Prize in physics, chemistry, medicine and economics between 2002 and 2014.

The predictions are based on the reports by the Thompson Reuters Science Watch Hall of Citation Laureates, and reflect how often the scientists' work gets cited. Many but not all of the scientists highlighted by the Hall of Citation Laureates do go on to win the Nobel Prize. Likewise, some of the actual Nobel Prize winners are scientists overlooked by the Hall of Citation Laureates.

We consider the complete pool of predicted and actual Nobel Prize winners between 2002 and 2014. We collected some basic information on these scientists, as well as their pictures, and had them evaluated by a large group of undergraduate students in economics in the UK. In our analysis, we seek to establish whether those scientists who go on to claim the Nobel Prize are any more different with respect to their attractiveness than the rest of the sample. Note that we only consider scientists who are arguably at the very top of their disciplines, so that the winners and non-winners should be a-priori very similar. Nevertheless, given the magnitude of the potential benefits that accrue to Nobel Prize winners (besides receiving a substantial monetary award, Rablen and Oswald, 2008, find that winning the Nobel Prize extends the life of the winner by 1-2 years), even a marginal impact of physical attractiveness can have considerable implications.

In the next section, we describe the data used in our analysis in more detail. This is followed by discussion of the results. The last section concludes.

4.2 Data

Our data set includes top scientists in four scientific disciplines: physics, chemistry, medicine and economics. We include those who were reported on the Thompson Reuters Science Watch Hall of Citation Laureates web site* as being most likely to receive the Nobel Prize, and the scientists who actually received this award, in both cases between 2002 and 2014. Thomson Reuters has been analysing citations data to predict the most likely Nobel Prize winners since 2002. Therefore, only top and most cited scientists, as well as actual laureates (not all winners were predicted by Thompson Reuters), are included in our data. All scientists included in our study are listed in the Appendix C. Summary statistics are reported in Table 4-1.

The four disciplines are approximately equally represented: medicine accounts for 27% of the sample, the highest share, while the lowest share is that of economics, with 22%. These small differences may reflect the different attitudes to collaborative research in the four disciplines: scientists who collaborated on an important achievement often receive the Nobel Prize together. The top scientists are predominantly males: women account only for 3.6% of the sample. Women are slightly more represented among the actual winners, nevertheless, accounting for

* See http://sciencewatch.com/nobel/hall-citation-laureates.

5.8% of that subsample. By disciplines, women appear most often in medicine, accounting for 5.7%, with all other disciplines having less than 3% (physics being worst, with 2.4%).

Age refers to the scientist's age when first listed as a likely candidate for the Prize, or when awarded the Prize, whichever comes first. The typical scientists given, or predicted to receive, the Nobel Prize, is in his 60s.

Besides basic information on the scientists, we also obtained their pictures, either from their professional websites, or from Wikipedia. We showed the pictures to undergraduate students in Economics at Brunel University and asked them to rank the attractiveness of the scientists, from 0 to 10 (highest). The students were asked to take account of the age and gender of the scientists when making their assessment, and to evaluate their general attractiveness rather than their own personal preferences about the person in question. Overall, 105 students participated in this exercise, with the average picture evaluated by 21 students (ranging from 15 to 23). Students were shown the pictures on the screen, with 2-3 seconds per picture, and were asked to write down the score that occurred to them spontaneously, without consulting with others.

Undergraduate students do not find top scientists particularly attractive, with the average attractiveness score being only 3.5 out of 10. Figure 4-1 shows the pictures, average score and discipline of the three top scientists, who excel not only by their scientific contribution but were also considered most handsome by our sample of students. Since no economist made it into the top three, we also report the top three top economists in Figure 4-2.

Some student assessors' scores may be unreasonably low or high, including one student who ranked all pictures as 0. Therefore, as a robustness check, we excluded all assessments with the average score lower than 1 (there were 14 such cases) or higher than 8 (1 case). The basic statistics on the assessors are reported in panels B (full set of assessors) and C (restricted set) of Table 4-1. The average age of the assessors is 21.5 and 60% of them are male. Female assessors are somewhat kinder to our set of scientists than male assessors, with their average score being 3.4 compared to 3.3 among male assessors. Once we drop very low and very high assessors, the situation reverses, with average female assessor score of 3.5 and 3.6 for male assessors.

Table 4-1 Summary statistics

A. Scientists	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Nobel Prize Winner	324	0.373	0.484	0	1
Male	324	0.966	0.181	0	1
Age	318	63.745	10.831	34	94
Attractiveness Score	324	3.464	0.693	2.04	6.55
Attractiveness (restricted set)	324	3.867	0.732	2.19	6.65
Physics	324	0.259	0.439	0	1
Chemistry	324	0.241	0.428	0	1
Medicine	324	0.272	0.445	0	1
Economics	324	0.228	0.420	0	1
Black & white	324	0.167	0.373	0	1
Headshot	324	0.917	0.277	0	1
Suit	324	0.685	0.465	0	1
Resolution	324	701425	2117773	5184	2E+07
B. Assessors (full set)	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Male	101	0.604	0.492	0	1
Age	99	21.50	1.400	19	27
Av. Score Male Assessors	61	3.299	1.639	0.00	8.92
Av. Score Female Assessors	40	3.400	1.400	0.30	5.80
C. Assessors (restricted set)	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Male	90	0.578	0.497	0	1
Age	89	21.40	1.400	19	27
Av. Score Male Assessors	52	3.595	1.165	1.21	6.83
Av. Score Female Assessors	38	3.500	1.200	1.30	5.80

Notes: The restricted set of assessors omits those with average scores below 1 (14 assessors) or above 8 (1 assessor).

We report also some basic information on the pictures: whether it was black and white (16.7%), headshot (head and shoulders only, 91.7%), whether the scientist is wearing a suit in the picture (68.5%), and what is the resolution of the picture. The nature and style of the picture can potentially affect how the assessors perceive the person depicted in it.

Figure 4-1 Three most attractive top scientists across all disciplines

		
1. Nicholas B. Lydon (6.55, Medicine)	**2. Jacqueline K. Barton (5.82, Chemistry)**	**3. Juan Ignacio Cirac (5.22, Physics)**

Figure 4-2 Three most attractive top economists

		
1. David E. Card (4.73)	**2. Edmund S. Phelps (4.65)**	**3. Philippe M. Aghion (4.61)**

4.3 Do attractive scientists get the prize?

To analyse whether attractiveness has any bearing on whether a top scientist gets the Nobel Prize, we run probit regressions on our sample, with the dependent variable taking the value of 1 if the scientist has been awarded the Nobel Prize by 2014, and 0 otherwise. Note that it is entirely possible that some of the scientists that do not have the Nobel Prize by 2014 will receive it in the future (or will have died before receiving it); this will serve to bias our results downwards, against finding any significant effects.

It is also important to note that as we consider only top scientists, the differences in productivity among them should be relatively small. Whether one is awarded the Nobel Prize then could be considered almost arbitrary (random). Alternatively, it is indeed possible that the final choice is affected by factors not related to the scientists' productivity: physical attractiveness could well be such a factor.

$$P(Y=1|X) = \Phi(Sex, Age, Score, Discipline, B\&W, H\&S, Suit, Resolution)$$

We report our regression results (marginal effects evaluated at means of variables) based on the full set of assessors in Table 4-2. We control for the scientists gender, age when their name first appears in our data (first mention by Thomson Reuters or actual award, whichever comes first), average attractiveness score, discipline dummies, and picture characteristics. When we only control for scientists' characteristics (columns 1 and 2), physical attractiveness appears to have a negative effect on the probability of receiving the Nobel Prize. This effect is marginally significant (at the 10% level), when age is included as a quadratic polynomial; given the relatively small sample size, it is not surprising that not many coefficients are significant. This would imply that being attractive presents a distinct disadvantage, with each point on the 0-10 scale reducing the probability of receiving the prize by 6.7% (each one-standard-deviation reduces the probability by 4.7%), which is not negligible.

Table 4-2 Beauty of Nobel Prize winners (full set of assessors)

	(1)	(2)	(3)	(4)	(5)
Male	-0.3033	-0.3019*	-0.3601**	-0.3116	-0.4159**
	(0.1598)	(0.1604)	(0.1800)	(0.1811)	(0.1869)
Age	0.0037	-0.0263	-0.0299	0.0051	0.0030
	(0.0027)	(0.0248)	(0.0252)	(0.0277)	(0.0272)
Age squared		0.0002	0.0003	0.0000	0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Score	-0.0680	-0.0677*	0.6109*	-0.0646	0.5567***
	(0.0413)	(0.0413)	(0.3538)	(0.0472)	(0.1509)
Score squared			-0.0951**		
			(0.0492)		
Chemistry				-0.1453	-0.1354
				(0.0874)	(0.0887)
Medicine				-0.0485	-0.0395
				(0.0847)	(0.0857)
Economics				-0.1741	-0.2179**
				(0.0869)	(0.0896)
Black & white				0.7197	1.1291*
				(0.1083)	(0.6719)
Head & shoulders				0.1634	1.8090***
				(0.1097)	(0.4887)
Resolution				0.0000	0.0002***
				(0.0000)	(0.0001)
Suit				0.1894	0.7463**
				(0.0670)	(0.3245)
Black & white * Score					-0.1212
					(0.1901)
Head & shoulders * Score					-0.4862***
					(0.1431)
Resolution * Score					-0.0001***
					(0.0000)
Suit * Score					-0.1560*
					(0.0895)
N	318	318	318	318	318

Notes: Marginal effects evaluated at means, with robust standard errors in parentheses. Significance levels denoted as: *** 1%, ** 5%, and * 10%.

Adding a squared term of the attractiveness score (column 3) changes the relationship into a hump-shaped one. The peak effect is attained at a score of 3.21, which is just below the sample average: average-looking top scientists have a better chance of getting the Nobel Prize than either the plain looking ones, or the good looking.

Finally, in the last two columns, we add we add discipline dummies and picture characteristics. Given that all four disciplines are almost equally represented in our data, membership in a particular discipline should not make much difference: indeed, the dummies are mostly insignificant. Picture characteristics on their own should also not matter, unless those deciding on awarding the prize used the same pictures. They could, however, affect how our sample of students perceived the attractiveness of the scientists, which could, in principle, skew our results. To account for this possibility, we add interaction terms between picture characteristics and the attractiveness score. When we do so, we find that the average attractiveness now appears to have a significant and positive effect on the probability of receiving the Nobel Prize. As for picture characteristics, the picture being of head and shoulders and the scientist in it wearing a suit both significantly reduce the probability of being awarded the prize. Most of our pictures have these two characteristics. Therefore, given the size of the interaction terms, the results in the last column effectively confirm the previous result, that being more attractive is associated with a lower probability of receiving the Nobel Prize.

In Table 4-3, we report the results based on the restricted set of assessors. The results are very much in line with those reported in Table 4-2, the only difference being that they are slightly less significant.

Table 4-3 Beauty of Nobel Prize winners (restricted set of assessors)

	(1)	(2)	(3)	(4)	(5)
Male	-0.2887*	-0.2868*	-0.3109	-0.2976*	-0.4058**
	(0.1567)	(0.1572)	(0.1628)	(0.1769)	(0.1819)
Age	0.0037	-0.0253	-0.0305	0.0057	0.0018
	(0.0028)	(0.0249)	(0.0255)	(0.0279)	(0.0275)
Age squared		0.0002	0.0003	0.0000	0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Score	-0.0594	-0.0576	0.5334	-0.0637	0.4331***
	(0.0392)	(0.0392)	(0.3558)	(0.0442)	(0.1280)
Score squared			-0.0750*		
			(0.0445)		
Chemistry				-0.1448*	-0.1328
				(0.0872)	(0.0872)
Medicine				-0.0494	-0.0448
				(0.0843)	(0.0852)
Economics				-0.1696**	-0.2113
				(0.0873)	(0.0891)
Black & white				0.7228***	0.7785
				(0.1087)	(0.6417)
Head & shoulders				0.1620	1.6780***
				(0.1090)	(0.4593)
Resolution				0.1881***	0.5955*
				(0.0668)	(0.3518)
Suit				0.0000	0.0002**
				(0.0000)	(0.0001)
Black & white * Score					-0.0171
					(0.1645)
Head & shoulders * Score					-0.4006***
					(0.1231)
Suit * Score					-102.1994
					(88.4106)
Resolution * Score					-0.0001**
					(0.0000)
N	318	318	318	318	318

Notes: Marginal effects evaluated at means, with robust standard errors in parentheses. Significance levels denoted as: *** 1%, ** 5%, and * 10%.

Of the scientists' own characteristics, only gender is significant, with being a male having a negative effect on the probability of being a Nobel Prize laureate. This is not to say that women in general are more likely to succeed in this particular contest. Rather, in our sample, there are more women among the winners than in the sample overall, as discussed above. As for age, it is not significant. When considering a quadratic polynomial of age, the effect (though still not significant) appears U-shaped, with the lowest probability of winning the Nobel Prize at the age of 50.

4.4 Conclusions

We consider the effect of physical attractiveness on the probability of receiving the Nobel Prize. We collect pictures of and details on 324 top scientists in physics, chemistry, medicine and economics, who were either predicted to get the Nobel Prize, or have actually received it. We had these pictures rated for their attractiveness by a broad sample of UK undergraduate students, with each picture on average being evaluated by 21 assessors. We find that, overall, being more attractive reduces the probability of receiving the Nobel Prize. When we allow for the relationship being non-linear, it appears hump-shaped, with average-looking scientist having the best odds of being awarded the Nobel. The magnitude of the effect is potentially large: assuming the relationship is linear, each one-standard-deviation change in attractiveness is associated with approximately 4.7% reduction in the probability of winning the Nobel Prize. Given that getting the Prize is a very unlikely outcome indeed, a probability difference of this magnitude is not negligible.

Our results reveal correlation rather than causality. In particular, we cannot tell what mechanism drives our findings. One possible explanation is discrimination, whereby the selection committee would (subconsciously) consider attractive scientists as less serious or less devoted. Another possibility is that attractive scientists have more and better alternative options besides hard work, whether in the labour market (as the previous literature clearly demonstrates), in their social life, or indeed in their love and family life. As a result, they would have less time left for pure science. Future research will hopefully shed more light on these issues.

Appendix C: Data Appendix

THOMSON REUTERS' NOBEL PRIZE NOMINEES CHEMISTRY

No	Year	Name	Date of Birth-Date of Death	Nationality	Residence	Notable Awards
001-C	2013	A. Paul Alivisatos	12/10/1959	American	US	Linus Pauling Award (2011), Wolf Prize (2012)
002-C	2013	Bruce N. Ames	16/12/1928	American	US	Bolton S. Corson Medal (1980), Gairdner Foundation International Award (1983), The Japan Prize (1997), National Medal of Science (1998), Thomas Hunt Morgan Medal (2004)
003-C	2011	Allen J. Bard	18/12/1933	American	US	Priestly Medal (2002), Wolf Prize (2008), National Medal of Science (2011)
004-C	2009	Jacqueline K. Barton	07/05/1952	American	US	NFS Waterman Award (1985), Weizmann Women and Science Award (1998), ACS Gibbs Medal (2006), National Medal of Science (2011)
005-C	2002	Adrian Bax	1956	American	US	National Academy of Sciences (2002)
006-C	2010	Patrick O. Brown	1954	American	US	Takeda Award (2002)
007-C	2012	Louis E. Brus	1943	American	US	Irving Langmuir Prize in Chemical Physics (2001), National Academy of Sciences (2004), ACS Award in the Chemistry of Materials (2005), R. W. Wood Prize (2006), Kavli Prize (2008), Bower Award and Prize for Achievement in Science (2012)
008-C	2006	Gerald R. Crabtree	18/12/1946	American	US	
009-C	2007	Samuel J. Danishefsky	10/03/1936	American	US	Wolf Prize (1995/6), Benjamin Franklin Medal (2006),
010-C	2006	David A. Evans	11/01/1941	American	US	Welch Award (2012)
011-C	2013	M. G. Finn	23/10/1958	American	US	Alexander von Humboldt Foundation Research Award (2012)
012-C	2013	Valery V. Fokin		American	US	
013-C	2011	Jean M. J. Frechet	19/08/1944	American	US	Arthur C. Cope Award (2007), Dickson Prize (2007), Japan

						Prize (2013)
014-C	2012	Akira Fujishima	10/03/1942	Japanese	Japan	Japan Prize (2004), Japan Academy Prize (2004)
015-C	2009	Bernd Giese	02/07/1940	German	Germany	Emil Fischer Medal of the Gesellschaft Deutscher Chemiker (2006), Norris Award in Physical Organic Chemistry of the American Chemical Society (2009), Paracelsus Prize of the Swiss Chemical Society (2012)
016-C	2009	Micheal Gratzel	11/05/1944	Swiss	Switzerland	Balzan Prize, Galvani Prize, Faraday Medal, Harvey Prize
017-C	2003	Robert Howard Grubbs	27/02/1942	American	US	Nobel Prize (2005)
018-C	2012	Masatake Haruta	27/09/1947	Japanese	Japan	Spiers Memorial Award (2011)
019-C	2012	Graham J. Hutchings	03/02/1951	British	UK	Davy Medal of Royal Society(2013)
020-C	2011	Martin Karplus	15/03/1930	Austrian-American	US	Nobel Prize (2013)
021-C	2010	Susumu Kitagawa		Japanese	Japan	The Chemical Society of Japan Award for Creative Work (2001),The Japan Society of Coordination Chemistry Award (2007), Humboldt Research Award (2008), The Chemical Society of Japan Award (2009)
022-C	2006	Steven V. Ley	10/12/1945	British	UK	Humboldt Award (2004), Royal Medal (2011), Longstaff Prize (2013)
023-C	2008	Charles Lieber	1959	American	US	Wolf Prize, Feynman Prize, World Technology Award (2003, 2004)
024-C	2010	Stephen J. Lippard	12/10/1940	American	US	National Medal of Science (2005)
025-C	2009	Benjamin List	1968	German	US	
026-C	2006	Tobin J. Marks	25/10/1944	American	US	National Medal of Science (2005), NAS Award in Chemical Sciences
027-C	2008	Krzysztof Matyjaszewski	08/04/1950	Polish-American	US	Wolf Prize (2011), Humboldt Prize (1999)
028-C	2013	Chad A. Mirkin	23/10/1963	American	US	Feynman Prize (2002), Lemelson-MIT Prize (2009), Linus

						Pauling Medal (2013)
029-C	2002	K. C. Nicolaou	05/07/1946	Cypriot-American	US	Linus Pauling Award, Benjamin Franklin Medal (2011)
030-C	2006	Stuart L. Schreiber	06/02/1956	American	US	Ciba-Geigy Drew Award (1992)
031-C	2009	Gary B. Schuster	06/08/1946	American	US	Charles Holmes Herty Medal (2006)
032-C	2007	Dieter Seebach	31/10/1937	German	Germany	Marcel Benoist Prize
033-C	2013	Nadrian C. Seeman	16/12/1945	American	US	Kavli Prize
034-C	2013	K. Barry Sharpless	28/04/1941	American	US	Scheele Award (1991), Hrvey Prize (1998), Benjamin Franklin Medal (2001), Nobel Prize (2001)
035-C	2008	Dan Schechtman	24/01/1941	Israeli	Israel	Israel Prize (1998), Wolf Prize (1999), Nobel Prize (2011)
036-C	2003	Seiji Shinkai	05/07/1944	Japanese	Japan	
037-C	2002	Sir Fraser Stoddart	24/05/1942	Scottish	UK-US	
038-C	2011	Donald A. Tomalia	1938	American	US	
039-C	2007	Barry Trost	13/06/1941	American	US	Arthur C. Cope Award (2004)
040-C	2008	Roger Y. Tsien	01/02/1952	Chinese-American	US	Gairdner Foundation International Award (1995), Heineken Prize (2002), Wolf Prize (2004), E. B. Wilson Medal (2008), Nobel Prize (2008)
041-C	2011	Fritz Vögtle	08/03/1939	German	Germany	
042-C	2002	George M. Whitesides	03/08/1939	American	US	National Medal of Science (1998), Kyoto Prize (2003), Dan David Prize (2005), Priestley Medal (2007)
043-C	2010	Omar M. Yaghi	1965	Jordanian-American	US	

NOBEL WINNERS NOT PREDICTED BY THOMSON REUTERS: CHEMISTRY

044-C		Michael Levitt	09/05/1947	American, Israeli, British	US	Nobel Prize (2013)

045-C	Arieh Warshel	20/10/1940	Israeli, American	US	Tolman Medal (2003), Nobel Prize (2013)
046-C	Robert J. Lefkowitz	15/04/1943	American	US	National Medal of Science (2007), Nobel Prize (2012)
047-C	Brian K. Kobilka	30/05/1955	American	US	Nobel Prize (2012)
048-C	Richard F. Heck	15/08/1931	American	Phillippines	Nobel Prize (2010)
049-C	Ei-ichi Negishi	14/07/1935	Japanese	US	Nobel Prize (2010)
050-C	Akira Suzuki	12/09/1930	Japanese	Japan	Nobel Prize (2010)
051-C	Venkatraman Ramakrishnan	1952	American, British	UK	Louis-Jeantet Prize (2007), Nobel Prize (2009), Padma Vibhushan (2010)
052-C	Thomas A. Steitz	23/08/1940	American	US	Nobel Prize (2009)
053-C	Ada E. Yonath	22/06/1939	Israeli	Israel	Harvbey Prize (2002), Wolf Prize (2006), Albert Einstein Award (2008), Nobel Prize (2009)
054-C	Osamu Shimomura	27/08/1928	Japanese	US	Nobel Prize (2008)
055-C	Martin Chalfie	15/01/1947	American	US	Nobel Prize (2008)
056-C	Gerhard Ertl	10/10/1936	German	Germany	Wolf Prize (1998), Nobel Prize (2007)
057-C	Roger D. Kornberg	24/04/1947	American	US	Nobel Prize (2006), Louisa Gross Horwitz Prize (2006), Gairdner Foundation International Award (2000), Harvey Prize (1997)
058-C	Yves Chauvin	10/10/1930	French	France	Nobel Prize (2005)
059-C	Richard R. Schrock	04/01/1945	American	US	Nobel Prize (2005)
060-C	Aaron Ciechanover	01/10/1947	Israeli	Israel	Nobel Prize (2004)
061-C	Avram Hershko	31/12/1937	Israeli	Israel	Nobel Prize (2004)
062-C	Irwin Rose	16/06/1926	American	US	Nobel Prize (2004)
063-C	Peter Agre	30/01/1949	American	US	Nobel Prize (2003)
064-C	Roderick MacKinnon	19/02/1956	American	US	Albert Lasker Award (1999), Louisa Gross Horwitz Prize (2003), Nobel Prize (2003)

065-C	John B. Fenn	15/06/1917-10/12/2010	American	US	Nobel Prize (2002)
066-C	Koichi Tanaka	03/08/1959	Japanese	Japan	Nobel Prize (2002)
067-C	Kurt Wuthrich	04/10/1938	Swiss	Switzerland	Kyoto Prize (1998), Nobel Prize (2002)

THOMSON REUTERS' NOBEL PRIZE NOMINEES: ECONOMICS

No	Year	Name	Date of Birth-Date of Death	Nationality	Residence	Research Interests	Notable Awards
068-E	2008	Armen A. Alchian	12/04/1914-19/02/2013	American	US	Property rights, transaction costs, institutional economics	
069-E	2010	Alberto F. Alesina	29/04/1957	Italian	US	The Political business cycles, the political economy of fiscal policy, budget deficits, The process of European integration, The effect of alternative electoral systems on economic policies.	
070-E	2012	Sir Anthony B. Atkinson	04/09/1944	British	UK	Distribution of income and wealth, Poverty and welfare state, European social agenda, Global public economics, welfare economics	Chevalier de la Légion d'Honneur (2001), A.SK Social Science Award (2007)
071-E	2002	Robert J. Barro	28/09/1944	American	US	Empirical determinants of economic growth, economic effects of public debt and budget deficits, the formation of monetary policy	Adam Smith Award (1998)
072-E	2006	Jagdish N. Bhagwati	26/07/1934	American	US	International trade, economic policy reforms, immigration	Seidman Distinguished Award in International Political Economy (1998), Padma Vibhushan Award (2000),
073-E	2013	David E. Card	1956	Canadian	US	Labour Economics	John Bates Clark Medal (1995)
074-E	2012	Angus S. Deaton	19/10/1945	British	US	Determinants of health in rich and poor	John Kenneth Galbraith Award (2009)

						countries, measurement of poverty in India and around the world, analysis of household surveys	
075-E	2008	Harold Demsetz	31/05/1930	American	US	Property rights, business firm, problems in monopoly, competition and antitrust, bioeconomics	Western Economics Association Distinguished Teaching Award (1981)
076-E	2011	Douglas W. Diamond	1953	American	US	Financial intermediaries, financial crises and liquidity	
077-E	2006	Avinash K. Dixit	06/08/1944	Indian-American	US	International trade, microeconomics, investment	
078-E	2003	Robert F. Engle	10/10/1942	American	US	Econometrics	
079-E	2002	Eugene F. Fama	14/02/1939	American	US	Foundations and Theory of Finance	Deutsche Bank Prize in Financial Economics (2005), CME Fred Arditti Innovation Award (2007), Nobel Prize (2013)
080-E	2009	Ernst Fehr	21/06/1956	Austrian	Austria	Behavioral Economics	Gossen Prize (1999), Marcel Benoist Prize (2008), Vorarlberg Science Prize (2012), Gottlieb Duttweiler Prize (2013)
081-E	2008	Martin S. Feldstein	25/10/1939	American	US	Public pension systems, investment behaviour	John Bates Clark Medal (1977)
082-E	2002	Kenneth R. French	10/03/1954	American	US	Financial Economics, Fama-French Three Factor Model	
083-E	2009	Jordi Gali	04/01/1961	Spanish	Spain	Causes of business cycles, optimal monetary policy, time series analysis	Yrjö Jahnsson Award (2005)
084-E	2009	Mark L. Gertler	31/03/1951	American	US	Monetary policy, financial crisis	
085-E	2002	Sir Clive William John Granger	04/09/1934-27/05/2009	British	US	Financial Economics, Econometrics	Nobel Prize (2003)
086-E	2007	Gene M. Grossman	11/12/1955	American	US	International Trade, Political Economy, Economic Growth	Harry G. Johnson Prize (1985),

087-E	2008	Lars P. Hansen	26/10/1952	American	US	Generalized Method of Moments, the linkages between financial and real sectors of the economy	Nobel Prize (2013)
088-E	2006	Oliver D. Hart	09/10/1948	British-American	US	Contract Theory, theory of firm, corporate finance, law and economics	
089-E	2011	Jerry A. Hausman	05/05/1946	American	US	Econometrics, Applied Microeconomics	Frisch Medal (1980), John Bates Clark Medal (1985)
090-E	2007	Elhanan Helpman	30/03/1946	Israeli-American	US	International trade, political economy, economic growth	Israel Prize (1991)
091-E	2013	Sir David F. Hendry	06/03/1944	British	UK	Econometric methodology, time series econometrics, applied macroeconometirics	Guy Medal in Bronze (1986)
092-E	2006	Bengt R. Holmström	18/04/1949	Finnish	US	Contracting and incentives, moral hazard, mechanism design, theory of firm, corporate governance, the demand and supply of liquidity and its relationship with crises	The Banque de France-TSE Senior Prize in Monetary Economics and Finance (2012)
093-E	2006	Dale W. Jorgenson	07/05/1933	American	US	Economic theory, information technogology and economic growth, energy and the environment, tax policy and the investment behaviour, applied econometrics	John Bates Clark Medal
094-E	2002	Daniel Kahneman	05/03/1934	American-Isreali	US	Psychology, economics	The Hilgard Award for Career Contributions to General Psychology (1995), The Nobel Prize in Economic Sciences (2002), The Lifetime Contribution Award of the American Psychological Association (2007), the Presidential Medal of Freedom (2013)
095-E	2010	Nobuhiro Kiyotaki	24/06/1955	Japan	US	Monetary and macroeconomics	Nakahara Prize (1997), Yrjö Jahnsonn Award (1999)

096-E	2013	Alan B. Krueger	17/09/1960	American	US	Economics of education, terrorism, labor demand, income distribution, social insurance, labor Mrket regulation, environmental economics	Kershaw Prize (1997), Mahalonobis Memorial Medal (2001), IZA Prize (2006)
097-E	2011	Anna O. Krueger	12/02/1934	American	US	Economic development, international trade and finance, economic policy reform	Robertson Prize (1984)
098-E	2006	Paul Krugman	28/02/1953	American	US	International economics, macroeconomics	John Bates Clark Medal (1991), Principe de Asturias Prize (2004), Nobel Prize (2008)
099-E	2007	Paul R. Milgrom	20/04/1948	American	US	Action theory, Incentive theory, market design	Erwin Plein Nemmers Prize (2008), BBVA Frontier of Knowledge Award (2013)
100-E	2010	John Hardman Moore	07/05/1954	British	UK	Economic theory, Nature of contracts, money, liquidity and the aggregate economy	Yrjö Jahnsson Award (1999), Stephen A. Ross Prize (2010)
101-E	2010	Kevin M. Murphy	1958	American	US	Income inequality, economic growth, valuing medical research, rational addiction, unemplyment	John Bates Clarck Medal (1997) John Von Neumann Award (2008)
102-E	2009	William D. Nordhaus	31/05/1941	American	US	Environmental economics	
103-E	2013	Sam Peltzman	1940	American	US	Economics of government regulation, industrial organization, the growth of government, the political economy of public education, economic analysis of voters and legislators	
104-E	2013	M. Hashem Peseran	30/03/1946	British-Iranian	UK-US	Econometrics, macroeconomics, Iranian economics	
105-E	2013	Peter C. B. Phillips	23/03/1948	Brtish	US	Econometrics	
106-E	2013	Richard A. Posner	11/01/1939	American	US	Economic analysis of law, the economics of	Ronald H. Coase Medal (2010)

						justice	
107-E	2009	Matthew J. Rabin	27/12/1963	American	US	Behavioural economics, Game Theory	John Bates Clark Medal (2001), John Von Neumann Award (2006)
108-E	2005	Paul Micheal Romer	07/10/1955	American	US	Economic growth, emerging markets, international economic policy, political economy	H. C. Recktenwald Prize in Economics
109-E	2012	Stephen A. Ross	07/02/1944	American	US	Financial economics	
110-E	2008	Thomas J. Sargent	19/07/1943	American	US	Macroeconomics, Monetary economics	NAS Award (2011), Nobel Prize (2011)
111-E	2012	Robert J. Shiller	29/03/1946	American	US	Financial economics, behavioural finance	Deutsche Bank Prize (2009), Nobel Prize (2013)
112-E	2008	Christopher A. Sims	21/10/1942	American	US	Macroeconomics, Econometrics, Time Series	Nobel Prize (2011)
113-E	2009	John B. Taylor	08/12/1946	American	US	Monetary economics, macroeconomics	Gugenheim Fellowship for Social Sciences
114-E	2002	Richard H. Thaler	12/09/1945	American	US	Behavioural Finance	
115-E	2007	Jean Tirole	09/08/1953	French	France	Macroeconomics, Game Theory	Gugenheim Fellowship for Social Sciences
116-E	2011	Gordon Tullock	13/02/1922	American	US	Law and economics, public choice theory	
117-E	2009	Martin L. Weitzman	01/04/1942	American	US	Environmental economics, climate change, the economics of catastrophes, long-run discountring, green accounting, alternative instruments of controlling pollution	
118-E	2011	Halbert L. White	19/10/1950-31/03/2012	American	US	Asymptotic theory for econometricians, estimation, inference, specification analysis	Gugenheim Fellowship for Social Sciences
119-E	2006	Oliver E. Williamson	27/09/1932	American	US	Costs of transactions, information impactedness, microeconomics	John Von Neumann Award (1999), Nobel Prize (2009)
120-E	2007	Robert B. Wilson	16/05/1937	American	US	Market design, pricing, negoitiation, industrial organization, information economics	

121-E	2013	Joshua D. Angrist	18/09/1960	Israeli-American	US	Econometrics, Labor economics	John Von Neumann Award (2011)

NOBEL WINNERS NOT PREDICTED BY THOMSON REUTERS: ECONOMICS

No	Year	Name	Date of Birth-Date of Death	Nationality	Residence	Research Interests	Notable Awards
122-E		Alvin E. Roth	18/12/1951	American	US	Game Theory, Market Desıgn, Experimental Economics	Nobel Prize (2012)
123-E		Lloyd S. Shapley	02/06/1923	American	US	Shapley Value, Stochastic Games, The Bondareva-Shapley Theorem, The Shapley-Shubik Power Index	Nobel Prize (2012), John Von Neumann Prize
124-E		Peter A. Diamond	29/04/1940	American	US	Political Economics, Welfare Economics, Behavioural Economics	Nobel Prize (2010)
125-E		Dale T. Mortensen	02/02/1939-09/01/2014	American	US	Labour Economics	IZA Prize (2005), Nobel Prize (2010)
126-E		Christopher A. Pissarides	20/02/1948	Cypriot, British	UK	Macroeconomics, Labour Economics, Economic Growth, Economic Policy	IZA Prize (2005), Nobel Prize (2010)
127-E		Elinor Ostrom	07/08/1933-12/06/2012	American	US	Public Economics, Public Choice Theory	John J. Carty Award (2004), Nobel Prize (2009)
128-E		Leonid Hurwicz	21/08/1917-24/06/2008	Polish	US	Mechanism Design	National Medal of Science (1990), Nobel Prize (2007)
129-E		Eric S. Maskin	12/12/1950	American	US	Mechanism Design Theory	Nobel Prize (2007)
130-E		Roger B. Myerson	29/03/1951	American	US	Game Theory	Nobel Prize (2007)
131-E		Edmund S. Phelps	26/07/1933	American	US	Micro Foundations of Macroeoconomics, Natural Rate of Unemployment	Nobel Prize (2006)
132-E		Robert J. Aumann	08/06/1930	Israeli,	US	Game Theory	Nobel Prize (2005), John Von

			American			Neumann Prize, Harvey Prize, Israel Prize
133-E	Thomas C. Schelling	14/04/1921	American	US	Game Theory	Nobel Prize (2005)
134-E	Finn E. Kydland	01/12/1943	Norwegian	US	New Classical Economics, Real Business Cycle Theory, Time Consistency in Economic Policy	Nobel Prize (2004)
135-E	Edward C. Prescott	26/12/1940	American	US	Real Business Cycle Theor, Time Consistency in Economıc Policy	Nobel Prize (2004)
136-E	Vernon L. Smith	01/01/1927	American	US	Behavioral Economics, New Classical Economics	Nobel Prize (2002)

THOMSON REUTERS' NOBEL PRIZE NOMINEES: PHYSICS

No	Year	Name	Date of Birth-Date of Death	Nationality	Residence	Notable Awards
137-P	2009	Yakir Aharonov	28/08/1932	Israeli	US	National Medal of Science (2010), Wolf Prize (1998)
138-P	2011	Alain Aspect	15/06/1947	French	France	Wolf Prize (2010), Danish Niels Bohr International Gold Medal (2013), Balzan Prize (2013)
139-P	2012	Charles H. Bennett	1943	American	US	Harvey Prize (2008)
140-P	2010	Charles L. Bennett	1956	American	US	Harvey Prize (2006), Shaw Prize (2010), Gruber Cosmology Prize (2012), Karl G. Jansky Prize (2013)
141-P	2009	Sir Micheal V. Berry	14/03/1941	British	UK	National Academy of Science (1995), Wolf Prize (1998), Polya Prize (2005)
142-P	2012	Gilles Brassard	1955	Canadian	Canada	ForMemRS (2013)
143-P	2012	Leight T. Canham	1958	British	UK	
144-P	2011	John F. Clauser	01/12/1942	American	US	Wolf Prize (2010)
145-P	2006	Emmanuel Desurvire	07/06/1955	French	France	

146-P	2010	Thomas W. Ebbesen	1954	Norwegian	France	NEC Research Prize (1992), Randers Prize (2001), Agile Europhysics Prize (2001), Prix France Telecom (2005), Tomassoni Prize (2009), Scola Physica Romana Medal (2009), Quantum Electronics and Optics Prize (2009)
147-P	2013	François Englert	06/10/1932	Belgian	Belgium	Wolf Prize (2004), Sakurai Prize (2010), Nobel Prize (2013)
148-P	2006	Albert Fert	07/03/1938	French	France	Wolf Prize (2006), Japan Prize, Nobel Prize (2007)
149-P	2008	Andre K. Geim	21/10/1958	Dutch-British	UK	Ig Nobel Prize (2000), Mott Prize (2007), Nobel Prize (2010), Knight Bachelor (2012), Copley Medal (2013)
150-P	2002	Micheal B. Green	22/05/1946	British	UK	Dirac Prize, Fundamental Physics Prize (2013)
151-P	2006	Peter Grünberg	18/05/1939	German	Germany	Wolf Prize (2006), European Inventor of the Year (2006), Japan Prize (2007), Nobel Prize (2007)
152-P	2006	Alan H. Guth	27/02/1947	American	US	Dirac Prize (2004), Franklin Medal (2009), Fundamental Physics Prize (2012)
153-P	2012	Stephen E. Harris	29/10/1936	American	US	Frederic Ives Medal (1999), Arthur L. Schawlow Prize (2002), Harvey Prize (2007)
154-P	2012	Lene V. Hau	13/10/1959	Danish	US	The Ole Romer Medal (2001), George Ledlie Prize (2008), Rigmor and Carl Holst-Knudsen Award for Scientific Research
155-P	2013	Peter W. Higgs	29/05/1929	British	UK-Scotland	Dirac Medal (1997), Wolf Prize (2004), Sakurai Prize (2010), Nobel Prize (2013)
156-P	2013	Hideo Hosono	07/09/1953	Japanese	Japan	Medal of Honor (Purple Ribbon), T, Matthias Prize, Japanese Society of Applied Physics Research Achievement Award
157-P	2009	Juan Ignacio Cirac	11/10/1965	Spanish	Germany	Prince of Austria Award (2006), Wolf Prize (2013)
158-P	2007	Suimo Iijima	02/05/1939	Japanese	Japan-Korea	Benjamin Franklin Medal (2002), Balzan Prize (2007), Kavli Prize (2008)
159-P	2011	Sajeev John	1956	Indian	Canada	King Faisal International Prize (2001)
160-P	2006	Andrei Linde	02/03/1948	American-	US	Oscar Klein Medal (2002), Dirac Medal (2002), Gruber

				Russian		Cosmology Prize (2004), Fundamental Physics Prize (2012)
161-P	2013	Geoffrey W. Marchy	29/09/1954	American	US	Henry Draper Medal 2001), Shaw Prize (2005)
162-P	2013	Michel G. E. Mayor	12/01/1942	Swiss	Switzerland	Balzan Prize (2000), Albert Einstein Medal (2004), Shaw Prize (2005)
163-P	2007	Arthur B. Mcdonald	29/08/1943	Canadian	Canada	Benjamin Franklin Medal (2007)
164-P	2002	Shuji Nakamura	22/05/1954	Japanese	US	Asahi Prize (2001), Benjamin Franklin Medal (2002), Harvey Prize (2009)
165-P	2006	Masataka Nakazawa	17/09/1952	Japanese	Japan	Wood Prize (2005)
166-P	2008	Kostya Novoselov	23/08/1974	Russian-British	UK	Nicholas Kurti Prize (2007), EuroPhysics Prize (2008), Nobel Prize (2010)
167-P	2011	Hideo Ohno	18/12/1954	Japanese	UK	IBM Japan Science Award (1998), the IUPAP Magnetism Prize (2003), Japan Academy Prize (2005)
168-P	2010	Lyman A. Page	24/09/1957	American	US	Shaw Prize (2010)
169-P	2006	David N. Payne	13/08/1944	British	UK	Tyndall Award (1991), Benjamin Franklin Medal (1998)
170-P	2009	Sir John B. Pendry	04/07/1943	British	UK	Dirac Prize (1996), Royal Medal (2006), Isaac Newton Medal (2013)
171-P	2008	Sir Roger Penrose	08/08/1931	British	UK	Wolf Prize (1988), Dirac Medal (1989), Copley Medal (2008)
172-P	2010	Saul Perlmutter	22/09/1959	American	US	Shaw Prize (2006), Gruber Prize (2007), Nobel Prize (2011)
173-P	2013	Didier Queloz	23/02/1966	Swiss	Switzerland-US	
174-P	2007	Martin J. Rees	23/06/1942	British	UK	Balzan Prize (1989), Bower Award (1998), Gruber Prize (2001), Faraday Prize (2004), Crafoord Prize (2005), Sir Isaac Newton Medal (2012)
175-P	2010	Adam G. Riess	16/12/1969	American	US	Shaw Prize (2006), Nobel Prize (2011)
176-P	2008	Vera C. Rubin	23/07/1928	American	US	Gruber International Prize, Bruce Medal, Dickson Medal, National Medal of Science

177-P	2010	Brian P. Schmidt	24/02/1967	American-Austrialian	Australia	Shaw Prize (2006), Nobel Prize (2011)
178-P	2009	Scheldon Schultz	21/01/1933	American	US	
179-P	2002	John H. Schwarz	22/10/1941	American	US	National Academy of Science (1989), Dirac Medal (1989), Fundamental Physics Prize (2013)
180-P	2009	David R. Smith		American	US	Descartes Prize (2005)
181-P	2010	David N. Spergel	25/03/1961	American	US	MacArthur Fellowship
182-P	2006	Paul J. Steinhardt	25/12/1952	American	US	
183-P	2002	Yoshinori Tokura	01/03/1954	Japanese	Japan	Asahi Prize (2002), Purple Ribbon Medal (2003), James J. MacGroddy Prize (2005)
184-P	2007	Yoji Totsuka	06/03/1942-10/08/2008	Japanese	Japan	Asahi Prize (1987), Benjamin Franklin Medal (2007)
185-P	2002	Edward Witten	26/08/1951	American	US	Dirac Medal (1985), Albert Einstein Medal (1985), National Medal of Sicence (2002), Harvey Prize (2005), Crafoord Prize (2008), Isaac Newton Medal (2010), Fundamental Physics Prize (2012)
186-P	2012	William K. Wootters		American	US	
187-P	2011	Eli Yablonovitch	15/12/1946	American	US	Adolph Lomb Medal, Wood Prize
188-P	2011	Anton Zeilinger	20/05/1945	Austrian	Austria	Isaac Newton Medal (2007), Wolf Prize (2010)
189-P	2009	Peter Zoller	16/09/1952	Austrian	Austria	Max Planck Medal (2005), Dirac Medal (2006), Benjamin Franklin Medal (2010), Wolf Prize (2013)
NOBEL WINNERS NOT PREDICTED BY THOMSON REUTERS						
190-P		Serge Haroche	11/09/1944	French	France	CNRS Gold Medal (2009), Nobel Prize (2012)
191-P		David J. Wineland	24/02/1944	American	US	National Medal of Science (2007), Nobel Prize (2012)
192-P		Charles Kuen Kao	04/11/1933	American, British, Hong	US, UK, China, Hong	Faraday Medal (1989), Japan Prize (1996), Nobel Prize (2009)

			Kong	Kong	
193-P	Yoichiro Nambu	18/01/1921	American	US	US National Medal of Science (1982), Dirac Medal (1986), J. J. Sakurai Prize (1994), Wolf Prize (1994/1995), Nobel Prize (2008)
194-P	John C. Mather	07/08/1946	American	US	Nobel Prize (2006)
195-P	George F. Smoot	20/02/1945	American	France	Albert Einstein Medal (2003), Nobel Prize (2006), Oersted Medal (2009)
196-P	Roy J. Glauber	01/09/1925	American	US	Albert A. Michelson Medal (1985), Nobel Prize (2005)
197-P	David J. Gross	19/02/1941	American	US	Dirac Medal (1988), Harvey Prize (2000), Nobel Prize (2004)
198-P	H. David Politzer	31/08/1949	American	US	Nobel Prize (2004)
199-P	Frank Wilczek	15/05/1951	American	US	Sakurai Prize (1986), Dirac Medal (1994), Lorentz Medal (2002), Nobel Prize (2004)
200-P	Alexei A. Abrikosov	25/06/1928	Russian	Russia	Nobel Prize (2003)
201-P	Vitaly L. Ginzburg	04/10/1916-08/11/2009	Russian	Russia	Wolf Prize (1994-1995), Nobel Prize (2003)
202-P	Anthony J. Leggett	26/03/1938	American, British	US	Maxwell Medal and Prize (1975), Dirac Medal (1992), Wolf Prize (2002/2003), Nobel Prize (2003)
203-P	Raymond Davis	14/10/1914-31/05/2006	American	US	Wolf Prize (2000), National Medal of Science (2001), Nobel Prize (2002)
204-P	Masatoshi Koshiba	19/09/1926	Japanese	Japan, US	Humboldt Prize (1997), Wolf Prize (2000), Nobel Prize (2002)
205-P	Riccardo Giacconi	06/10/1931	American, Italian	US	Elliott Cresson Medal (1980), Nobel Prize (2002)

THOMSON REUTERS' NOBEL PRIZE NOMINEES: MEDICINE

No	Year	Name	Date of Birth-	Nationality	Residence	Notable Awards

			Date of Death			
206-M	2008	Shizuo Akira	27/01/1953	Japan	Japan	Gairdner Foundation International Award (2011), Robert Koch Prize (2004), The Milstein Award (2007), The William B. Coley Award (2006)
207-M	2012	C. David Allis	22/03/1951	American	US	Massry Prize (2003), Gairdner Foundation International Award (2007)
208-M	2008	Victor R. Ambros	1953	American	US	Gairdner Foundation International Award (2008), Massry Prize (2009), Dickson Prize (2009)
209-M	2002	Sir Micheal J. Berridge	22/10/1938	British	UK	William Bate Hardy Prize (1987), Gairdner Foundation International Award (1988), Albert Lasker Basic Medical Reserach Award (1989), Royal Medal of the Royal Society (1991), Wolf Prize (1994/5), Shaw Prize (2005)
210-M	2008	Bruce A. Beutler	29/12/1957	American	US	Koch Prize (2004), Balzan Prize (2007), Shaw Prize (2011), Nobel Prize (2011)
211-M	2013	Sir Adrian P. Bird	03/07/1947	British	UK	Gabor Medal (1999), Grand Prix Charles Leopold Mayer (2008), Gairdner Foundation International Award (2011)
212-M	2009	Elizabeth H. Blackburn	26/11/1948	Australian	US	Harvey Prize (1999), Lasker Award, Nobel Prize (2009)
213-M	2006	Mario R. Capecchi	06/10/1937	American	US	Lasker Award (2001), Wolf Prize (2002), Nobel Prize (2007)
214-M	2013	Howard Cedar	12/01/1943	Israeli-American	Israel	Wolf Prize (2008), EMET Prize (2009), Gairdner Foundation Internatonal Award (2011)
215-M	2006	Pierre Chambon	07/02/1931	French	France	Harvey Prize (1987), Horwitz Prize (1999), Lasker Award (2004), Gairdner Foundation International Award (2010)

216-M	2011	Robert L. Coffman	1947	American	US	
217-M	2010	Douglas L. Coleman	06/10/1931	Canadian	US	Shaw Prize (2009), Gairdner Foundation International Award (2005), Lasker Award (2010)
218-M	2002	Francis S. Collins	14/04/1950	American	US	National Medal of Science (2008), Pro Bono Humanum Award of the Galien Foundation (2012)
219-M	2008	Rory Collins		British	UK	
220-M	2011	Brian J. Druker	1955	American	US	Lasker Clinical Award (2009)
221-M	2007	R. John Ellis	12/02/1935	British	UK	Gairdner Foundation International Award (2004), International Medal of Cell Stress Society (2007)
222-M	2006	Ranold M. Evans	17/04/1949	American	US	Lasker Award (2004), Gairdner Foundation International Award (2006), Harvey Prize (2006), Albany Prize (2007), Wolf Prize (2012)
223-M	2006	Sir Martin Evans	01/01/1941	British	UK	Lasker Award (2001), Nobel Prize (2007)
224-M	2010	Jeffrey M. Friedman	20/07/1954	American	US	Gairdner Foundation International Award (2005), Shaw Prize (2009)
225-M	2007	Fred H. Gage	08/10/1950	American	US	Christopher Reeve Research Medal (1997), Max Planck Research Prize (1999), National Academy of Sciences (2003)
226-M	2009	Carol Greider	15/04/1961	American	US	Lasker Award (2006), Loisa Gross Horwitz Prize (2007), Nobel Prize (2009)
227-M	2012	Micheal Grunstein	1946	Romanian	US	Massry Prize (2003)
228-M	2007	F. Ulrich Hartl	10/03/1957	German	Germany	Feldberg Prize (2003), Gairdner Foundation International Award (2004), Lasker Award (2011), Massry Prize (2011), Shaw Prize (2012)

229-M	2008	Jules A. Hoffman	02/08/1941	French	France	Nobel Prize (2011)
230-M	2007	Arthur L. Horwich	1951	American	US	Gairdner Foundation International Award (2004), Wiley Prize (2007), Lousia Gross Horwitz Prize (2008), Lasker Award (2011), Shaw Prize (2012)
231-M	2012	Anthony R. Hunter	23/08/1943	British	US	Wolf Prize (2005)
232-M	2012	Richard O. Hynes	29/10/1944	British	US	Gairdner Foundation International Award (1997)
233-M	2006	Sir Alec J. Jefferys	09/01/1950	British	UK	Lasker Award (2005), Great Briton Award (2006)
234-M	2006	Elwood W. Jensen	13/01/1920-16/12/2012	American	US	Brnker International Award (2004), Lasker Award (2004)
235-M	2013	Daniel J. Klionsky	1958	American	US	
236-M	2002	Alfred G. Knudson	09/08/1922	American	US	Albert Lasker Award (1998), Kyoto Prize (2004)
237-M	2002	Eric S. Lander	03/02/1957	American	US	Gairdner Foundation International Award (2002)
238-M	2011	Robert S. Langer	29/08/1948	American	US	Gairdner Foundation International Award (1996), Wolf Prize (2013), Biotechnology Heritage Award (2014), Breakthrough Prize in Life Sciences (2014)
239-M	2011	Nicholas B. Lydon	27/02/1957	British	UK	Lasker Award (2009), Japan Prize (2012)
240-M	2007	Joan Massague	30/04/1953	Spanish	Spain	
241-M	2010	Ernest A. Mcculloch	27/04/1926-19/01/2011	Canadian	Canada	Lasker Award (2005)
242-M	2011	Jaques F. A. P. Miller	02/04/1931	French-	Australia	

				Australian		
243-M	2013	Noboru Mizushima		Japanese	Japan	
244-M	2011	Timothy R. Mossman		American	US	
245-M	2002	Yasutomi Nishizuka	12/07/1932-04/10/2004	Japanese	Japan	Gairdner Foundation International Award (1988), Albert Lasker Award (1989), Kyoto Prize (1992), Wolf Prize (2004)
246-M	2009	Seiji Ogawa	19/01/1934	Japanese	Japan-US	Japan Prize, Gairdner Foundation International Award (2003)
247-M	2013	Yoshinori Ohsumi	09/02/1945	Japanese	Japan	Asahi Prize (2009), Kyoto Prize (2012)
248-M	2012	Anthony J. Pawson	18/10/1952	British-Canadian	Canada	Wolf Prize (2005)
249-M	2008	Sir Richard Peto	14/05/1943	British	UK	Guy Medal (1986), Royal Medal (2002), Heineken Prize for Medicine (2008)
250-M	2013	Aharon Razin	06/04/1935	Israeli	Israel	Wolf Prize (2008), Israel Prize (2004)
251-M	2009	James E. Rothman	03/10/1950	American	US	Lasker Award (2002), Nobel Prize (2013)
252-M	2012	Erkki Ruoslahti		American	US	Gairdner Foundation International Award (1997), Japan Prize (2005),
253-M	2008	Gary Ruvkun	26/03/1952	American	US	Gairdner Foundation International Award (2008), Benjamin Franklin Medal (2008), Lasker Prize (2008), Louisa Gross Horwitz Prize (2009), Mssry Prize (2009), Dan David Prize (2011), Wolf Prize (2014)
254-M	2011	Charles L. Sawyers	1959	American	US	Lasker Award (2009)

255-M	2009	Randy Schekman	30/12/1948	American	US	Lasker Award (2002), Louisa Gross Horwitz Prize (2002), Massry Prize (2010), Nobel Prize (2013)
256-M	2013	Dennis J. Slamon	08/08/1948	American	US	Gairdner Foundation International Award (2007)
257-M	2006	Oliver Smithies	23/06/1925	British-American	US	Lasker Award 82001), Wolf Prize (2002), Nobel Prize (2007)
258-M	2010	Ralph M. Steinman	14/01/1943	Canadian	US	Gairdner Foundation International Award (2003), Lasker Award (2007), Heineken Prizes (2010), Nobel Prize (2011)
259-M	2009	Jack W. Szostak	09/10/1952	Canadian	US	Lasker Award (2006), Nobel Prize (2009)
260-M	2012	Masatoshi Takeichi	27/10/1943	Japanese	Japan	Japan Prize
261-M	2010	James E. Till	25/08/1931	Canadian	Canada	Gairdner Foundation International Award (1969), Lasker Award
262-M	2002	J. Craig Venter	14/10/1946	American	US	Kistler Prize (2008), ENI Award (2008), Medal of Science (2008)
263-M	2002	Bert Vogelstein	02/06/1949	American	US	Gairdner Foundation International Award (1992), Dickson Prize (1994), Louisa Gross Horwitz Prize (1998), Harvey Prize
264-M	2011	Joseph P. Vacanti		American	US	
265-M	2002	Robert A. Weinberg	11/10/1942	American	US	National Medal of Science (1997), Wolf Prize (2004), Hope Funds Award (2009),
266-M	2010	Shinya Yamanaka	04/09/1962	Japanese	Japan	Robert Koch Prize (2008), Shaw Prize (2008), Gairdner Foundation International Award (2009), Wolf Prize (2010), Nobel Prize (2012)

NOBEL WINNERS NOT PREDICTED BY THOMSON REUTERS: MEDICINE

267-M	Thomas C. Sudhof	22/12/1955	American	US	Albert Lasker Award (2013), Nobel Prize (2013)
268-M	Sir John B. Gurdon	02/10/1933	British	US, UK	Wolf Prize (1989), Albert Lasker Award (2009), Nobel Prize (2012)
269-M	Robert G. Edwards	27/09/1925-10/04/2013	British	UK	Nobel Prize (2010)
270-M	Harald Zur Hausen	11/03/1936	German	Germany	Nobel Prize (2008)
271-M	Andrew Z. Fire	27/04/1959	American	US	Nobel Prize (2006)
272-M	Craig C. Mello	18/10/1960	American	US	Nobel Prize (2006)
273-M	Barry J. Marshall	30/09/1951	Australian	Australia	Nobel Prize (2005)
274-M	J. Robin Warren	11/06/1937	Australian	Australia	Nobel Prize (2005)
275-M	Richard Axel	02/07/1946	American	US	Nobel Prize (2004)
276-M	Linda B. Buck	29/01/1947	American	US	Nobel Prize (2004)
277-M	Paul C. Lauterbur	06/05/1929-27/03/2007	American	US	Harvey Prize (1986), Bower Award (1990), Nobel Prize (2003),
278-M	Sir Peter Mansfield	09/10/1933	British	UK	Nobel Prize (2003)
279-M	Sydney Brenner	13/01/1927	South African	US	Harvey Prize (1987), Copley Medal (1991), Nobel Prize (2002)
280-M	H. Robert Horvitz	08/05/1947	American	US	Nobel Prize (2002)
281-M	John E. Sulston	27/03/1942	British	UK	Nobel Prize (2002)

CHAPTER FIVE

PICKING WINNERS: ARE COMPETITION WINNERS BETTER THAN LOSERS

5.1 Introduction

Publication is very important for working in academia because wages, tenure, promotion, and funding opportunities are all based, to a large extent, on publications. Publication productivity can be measured by various means, such as publication rates, citations, journal quality, or altmetrics. Peer recognition of an author's publication by these measurements points to the reward system in academia, and it is closely associated with the allocation of monetary and non-monetary rewards. In social sciences, including economics, the number of citations received by others is one of the most commonly used measurements of peer recognition of a publication because it reflects the impact of that contribution onto peers (Laband and Piette, 1994). It also affects the author's market value out of academia (i.e., prestige, position in society). The rank of the journal where the paper published similarly matters in the reward system. It is generally assumed that the higher rank of the journal published the higher the quality of the paper (Laband and Tollison, 2003). One possible explanation is publishing in prestigious journals is advantageous on its own as many scientific bodies treat those research contributions differently compared to lower-ranked journal publications. For example, academic hiring and promotion boards commonly give more weight to the authors who published in high-ranking journals and funding committees increasingly use journal rankings as part of funding judgments (Seglen, 1997; Oswald, 2007). Another possibility to explain the advantages of publishing in elite journals is that publishing in a high rank journal will increase its impact. Consensus even links the classification of a journal published and the impact of a publication with the perception that top journals publish "more important" or "higher-impact" papers (Gordon, 1982; Saha *et al*., 2003). It may be the case that high-ranking journals are highly selective and choose trendy topics, which then have more exposure and receive more citations as a consequence (Young *et al*., 2008). Obtaining more citations in turn is desirable because it translates into direct benefits in the assessment process and the reward system. For instance, top universities are led by scholars who have been highly cited (Hamermesh *et al*., 1982; Bayers, 2005; Thursby, 2000; Goodall, 2006).

To explain success in scientific research, we recall the Matthew Effect attributed to Robert K. Merton in 1986. The idea of the Matthew Effect is derived from the biblical verse in the Gospel according to St Matthew (25:29) which is linked to the notion that the rich get richer and the poor get poorer. In principle, it refers to the accumulated advantage whereby those who already have attained certain and reputation status in turn continue to fare well whereas those without the benefits of similar status struggle to attain recognition. Merton (1968, p.58) argues that the Matthew Effect in science occurs 'in the accruing of greater increments of recognition for particular scientific contributions to scientists of considerable repute and the withholding of such recognition from scientists who have not yet made their mark'.

This notion has been applied widely in other fields such as sociology, education, arts, and scientific research. In sociology, Karl Marx's in his Conflict Theory argued that the rich set the regulations to keep the poor down while raising their own wealth. That is to say, rich people are likely to achieve more wealth because they benefit from the status to get jobs and investments, but on the other hand, poor people remain in poverty because they lack financial and job opportunities (Marx, 1844). From an education aspect, the Matthew Effect was investigated with respect to difference in academic performance among elementary school students. Stanovich (1986; 2000) finds that students who possess fundamental skills such as fast and fluent reading are likely to accomplish more and enhance their knowledge. However, those who struggle to read in turn tend to fall behind and struggle academically in their further education. In Arts, Ginsburgh and Van Ours (2003) examined the performance of musicians in an international competition for the piano and violin, the so-called the Queen Elizabeth competition. They show that the better-ranked musicians have more success than the lower ranked peers later in their musical career.

The Matthew Effect has been also identified as a factor explaining inequality in the scientific community. For example, considering two authors conducting similar topics, the more famous and better-known author is more likely to achieve success than the lesser-known author (Merton, 1968). Hence, scholars who succeed early in their academic career should also fare better later. Laurance *et al*. (2013) investigated the impact of academic biologists' characteristics on their long-term publication success. They found that publication success during one's PhD study (i.e., pre-PhD publication) was the strongest indicator of long-term publication success. Young biologists who publish their paper(s) earlier in their career have minor advantages. Early publication success is thus essential for aspiring young scholars, and looking for those who have published early and frequently is one of the simplest ways to identify the future rising stars. Some studies also pointed out that citation rates of papers not only reflect their quality but are also due to the prestige of authors. Tol (2009) hypothesises that there are increasing returns to scale in the prestige of authors or fame of papers for the 100 most eminent economists. He finds that highly reputable authors or often-cited papers are cited more often than the counterparts. Tol (2013) applied the same test to a sample of more than 31,000 economists using citation analysis from the RePEc. He found that often-cited authors gain citations which are disproportionate to the quality of their papers. He concluded that the existing Matthew effect is substantial for economists.

The purpose of this study is to determine whether explicit ranking of research quality (i.e. being a winner of the best-paper prize at a competition), which is a form of early success, is informative as a predictor of subsequent publication success. This study uses a sample of young and aspiring researchers nominated for the best paper award at CESifo area conferences: the Distinguished CESifo Affiliate Award. CESifo organizes annual conferences in eight research areas: Employment and Social Protection, Applied Microeconomics, Macro, Money and International Finance, Public Sector Economics, Global Economy, Economics of Education, Energy and Climate Economics, and Behavioural Economics. The conferences are open to all members of the CESifo network, who can also nominate candidates for Distinguished CESifo Affiliate Award. Our data cover the period since the inception of the award in 2008 until 2015. We use journal ranking and journal impact factor as a measure of the journal quality in this study because they are extensively used as the measurement of the importance or rank of a journal. Also, we investigate the relationship between winners and publication productivity when they get published in those journals measured by citations, journal rank, and journal impact factor.

The rest of this study is organised as follows. Section 2 describes the data, describes the Distinguished CESifo Affiliate Award and the outlines of the methodology used in this study. Section 3 reports the findings relative to the main research questions which are; whether the winners of the best paper award at the CESifo conferences are more likely to publish in good journals than the other candidates; and whether they display greater research productivity after they published. Section 4 concludes with the overall findings.

5.2 Methodology

5.2.1 Distinguished CESifo Affiliate Award

The CESifo is an international research network in the field of economics bringing together leading researchers working on a broad range of topics. The group was established in 1999 and aims to make Munich a hub of economic research and policy debate in Europe. The CESifo research network organizes a large number of events, including area conferences for its nine research areas as well as a number of other conferences, workshops and seminars, publishes a reputable discussion paper series, and publishes (or co-publishes) several regular publications.

The activities of CESifo are divided into nine areas: Applied Microeconomics; Behavioural Economics; Economics of Digitization; Economics of Education; Employment and Social Protection; Energy and Climate Economics; Global Economy; Macro, Money and International Finance; and Public Sector Economics.

The annual CESifo Area Conferences are open only to network members and their objective is to encourage international scientific collaboration and policy debates. Network members are allowed to nominate aspiring young economists for the Distinguished CESifo Affiliate prize. Out of the nominations received, the area director selects a short list of candidates who are invited to present their papers at the area conference. A selection committee consisting of three notable scholars from the area then selects the best paper for the award. The criteria for this prize are the candidates should be in the early stage of their career, i.e., being or close to completion of their PhD or have completed it no more than five years; and the paper should display scientific originality, policy relevance and quality of exposition. In a case of multiple-authors papers, the same criterion is also applied to co-authors (CESifo Group, 2017). The winner of the award receives a certificate, a monetary prize, and an invitation to join the research network with all the benefits associated with it, including the right to participate in future conferences, submit discussion paper to the CESifo series, and to visit one of the participating institutions of the CESifo network in Munich. Given the sizeable benefits associated with winning the prize, it is therefore of interest whether the winning paper indeed performs better in terms of probability of being published, the quality of the journal in which it is published, and the number of citations that it attracts.

5.2.2 Data

The data in this study consists of: (1) the names of nominees for the Distinguished CESifo Affiliate prize for the best paper presented at the CESifo area conferences between 2008 and 2015; (2) the title of the nominee's paper presented at the conference; (3) the information on the journal in which the paper was published (i.e., journal impact factor from the InCites™ Thomson Reuters 2014, and journal ranking from the Academic Journal Guide 2015); (4) the information on publication productivity (i.e., citation rates from Web of Science and Google Scholar). The list of nominees and winners was received directly from the CESifo. The titles of some papers have changed from those presented at the conferences; but fortunately, most titles were either identical or very similar to the original title. Papers for which we were not able to identify the published version by 2017 are marked as unpublished.[3] Citation rates were collected Web of Science and Google Scholar in December 2016 so as to provide enough time for the papers to be cited.

The nominees in our sample are predominantly males. Among the 164 nominees, males account for 69.5% and female account for only 30.5%. 34.15% of nominees have won the award. The breakdown by gender among the winners is similar to the nominees: 62.5% are male and 37.5% are female. We have information on eight CESifo area conferences, the Economics of Digitization Area is excluded in our analysis as it was only recently established and has not held any conferences yet.

3 In several instances, we confirmed with the author that the paper was indeed unpublished.

There are 22 papers for the Macro, Money and International Finance Area; 16 papers for the Applied Microeconomics area; 33 papers for the Public Sector Economics area; 22 papers for the Employment and Social Protection Area; 25 papers for the Global Economy Area; 17 papers for the Economics of Education area; 14 papers for the Energy and Climate Economics area; and 15 papers for the Behavioural Economics area. For all areas, the minimum number of nominees by year and research area is 2 while the maximum is 6. Team size, the number of co-author(s) for the conference paper, ranges from 1 to 4. Approximately 58% of all papers are single-author papers while 34.15% are 2-authors papers. Among 164 conference papers, the published papers account for 53%. The summary statistics of all data are reported in Appendix A.

5.2.3 Variables

5.2.3.1 Dependent variable

There are two kids of the dependent variable in which to answer the two questions in this study, which are the quality of the journal (i.e., journal ranking, journal impact factor) and the research productivity. The research productivity variable is constructed using citation counts, journal rankings, and journal impact factor. We construct three measures: weighted productivity, average productivity, and normalised citations.

The weighted productivity, which we consider as our main dependent variable, combines normalised citations from Web of Science and Google Scholar (together with a weight of 50%), normalised journal ranking from the Academic Journal Guide 2015 (30%), and normalised journal impact factor from Thomson Reuters Journal Citation Reports (20%). The average productivity assigns equal weights to our measures of citation counts, journal rank and impact factor. However, only the citation counts reflect the quality of an individual researcher or individual publication. Therefore, we also consider normalised citations as a separate metric of research productivity.

5.2.3.2 Independent variables

Our main independent variable is an indicator variable denoting whether the nominee has been selected as the winner of the best paper prize from the particular CESifo conference. The rest of control variables belong to three sets of characteristics: nominee's personal background, conference associated background, and article background. The summary of variables is shown in Tables 5-1 and 5-2. The nominee's personal background is only the candidate's gender. The conference associated background includes the year of nomination, the research area of the conference, the number of nominees for the particular year and research area, and the number of years between the nominated year and 2016. The article background includes the team size indicating the number of authors of the paper, citations, impact factor, journal ranking. The base categories for dummy variables include an unsuccessful nominee for nominee; male for gender; and Macro, Money and International Finance (MMI) for CESifo areas. Appendix D-1 shows the descriptive statistics.

Table 5-1 Summary of variables

Variable	Definition
Dependent variables	
ajg	Journal ranking from the Academic Journal Guide 2015
jif	Journal impact factor from the Thomson Reuters 2014
wprod	Weighted productivity
avgprod	Average productivity
avenormcite	Average normalised citation
Independent variables	
winner	Dummy variable of successful nominee
female	Dummy variable of female nominee
time	Number of year(s) between the nominated year and 2016
candidate	Number of nominees for the particular year and research area
teamsize	Number of author(s) for the paper
mmi	Dummy variable of Macro, Money and International Finance
am	Dummy variable of Applied Microeconomics area
pse	Dummy variable of Public Sector Economics
esp	Dummy variable of Employment and Social Protection area
ge	Dummy variable of Global Economy
ee	Dummy variable of Economics of Education
ece	Dummy variable of Energy and Climate Economics
be	Dummy variable of Behavioural Economics

Table 5-2 Coding of dummy variables

Nominee

Values	Codes	Percent	Frequency
Unsuccessful nominee	0	65.85	108
Winner	1	34.15	56
		100	164

Gender

Values	Codes	Percent	Frequency
Male	0	69.50	114
Female	1	30.50	50
		100	164

Conference paper

Values	Codes	Percent	Frequency
Unpublished	0	46.95	77
Published	1	53.05	87
		100	164

CESifo Area Conferences

Values	Codes	Percent	Frequency
mmi	1	13.41	22
am	2	9.76	16
pse	3	20.12	33
esp	4	13.41	22
ge	5	15.24	25
ee	6	10.37	17
ece	7	8.54	14
be	8	9.15	15
		100	164

5.2.4 Models

The empirical questions in this study are; whether being the winner of the best paper prize awarded for CESifo area conferences between 2008 and 2015 is correlated with the later success in terms of publishing in a high quality journal; and with publication productivity measured by citations, journal rankings, and journal impact factor. Therefore, there are two models in this study. The specification of the journal quality equation is:

$$JournalQuality_i = \alpha + \beta_1 * Winner_i + \beta_2 * Gender_i + \beta_3 * Time_i + \beta_4 * Candidates_i + \beta_5 * TeamSize_i + \beta_7 * CESifo_i + \varepsilon_i \quad (1)$$

And the specification of the research productivity equation is:

$$Productivity_i = \alpha + \beta_1 * Winner_i + \beta_2 * Gender_i + \beta_3 * Time_i + \beta_4 * Candidates_i + \beta_5 * TeamSize_i + \beta_7 * CESifo_i + \varepsilon_i \quad (2)$$

where $JournalQuality_i$ refers to journal ranking or journal impact factor for a journal, $Productivity_i$ denotes the research productivity, $Winner_i$ equals 1 if the nominee is winner and 0 otherwise, $Gender_i$ equals 1 if the gender of nominee is female and 0 otherwise, $Time_i$ denotes the accumulated years from the nominated year until 2016, $Candidates_i$ refers to the number of nominees by year of nomination and CESifo Research Areas, $TeamSize_i$ captures the number of authors in the paper, $CESifo_i$ stands for a set of CESifo Research Areas dummies. α is the level of non-qualified research productivity.

Before analysing the correlations, the empirical distribution of journal quality and research productivity is tested to identify whether parametric or non-parametric method is the most suitable method. Both graphical and numerical tests are used to check the normality of distribution (i.e., histogram, quantile-quantile (Q-Q) plot, Shapiro–Wilk normality test, and Shapiro–Francia normality test). Based on the graphical tests, most of the dependent variables are not normally distributed (see Appendix B). Shapiro–Wilk normality test and Shapiro–Francia normality test also imply a rejection of the assumption of the normality of the response distribution (see Appendix D-2). The standard regression, in a nutshell, is a suitable technique when the regression assumptions are met, however, it does not work well when conditions are nonstandard particularly with respect to the homoscedasticity and normality assumptions. Therefore, the estimation of the response functions using the standard ordinary least square model would produce coefficient estimates which are not a suitable representative of the entire model (Koenker and Bassett Jr., 1978; Dimelis and Louri, 2002; Hao and Naiman, 2007). In this case, we use the quantile regression approach, which is a non-parametric method, as it is more appropriate to analyse the relationship. The quantile regression relaxes the regression assumptions and offers a comprehensive view of the impact of independent variables on the central and non-central location, shape, and scale of the distribution of the dependent variable. The estimations of this technique are robust to outliers, unlike the least squares technique, and it also allows us to test for the differences in the effects on productivity by explanatory variables in various quantiles. In other words, conditional quantile models provide the flexibility to choose positions and focus on these population sections which are tailored to researchers' specific inquiries (Koenker, 2005; Hao and Naiman, 2007).

As this analysis is of non-experimental nature, endogeneity is a potential problem that should be considered. Endogeneity may arise due to various reasons such as measurement error, omitted variables, or correlation between a control variable and the error term. In this essay, we are unable to identify unambiguously the direction of causality, whether being winner causes the later success or, vice versa, whether more the contest winners are generally more productive than losers. This problem occurs due to lack of suitable control variables to address endogeneity. It is rather difficult to resolve this problem in this analysis because the data is collected from secondary sources. Therefore, we are unable to design the model that would avoid endogeneity between the response variable and covariates. Future research related to this topic should address this issue by means of be experimental analysis.

5.3 Findings

5.3.1 Does winning impacts on the probability of being published in a high-quality journal?

To examine whether winning the award affects the probability of publishing in a high-quality journal, we run ordered probit regressions on our sample, with the response taking the value from 0 to 5 as an ordinal variable of the journal rating listed in the Academic Journal Guide 2015.[4] The ordered probit model is applied to estimate correlations between the ordinal response and a set of covariates. In this study, the ordinal variable refers to a variable which is categorical and ordered, i.e., "not in the list", "2-rated journals", "3-rated journals", "4-rated journals" and "4*-rated journals", concerning the quality of the journal.

We report our regression results with marginal effects evaluated at means of variables based on the full set of covariates in Table 5-3. We control for nominee's gender, the number of years between the nomination year and 2016, the number of nominees for the particular year and research area, the number of authors for the paper, and the dummies of CESifo conference areas. Table 5-3 shows that the effect of the winner is marginally significant where winners are 26.85% more likely to get published in 4*-rated journals and 15.2% in 4-rated journals. Similarly, winners are 22.2 percentage points less likely to publish in 3-rated journals and 12.5% in 2-rated journals. Moreover, the papers in the Behavioural Economics area display a higher probability to get published in 4*-rated journals while those in the Energy and Climate Economics area have a lower chance of publishing in the top journals (i.e., 4* and 4-rated journals), by 26.5% and 15%, respectively. Not many of the remaining coefficients are significant due to the small sample size.

To confirm the effect of the winner on the quality of the journal, we apply journal impact factor in the analysis as it is one of the indicators of journal quality. For this reason, we use the linear-regression approach to examine the relationship instead of the ordered probit regressions due to the nature of journal impact factor data. The results from the linear-regression model are presented in Table 5-4.

4 Note that the rating regarding the Academic Journal Guide 2015 consists of 1,2,3,4, and 4*; however, the journal which is not in the list is set as 0.

Table 5-3 Impact of winner on journal ranking by Academic Journal Guide 2015

	(1) **AJG=0**	(2) **AJG=2**	(3) **AJG=3**	(4) **AJG=4**	(5) **AJG=5**
Winner	-0.0731 (0.0374)	-0.1252** (0.047)	-0.222** (0.0854)	0.1517* (0.0599)	0.2685** (0.0782)
Female	0.0022 (0.0161)	0.0038 (0.0276)	0.0068 (0.0494)	-0.0046 (0.0336)	-0.0082 (0.0596)
Time	0.0011 (0.0046)	0.0018 (0.0079)	0.0033 (0.0142)	-0.0022 (0.0097)	-0.0039 (0.017)
Candidates	0.0008 (0.0085)	0.0013 (0.0146)	0.0023 (0.0259)	-0.0016 (0.0177)	-0.0028 (0.0314)
Teamsize	0.0091 (0.0118)	0.0155 (0.0204)	0.0275 (0.0335)	-0.0188 (0.0242)	-0.0333 (0.0403)
AM	-0.0648 (0.0493)	-0.1111 (0.0811)	-0.1970 (0.1438)	0.1346 (0.1005)	0.2382 (0.159)
PSE	0.0229 (0.032)	0.0392 (0.0526)	0.0695 (0.0953)	-0.0475 (0.0625)	-0.0841 (0.1148)
ESP	-0.0163 (0.0329)	-0.028 (0.0595)	-0.0496 (0.1045)	0.0339 (0.0722)	0.0600 (0.1235)
GE	-0.0277 (0.0349)	-0.0474 (0.0634)	-0.0840 (0.1087)	0.0574 (0.0792)	0.1017 (0.1241)
EE	-0.0162 (0.0403)	-0.0278 (0.0726)	-0.0493 (0.1257)	0.0337 (0.0878)	0.0597 (0.1497)
ECE	0.0721 (0.0431)	0.1235* (0.053)	0.2190 (0.1228)	-0.1496* (0.0703)	-0.2649* (0.1275)
BE	-0.0984 (0.0583)	-0.1685 (0.0939)	-0.2989 (0.1504)	0.2043 (0.1121)	0.3615* (0.1587)
N	87	87	87	87	87

Notes: Marginal effects evaluates at means, with robust standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

The effect of the being a winner on the journal impact factor for all specifications is positive and significant. Considering Table 5-4 (columns 2), the coefficient of being the winner is 0.817, that is, a change from unsuccessful nominee to winner would translate into an increase in the quality of the journal published by 0.817, or approximately 40% (the mean of the dependent variable is 2.048).

Table 5-4 Impact of winner on journal impact factor, OLS regression

	(1) **OLS**	(2) **OLS**	(3) **OLS**
Winner	0.8060* (0.3324)	0.8170** (0.2652)	0.8000* (0.3392)
Female	-0.0888 (0.2060)	-0.0404 (0.2480)	-0.0662 (0.2365)
Time	0.5290 (0.4001)	-0.0697 (0.0662)	
Timesq	-0.0620 (0.0390)		
Candidates	-0.1250 (0.1916)	-0.1440 (0.1300)	-0.1540 (0.2214)
Teamsize	-0.0672 (0.2265)	-0.0764 (0.1981)	-0.1210 (0.1622)
AM	1.1720 (0.8645)	1.2770 (0.7476)	1.2540 (0.8001)
PSE	-0.5130 (0.5480)	-0.3510 (0.5081)	-0.3780 (0.5263)
ESP	0.4250 (0.4809)	0.5150 (0.5441)	0.4790 (0.4711)
GE	0.1340 (0.6097)	0.2910 (0.5408)	0.3040 (0.4948)
EE	-0.0806 (0.6478)	0.2760 (0.5535)	0.2900 (0.5222)
ECE	-0.6520 (0.6528)	-0.3550 (0.6297)	-0.2810 (0.5686)
BE	0.3590 (0.6418)	0.5990 (0.6530)	0.6990 (0.5994)
Constant	1.3590 (0.9933)	2.4420** (0.7609)	2.2110* (0.8590)
N	87	87	87

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

This section focuses on the first question regarding the relationship between the winner and the journal quality, which would imply that being winner presents a distinct benefit regarding the possibility to publish in the high-quality journals based on our sample. The next section will provide the answer to the second question, which focuses on the publication productivity after they get published.

5.3.2 Does winning impacts on publication productivity?

5.3.2.1 OLS and Median Regression Results

To analyse the effect of being the winner on publication productivity, quantile regression which is robust to outliers is employed as the main method, with the dependent variable (i.e., weighted productivity, average productivity, and average normalised citation) taking values from 0 to 1. We also run OLS regressions as a robustness check. The linear-regression model can be interpreted as the estimates of the difference in the mean of the dependent variable when a dummy value changes from 0 to 1 or a unit increase in a continuous independent variable, with the others are held constant while the quantile-regression model is the estimates of the difference in the specific quantile which is applied to quantification of effects. The 0.5th quantile (i.e., median) is the simplest quantile regression model to understand and constitutes a natural alternative to the linear-regression model that fits the conditional mean. The two methods endeavour to model the central location of the response distribution and the interpretation of the median-regression coefficient is similar to that of the linear-regression coefficient. We use bootstrapping approach for estimation of standard errors because the skewed distribution of the covariates which is mostly found in social sciences studies. The alternative method of inference such as bootstrapping approach is required instead of the asymptotic inference.

We report regressions' results comparing the effects obtained by OLS and median regression using the weighted productivity as the dependent variable in Table 5-5. We control for winner, gender, time, a squared term of time, candidates, team size, and CESifo Research Areas (columns 1 and 2); drop the squared term of time (columns 3 and 4), and drop also time (columns 5 and 6). The effect of the winning the award on the publication productivity index for all specifications is positive but significant only for the conditional-mean model (OLS). Considering columns 3, the coefficient of the winner in the conditional-mean model is 0.127, that is, a change from unsuccessful nominee to winner would translate into an increase in weighted productivity by 0.127, or approximately 41% (the mean of the dependent variable is 0.310). The results obtained with average productivity and average normalised citations, with the same independent variables as above, are reported in Tables 5-6 and 5-7.

Table 5-5 Impact of winner on weighted productivity, OLS and median regression

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)
Winner	0.1260**	0.0625	0.1270**	0.0640	0.1290**	0.0698
	(0.0484)	(0.0493)	(0.0440)	(0.0587)	(0.0402)	(0.0487)
Female	-0.0215	0.0030	-0.0172	-0.0073	-0.0147	-0.0042
	(0.0285)	(0.0445)	(0.0372)	(0.0436)	(0.0300)	(0.0345)
Time	0.0597	0.0753	0.0067	0.0009		
	(0.0385)	(0.0486)	(0.0111)	(0.0085)		
Timesq	-0.0054	-0.0072				
	(0.0042)	(0.0047)				
Candidates	0.0026	0.0015	0.0010	-0.0058	0.0020	-0.0057
	(0.0201)	(0.0180)	(0.0181)	(0.0225)	(0.0174)	(0.0138)
Teamsize	-0.0014	0.0039	-0.0022	0.0133	0.0021	0.0128
	(0.0257)	(0.0338)	(0.0262)	(0.0252)	(0.0200)	(0.0230)
AM	0.0764	0.0755	0.0857	0.1190	0.0880	0.1190
	(0.0695)	(0.0921)	(0.0674)	(0.1085)	(0.0632)	(0.0791)
PSE	-0.0377	-0.0503	-0.0234	-0.0112	-0.0208	-0.0094
	(0.0590)	(0.0590)	(0.0517)	(0.0645)	(0.0523)	(0.0501)
ESP	0.0527	0.0492	0.0606	0.0932	0.0641	0.0954
	(0.0480)	(0.0602)	(0.0618)	(0.0756)	(0.0477)	(0.0704)
GE	0.0558	0.0610	0.0696	0.0886	0.0684	0.0887
	(0.0621)	(0.0784)	(0.0560)	(0.0704)	(0.0571)	(0.0713)
EE	0.0270	-0.0130	0.0584	0.0139	0.0571	0.0195
	(0.0906)	(0.0835)	(0.0890)	(0.0744)	(0.0743)	(0.0900)
ECE	-0.0550	0.0015	-0.0288	0.0277	-0.0360	0.0259
	(0.0740)	(0.0902)	(0.0649)	(0.0928)	(0.0687)	(0.0830)
BE	0.0616	0.0691	0.0829	0.1110	0.0732	0.1100
	(0.0656)	(0.0688)	(0.0525)	(0.0793)	(0.0491)	(0.0718)
Constant	0.1010	0.0898	0.1960*	0.2400*	0.2190**	0.2390***
	(0.1138)	(0.1224)	(0.0884)	(0.0979)	(0.0799)	(0.0687)
N	87	87	87	87	87	87

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Considering the average productivity as the dependent variable, the effect of the winner on the publication productivity index for all specifications is again positive but significant only for the conditional-mean model. The coefficient of winner from the conditional-mean model (columns 3) is 0.136. In other words, a change from unsuccessful nominee to winner translates again into an increase of approximately 38% (on average productivity of 0.358). It is very similar to the effect obtained with weighted productivity as reported in Table 5-5.

Table 5-6 Impact of winner on average productivity, OLS and median regression

	(1) OLS	(2) QR(0.5)	(3) OLS	(4) QR(0.5)	(5) OLS	(6) QR(0.5)
Winner	0.1350***	0.0921	0.1360**	0.0870	0.1360**	0.0744
	(0.0396)	(0.0622)	(0.0420)	(0.0630)	(0.0458)	(0.0692)
Female	-0.0188	0.0127	-0.0132	-0.0014	-0.0123	-0.0132
	(0.0332)	(0.0393)	(0.0400)	(0.0475)	(0.0287)	(0.0348)
Time	0.0717	0.0942	0.0022	-0.0030		
	(0.0429)	(0.0544)	(0.0102)	(0.0090)		
Timesq	-0.0071	-0.0096				
	(0.0046)	(0.0055)				
Candidates	-0.0013	0.0015	-0.0034	-0.0054	-0.0031	-0.0006
	(0.0190)	(0.0214)	(0.0188)	(0.0223)	(0.0227)	(0.0261)
Teamsize	-0.0049	-0.0020	-0.0060	0.0001	-0.0046	-0.0007
	(0.0282)	(0.0326)	(0.0235)	(0.0283)	(0.0216)	(0.0343)
AM	0.1020	0.1060	0.1150	0.1710	0.1150	0.1730
	(0.0818)	(0.1147)	(0.0908)	(0.1096)	(0.0789)	(0.1223)
PSE	-0.0552	-0.0578	-0.0364	-0.0091	-0.0355	-0.0227
	(0.0658)	(0.0628)	(0.0754)	(0.0643)	(0.0603)	(0.0907)
ESP	0.0466	0.0600	0.0569	0.1230	0.0581	0.1170
	(0.0489)	(0.0769)	(0.0653)	(0.0658)	(0.0547)	(0.0699)
GE	0.0430	0.0898	0.0612	0.0505	0.0608	0.0626
	(0.0558)	(0.0870)	(0.0813)	(0.0724)	(0.0709)	(0.0888)
EE	0.0063	0.0146	0.0477	0.0697	0.0472	0.0631
	(0.0818)	(0.0796)	(0.0800)	(0.0861)	(0.0868)	(0.1047)
ECE	-0.0895	-0.0256	-0.0550	0.0141	-0.0574	0.0127
	(0.0735)	(0.1065)	(0.0861)	(0.0833)	(0.0660)	(0.0800)
BE	0.0748	0.0991	0.1030	0.1580	0.0995	0.1620
	(0.0680)	(0.1056)	(0.0769)	(0.0869)	(0.0582)	(0.0998)
Constant	0.1600	0.1020	0.2860**	0.2980**	0.2930**	0.2850*
	(0.1182)	(0.1507)	(0.1061)	(0.1042)	(0.0967)	(0.1262)
N	87	87	87	87	87	87

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Considering the model using the average normalised citations as the dependent variable, we apply a log transformation on the response variable due to the effect of the right-skewed response variable (see Appendix D-2). In this case, the skewness changes from 3.44 to -0.07 and the kurtosis changes from 16.5 to 2.9 after taking log transformation and the distribution of the data are normal as from the Shapiro-Wilk and Shapiro-Francia normality tests (see Appendix D-2).

Table 5-7 Impact of winner on log average normalised citations, OLS and median regression

	(1) **OLS**	(2) **QR(0.5)**	(3) **OLS**	(4) **QR(0.5)**	(5) **OLS**	(6) **QR(0.5)**
Winner	0.7390*	0.5460	0.7360**	0.5250	0.7550*	0.9520
	(0.3583)	(0.4696)	(0.2592)	(0.4794)	(0.3698)	(0.5162)
Female	-0.2090	-0.4680	-0.1990	-0.4360	-0.1540	-0.0389
	(0.3674)	(0.4570)	(0.3396)	(0.4059)	(0.3109)	(0.4191)
Time	0.4830	0.3120	0.1640	0.2130*		
	(0.3155)	(0.4730)	(0.0863)	(0.0886)		
Timesq	-0.0326	-0.0097				
	(0.0348)	(0.0527)				
Candidates	0.1060	0.0718	0.0977	0.0852	0.1190	0.0461
	(0.2208)	(0.2433)	(0.2128)	(0.3180)	(0.2091)	(0.3362)
Teamsize	0.1880	-0.0677	0.1760	-0.0788	0.2640	0.2090
	(0.2626)	(0.3064)	(0.1874)	(0.2283)	(0.2169)	(0.2580)
AM	0.5760	-0.1560	0.6310	-0.0170	0.6850	0.3220
	(0.5736)	(0.8570)	(0.6885)	(0.7649)	(0.7159)	(0.8261)
PSE	-0.1630	-0.5090	-0.0870	-0.5010	-0.0194	-0.0418
	(0.6123)	(0.6781)	(0.6287)	(0.6354)	(0.7254)	(0.7618)
ESP	1.3300**	1.1940*	1.3810*	1.2700*	1.4650**	1.2200
	(0.4914)	(0.5729)	(0.6279)	(0.6256)	(0.4905)	(0.6794)
GE	0.3750	0.9460	0.4900	1.0290	0.5140	0.5920
	(0.6295)	(1.0547)	(0.8448)	(1.1338)	(0.7710)	(1.1944)
EE	0.7100	0.4660	0.8980	0.5630	0.8680	0.8120
	(0.6967)	(0.7981)	(0.6156)	(0.5275)	(0.6333)	(0.8437)
ECE	1.1810	1.5150	1.3320	1.5860	1.1590	1.3720
	(0.9428)	(1.2108)	(0.9130)	(1.1808)	(0.8887)	(1.2469)
BE	-0.6570	-1.0380	-0.5380	-0.9230	-0.7570	-0.9620
	(0.6974)	(0.9308)	(0.6588)	(0.7596)	(0.7266)	(0.9414)
Constant	-6.052***	-5.061***	-5.445***	-4.945***	-4.851***	-4.650***
	(1.1654)	(1.1468)	(0.8721)	(1.1151)	(0.7820)	(1.3431)
N	84	84	84	84	84	84

Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Considering the location shifts on the log scale, the method to model the central location of the dependent variable is to deal with the conditional-mean model (OLS) relating winner to log of average normalised citations. Taking the estimate obtained in model (3), Table 5-7, changing the nominee status from unsuccessful nominee to winner more than doubles the conditional-mean average normalised citations: $e^{0.736}$=2.09. However, the effect of the winner in the corresponding fitted-median model at 0.5th quantile, or median, is not found (see Table 5-7, model 4).

Concerning the effect of time since the conference, the conditional median model at 0.5th quantile (Table 5-7, model (4)) shows a coefficient of 0.213, which indicates that each additional year after nomination increases the conditional-median average normalised citations by a factor of $e^{0.213}$ = 1.2374, indicating a 23.74% increase. However, the effect of time is not found in the conditional-mean model (See Table 5-7, model (3)).

To interpret the CESifo Area Conferences dummies, recall that the reference category is "MMI". In general, we see few differences in research productivity across areas, with the exception of "ESP". Candidates who presented in the area of Employment and Social policy display four time higher productivity: $e^{1.381}$ = 3.98 compared to "MMI". The corresponding fitted-median model at 0.5th quantile (See Table 5-7, model (4)) shows the "ESP" area coefficient as 1.27, which implies a slightly lower effect: $e^{1.27}$ = 3.56.

5.3.2.2 Individual Conditional Quantiles

We are also interested in the other quantiles of response distribution in addition to the median. For example, the benefits of being the winner may be more prominent among the lower or upper tails of productivity distribution than in the central location. The coefficients of the quantile regression model for 9 quantiles in Table 5-8 can be used to examine the impacts of independent variables on various quantiles of the publication productivity distribution. The estimates for weighted productivity across quantiles are presented in Table 5-8.

Table 5-8 Quantile regression estimates for weighted productivity across quantiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Q(0.10)	**Q(0.20)**	**Q(0.30)**	**Q(0.40)**	**Q(0.50)**	**Q(0.60)**	**Q(0.70)**	**Q(0.80)**	**Q(0.90)**
Winner	0.0749	0.0827	0.1130*	0.1080*	0.0640	0.0667	0.1090*	0.1330*	0.1210
	(0.0523)	(0.0444)	(0.0470)	(0.0449)	(0.0481)	(0.0417)	(0.0501)	(0.0590)	(0.0893)
Female	-0.0132	-0.0025	0.0085	0.0190	-0.0073	-0.0342	-0.0102	-0.0300	-0.0287
	(0.0589)	(0.0426)	(0.0444)	(0.0403)	(0.0447)	(0.0433)	(0.0454)	(0.0478)	(0.0830)
Time	0.0046	0.0007	0.0052	-0.0056	0.0009	0.0035	0.0064	0.0089	0.0016
	(0.0133)	(0.0098)	(0.0105)	(0.0108)	(0.0086)	(0.0082)	(0.0075)	(0.0108)	(0.0195)
Candidates	0.0009	0.0064	0.0296	-0.0017	-0.0058	-0.0015	-0.0029	0.0041	0.0018
	(0.0365)	(0.0373)	(0.0317)	(0.0302)	(0.0225)	(0.0192)	(0.0152)	(0.0219)	(0.0480)
Teamsize	-0.0517	-0.0393	-0.0071	0.0079	0.0133	0.0106	0.0249	0.0136	0.0683
	(0.0407)	(0.0276)	(0.0264)	(0.0238)	(0.0254)	(0.0278)	(0.0297)	(0.0376)	(0.0533)
AM	0.0724	0.0663	0.0866	0.1080	0.1190	0.1490	0.1160	0.1510	0.0831
	(0.1238)	(0.1017)	(0.0990)	(0.0932)	(0.0929)	(0.0964)	(0.0937)	(0.0926)	(0.1311)
PSE	-0.0026	-0.0197	-0.0578	-0.0021	-0.0112	-0.0397	-0.0302	-0.0458	-0.1040
	(0.0905)	(0.0838)	(0.0763)	(0.0703)	(0.0672)	(0.0640)	(0.0581)	(0.0754)	(0.1840)
ESP	-0.0251	0.0766	0.0687	0.1070	0.0932	0.0953	0.1070	0.1160	0.0973
	(0.1130)	(0.0981)	(0.0881)	(0.0792)	(0.0720)	(0.0715)	(0.0668)	(0.0812)	(0.0971)
GE	0.1100	0.0829	0.0628	0.0191	0.0886	0.1010	0.1200	0.0987	0.0286
	(0.1184)	(0.0899)	(0.0880)	(0.0876)	(0.0962)	(0.0949)	(0.0836)	(0.0743)	(0.1128)
EE	-0.0324	0.0720	0.0869	0.0668	0.0139	-0.0030	0.0157	0.0218	0.2820
	(0.1159)	(0.0966)	(0.0825)	(0.0693)	(0.0595)	(0.0593)	(0.1124)	(0.1613)	(0.1998)
ECE	0.0276	0.0098	-0.0077	0.0169	0.0277	-0.0045	0.0353	0.0200	-0.0419
	(0.0897)	(0.0960)	(0.0971)	(0.0913)	(0.0875)	(0.0929)	(0.0961)	(0.1017)	(0.1141)
BE	0.1540	0.1220	0.1180	0.0750	0.1110	0.0880	0.0685	0.0861	0.0248
	(0.0857)	(0.0865)	(0.0851)	(0.0900)	(0.0837)	(0.0841)	(0.0878)	(0.0806)	(0.0865)
Constant	0.1620	0.1640	0.0545	0.2160	0.2400*	0.2470*	0.2090*	0.2060	0.2580
	(0.1533)	(0.1589)	(0.1398)	(0.1297)	(0.1111)	(0.0979)	(0.0917)	(0.1045)	(0.1940)
N	87	87	87	87	87	87	87	87	87

Notes: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001; Bootstrap data resampling with 50 repetitions

We can see significant winner effects on publication productivity at some quantiles – at the 0.3th and 0.4th quantiles and then again at 0.7th and 0.8th quantile. The effect of covariates on the average productivity and the log average normalised citations are reported in Appendix D-3 and Appendix D-4 respectively. The results from the model using average productivity are in line with the results reported in Table 5-8, with the small difference in the effect and significance of covariates. However, the results from the model using log average normalised citations shows the positive effect of winner only in the lower quantiles (i.e., the 0.1th quantile, 0.2th quantile, 0.3th quantile) and the positive effect of time at the 0.2th quantile, 0.5th quantile, 0.6th quantile, and 0.7th quantile.

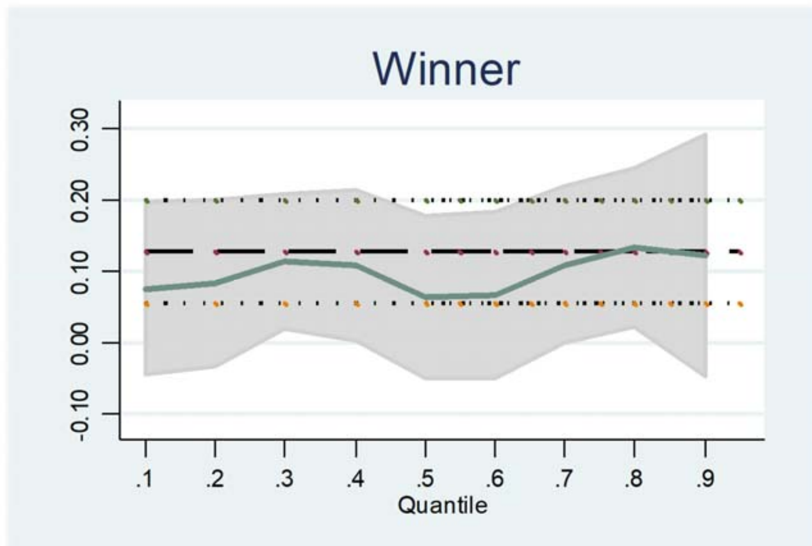
In this section, we illustrate the location shift along the distribution of response variable to understand the lower or upper tails of distribution rather than in the central location. The next section will describe the graphical view in which to provide some information of how the modifications of covariates generate shape shifts for a more comprehensive view.

5.3.2.3 Graphical Presentation of Results

In this section, we summarise the graphical patterns to determine the impact of predictors and how these predictors change the shape of the response distribution. Figure 5-1 shows a graphical view of the weighted productivity at various quantiles as a function of the winner, fixing other covariates using the estimated coefficients (see Table 5-8). However, the full set of the graphical view for other covariates are illustrated in Appendix D-5.

We draw a graph of the impact of the winner and the 95% confidence envelope based on bootstrap estimates with 50 repetitions data resampling. The effect of the winner can be explained by the change in a conditional-publication productivity quantile, fixing the other covariates. The confidence envelope (the thick horizontal line) merely crosses the zero line means the winner effect is positive and significant for the 0.3th, 0.4th, 0.7th, and 0.8th quantile. The effect of the winner is illustrated by the slight-downward slopes between the 0.3th quantile and the 0.4th quantile and the upward-slopes between the 0.7th quantile and the 0.8th quantile. In other words, changing the nominee status from candidate to winner decreases the response's scale at the 0.3th quantile and the 0.4th quantile; and increases the response's scale at the 0.7th quantile and the 0.8th quantile.

Figure 5-1 Quantile coefficients for weighted productivity



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

This section illustrates the graphical interpretations of quantile regression model estimates and quantitative measures of location shifts and shape shifts. In respect of the shifts in the response distribution; they are accountable for both location shifts and shape shifts. The graph only expresses patterns associated with the impacts of winner on publication productivity; the full set of the graphical view for other covariates for the quantile regression model using weighted productivity is in Appendix D-5. We explain the contribution of covariates on publication productivity using weighted productivity because it is considered the main response variable in this study. Also, the full sets of graphical view for the quantile regression model using average productivity and log of average normalised citations, which are the benchmark for publication productivity, are illustrated in Appendix D-6 and Appendix D-7 respectively.

5.4 Conclusions

We investigate whether the papers of the winners of the Distinguished CESifo Affiliate prize tend to fare better in terms of publication success and citations than papers written by the unsuccessful nominees. Our findings are mixed. Results of our analysis obtained with ordered probit (for journal rank) and OLS (for journal impact factor, weighted productivity, average productivity, and citations) suggest that young economists awarded the prize tend to publish their work in the higher ranked journals and their works are likely to be of higher quality measured by citations, journal rank, and journal impact factor. However, no such effect is found when using the non-parametric quantile regression method.

Our findings indicate correlation rather than causality: we are unable to reveal what mechanism lies behind the findings. One possible explanation is the winners' papers are indeed of higher quality than the other papers. Another possible explanation is that the results that we observe are driven by the so-called Matthew effect in research output whereby the early success of the winners in turn leads to subsequent favouritism among editors and referees.

Other factors, for example, the prestige and proficiency of the corresponding authors of the papers, can also play a role. Another issue is that young economists who are unsuccessful in the competition may, in fact, be as good as or even stand above the winners in publication success. For example, Ginsburgh and Weyers (2014) support this notion in their study that there is a little quality difference between being winner and nominee. Further research on these issues should shed more light on the impact of winners on their publication success and productivity.

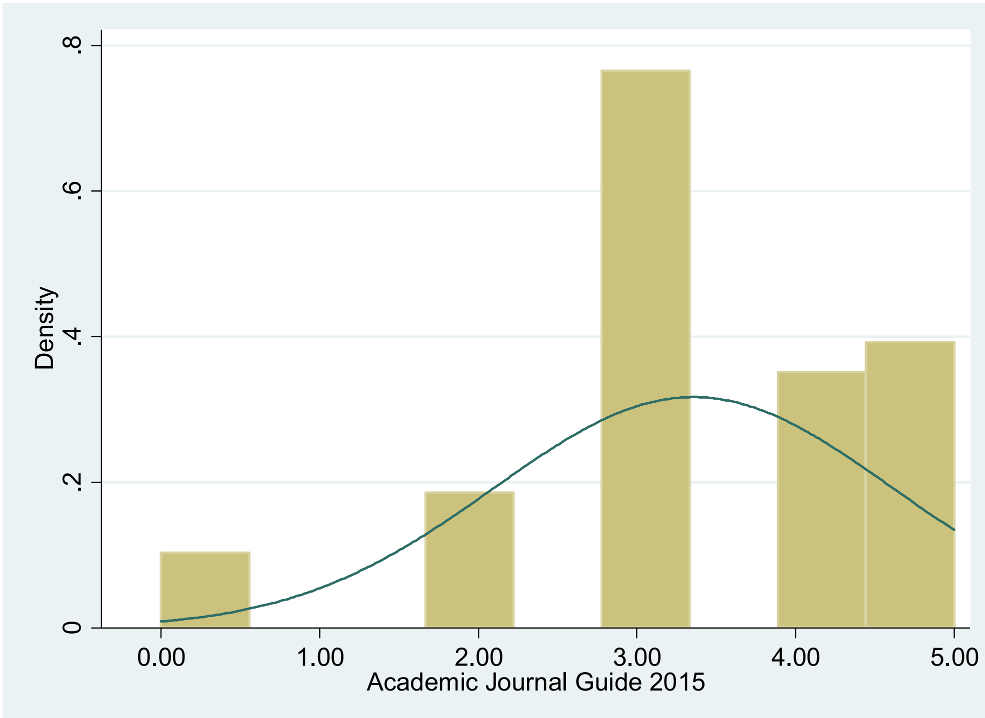
Appendix D

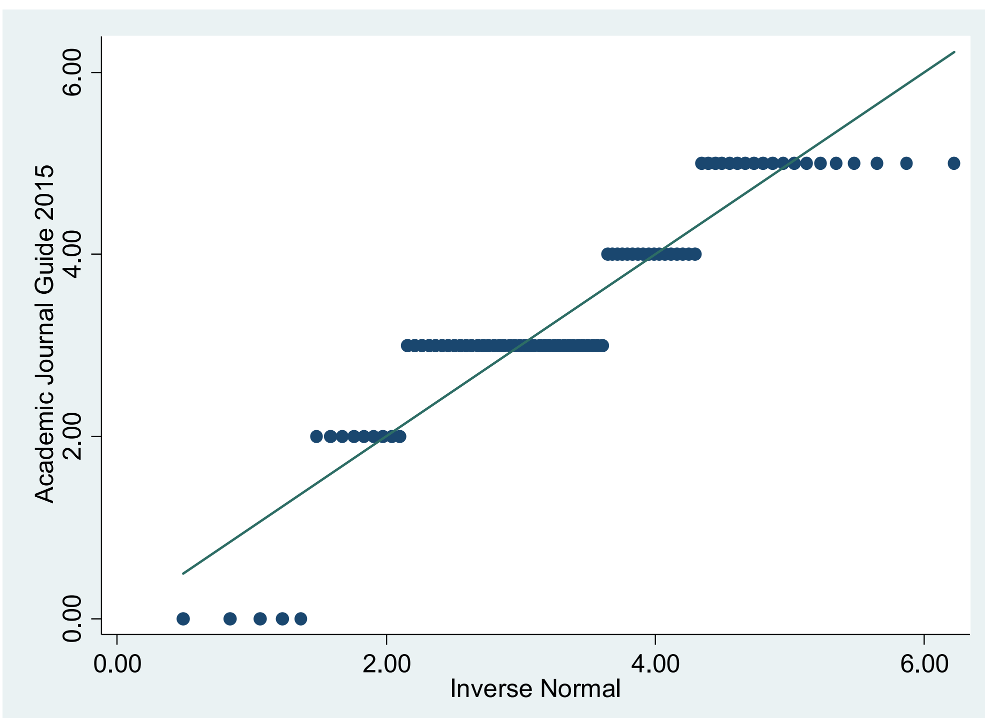
Appendix D – 1 Summary statistics

Nominees	N	Mean	Std.Dev.	Min	Max
candidates	164	3.341	1.048	2	6
year	164	2012	2.209	2008	2015
female	163	0.307	0.463	0	1
winner	164	0.341	0.476	0	1
wos	87	9.483	17.12	0	112
normwos	87	0.084	0.153	0	1
gscolar	87	53.67	92.02	0	515
normgs	87	0.104	0.179	0	1
avenormcite	87	0.094	0.164	0	1
jif	87	2.048	1.334	0	6.654
normjif	87	0.308	0.201	0	1
ajg	87	3.356	1.257	0	5
normajg	87	0.671	0.251	0	1
aveprod	87	0.358	0.169	0	0.847
wprod	87	0.310	0.158	0	0.908
logavenormcite	84	-3.276	1.438	-6.937	0
logwprod	86	-1.331	0.778	-6.532	-0.097
logaveprod	86	-1.185	0.812	-6.937	-0.166
yearpub	87	2013	2.038	2008	2016
teamsize	164	1.530	0.730	1	4
published	164	0.530	0.501	0	1
mmi	164	0.134	0.342	0	1
am	164	0.097	0.298	0	1
pse	164	0.201	0.402	0	1
esp	164	0.134	0.342	0	1
ge	164	0.152	0.361	0	1
ee	164	0.104	0.306	0	1
ece	164	0.085	0.280	0	1
be	164	0.091	0.289	0	1
time	164	4.171	2.209	1	8

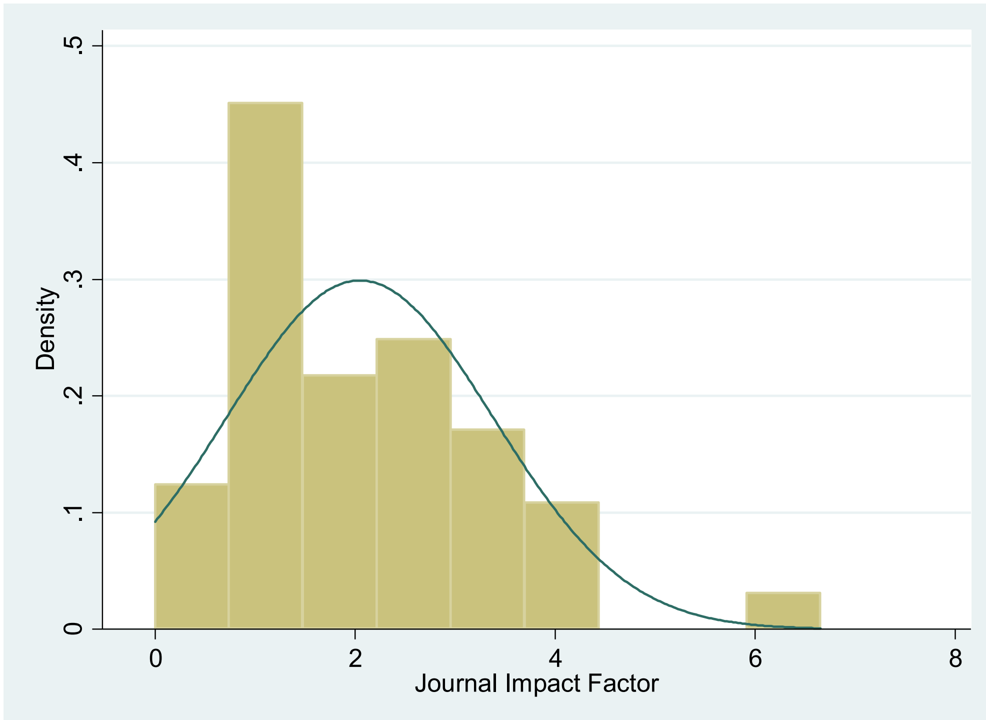
Appendix D – 2 Normality of distribution by variable

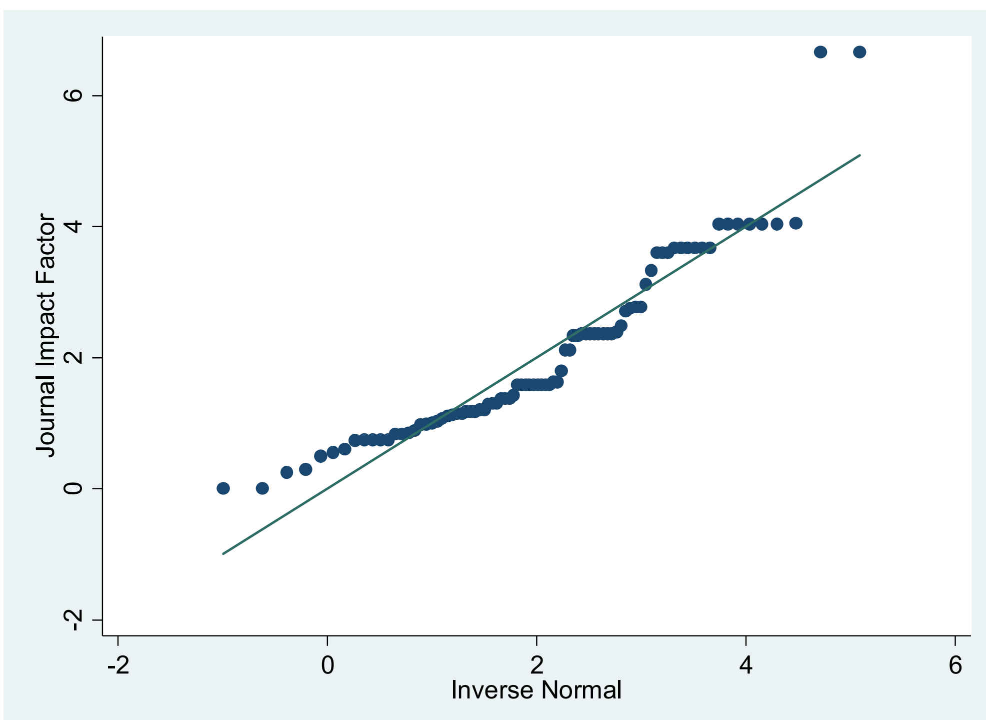
Academic Journal Guide 2015 (ajg) Skewness: -0.7311797, Kurtosis: 3.799147



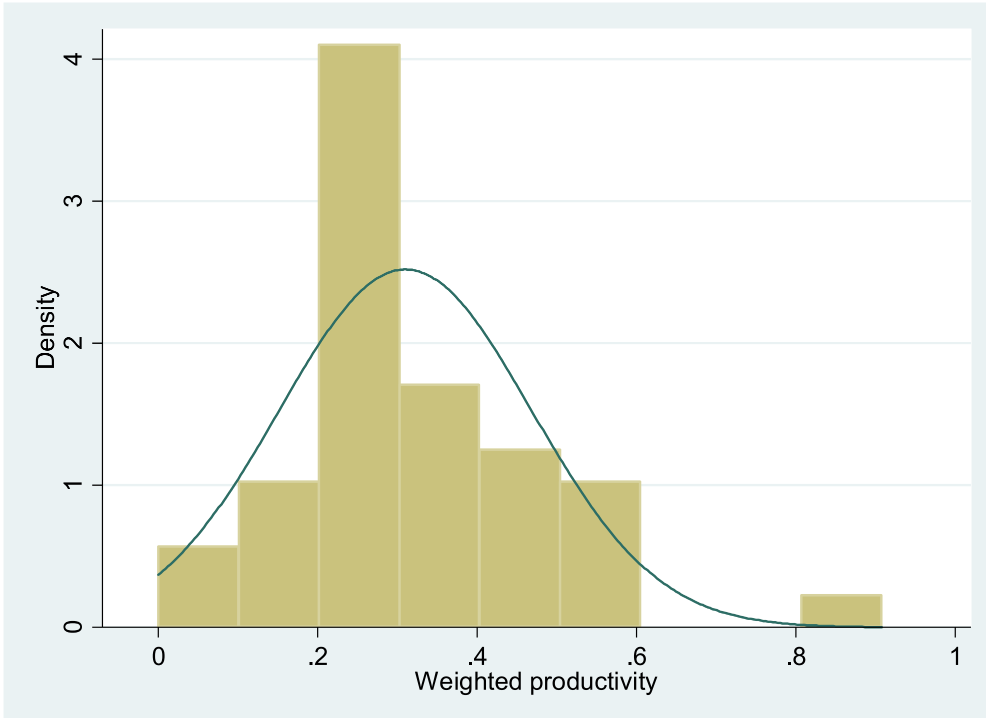


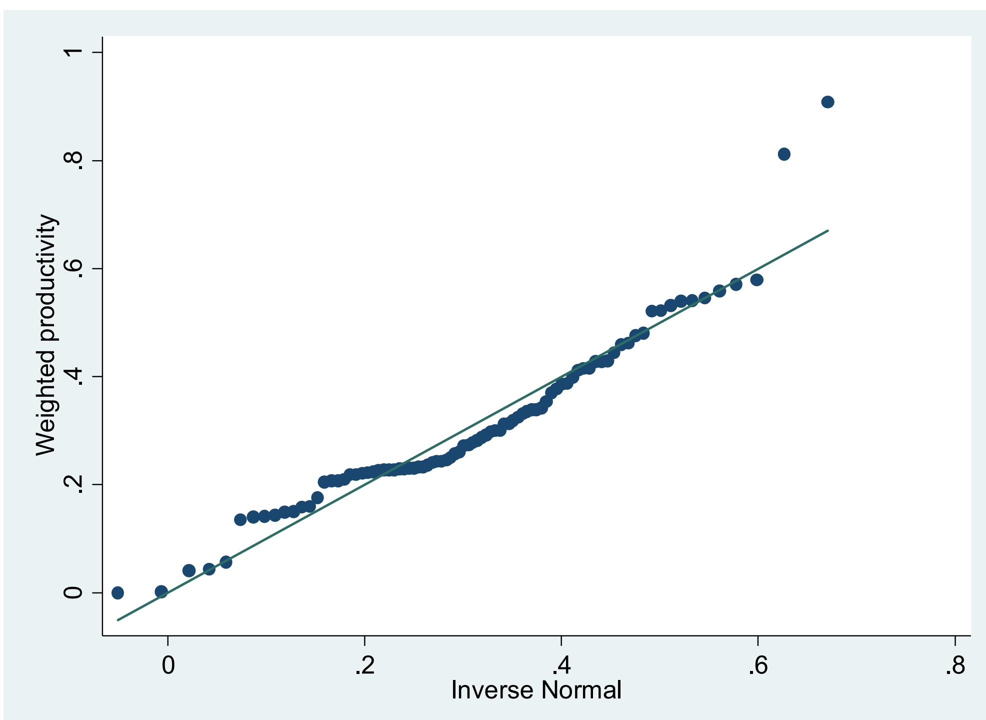
Journal Impact Factor (jif) Skewness: 1.088433, Kurtosis: 4.381859



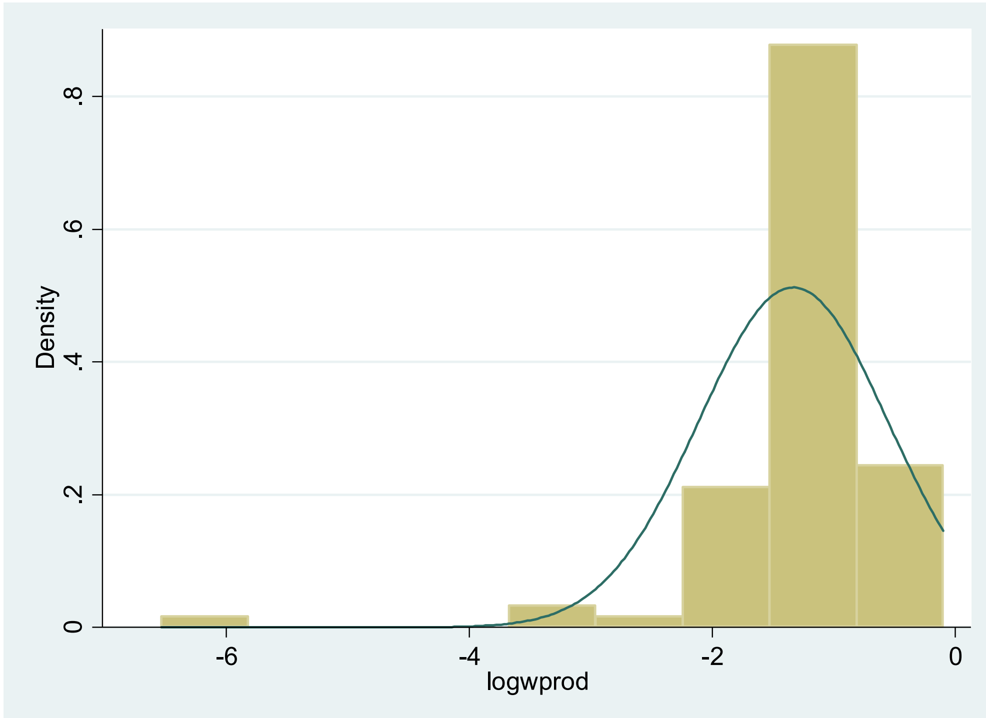


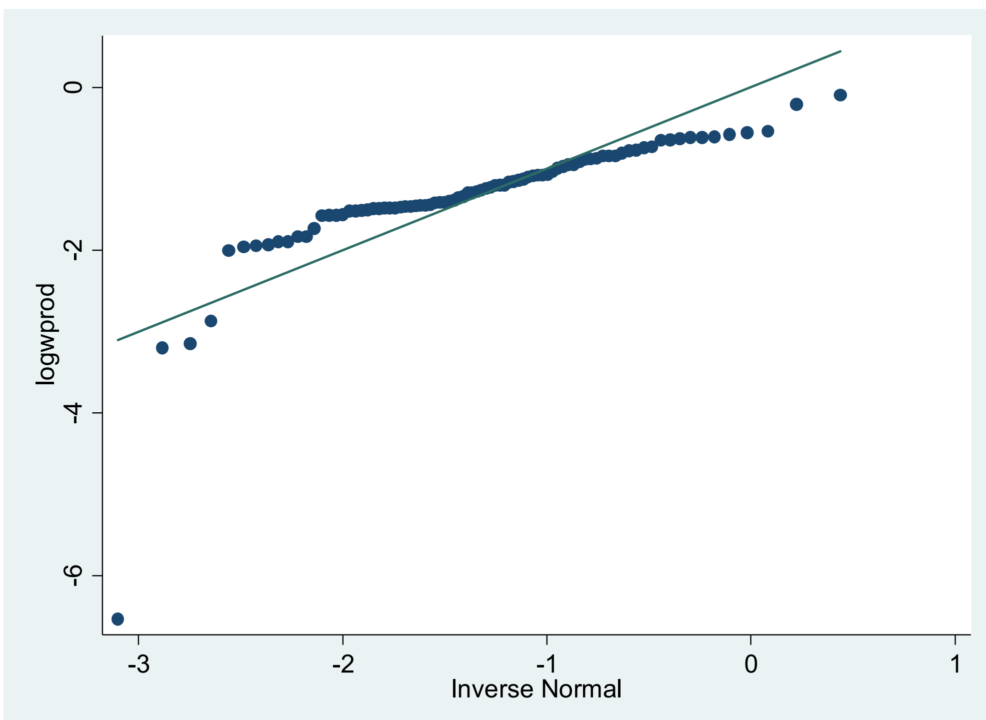
Weighted productivity (wprod) Skewness: 0.9492802, Kurtosis: 4.951004



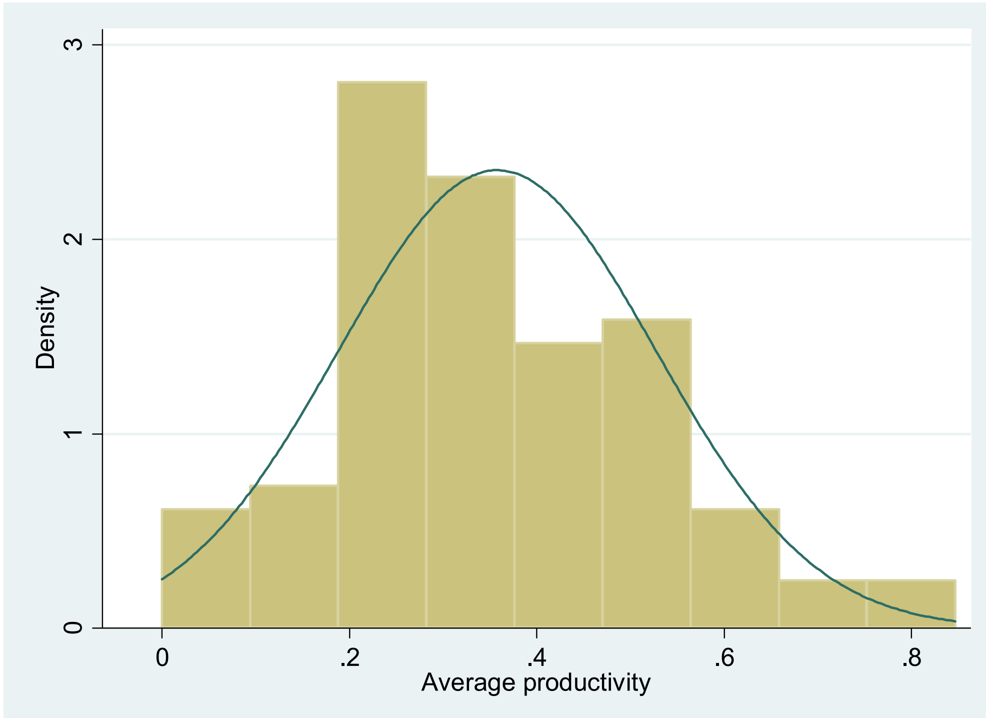


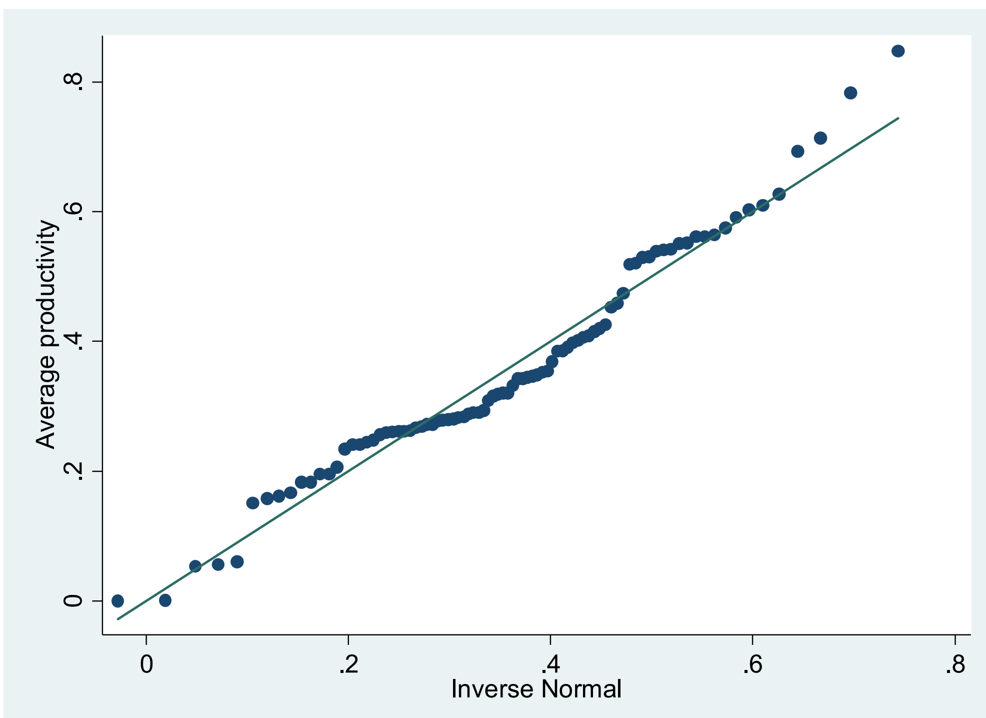
Log of weighted productivity (logwprod) Skewness: -3.763964, Kurtosis: 24.91667



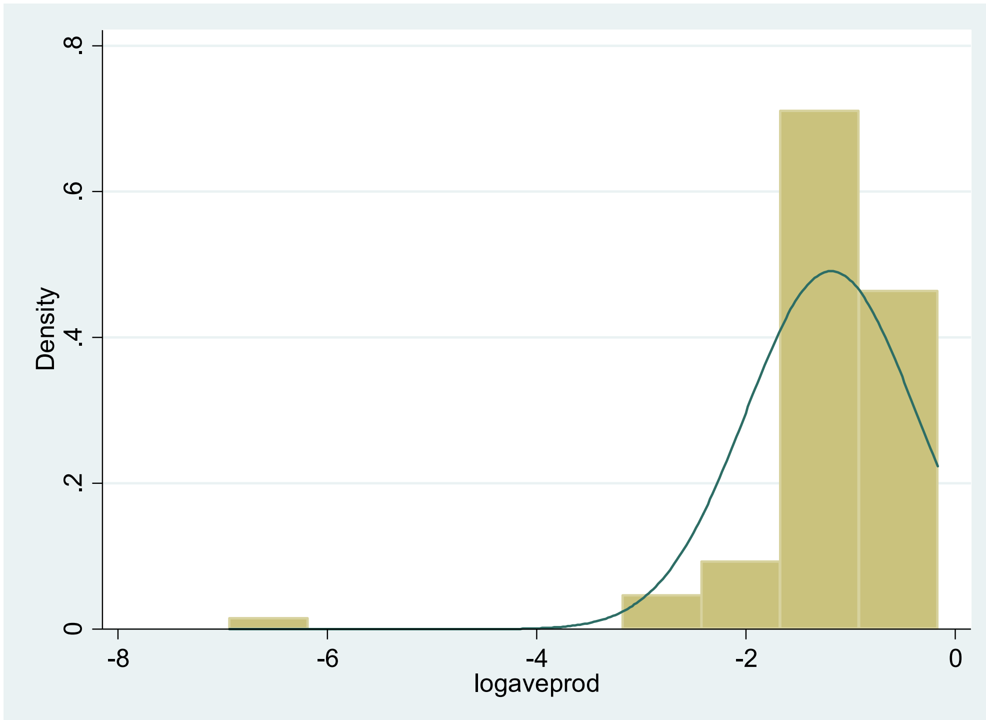


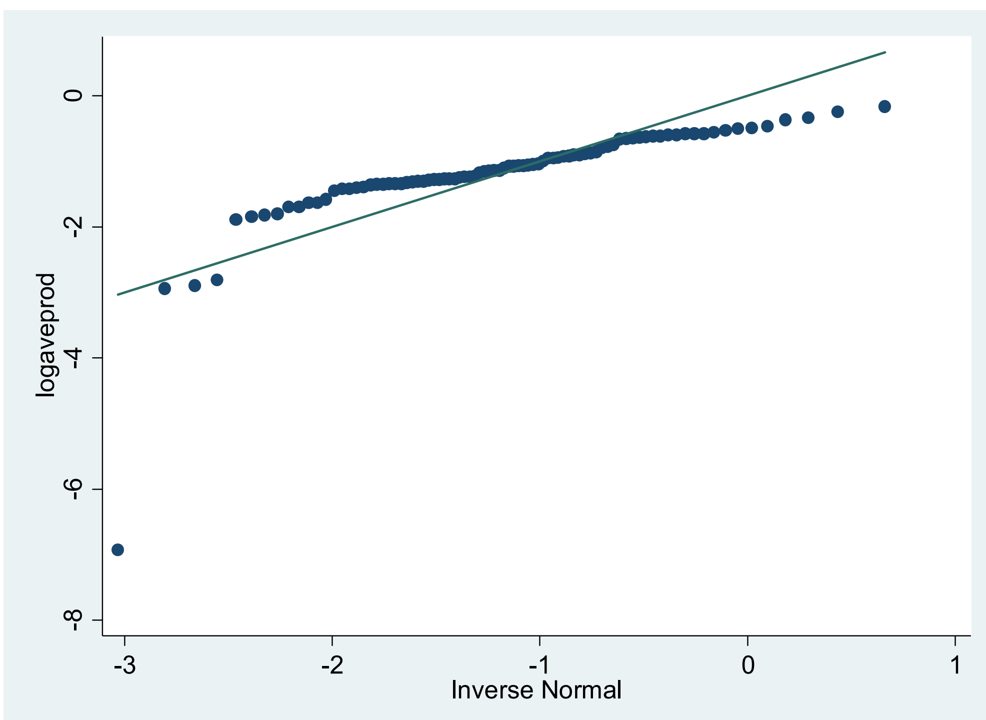
Average productivity (aveprod) Skewness: 0.4370532, Kurtosis: 3.158411



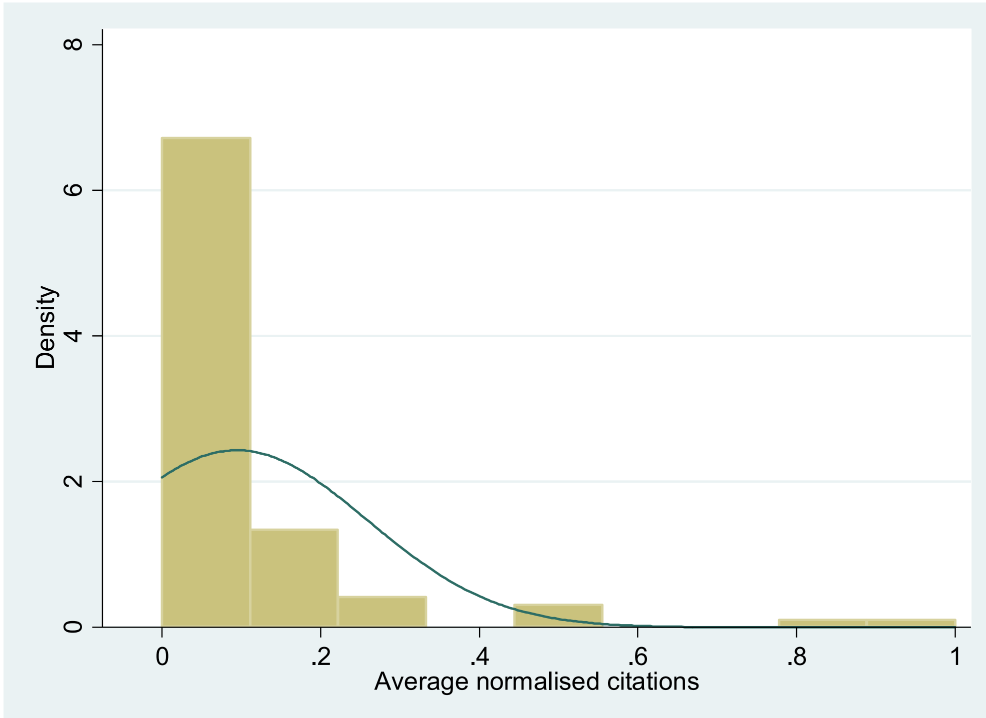


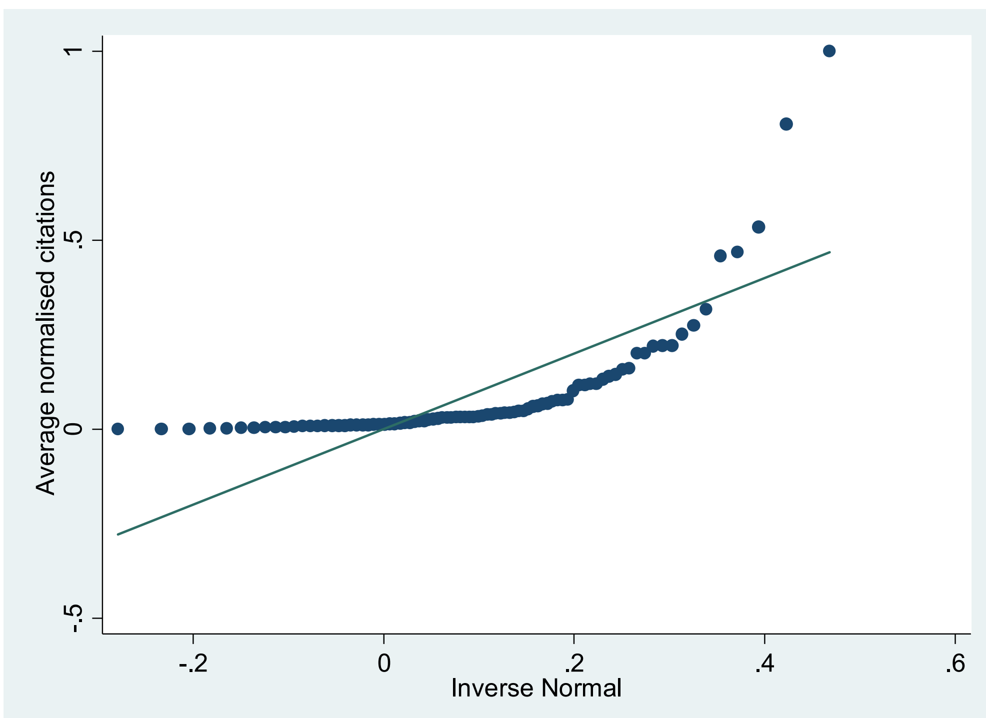
Log of average productivity (logaveprod) Skewness: -4.403526, Kurtosis: 30.77324



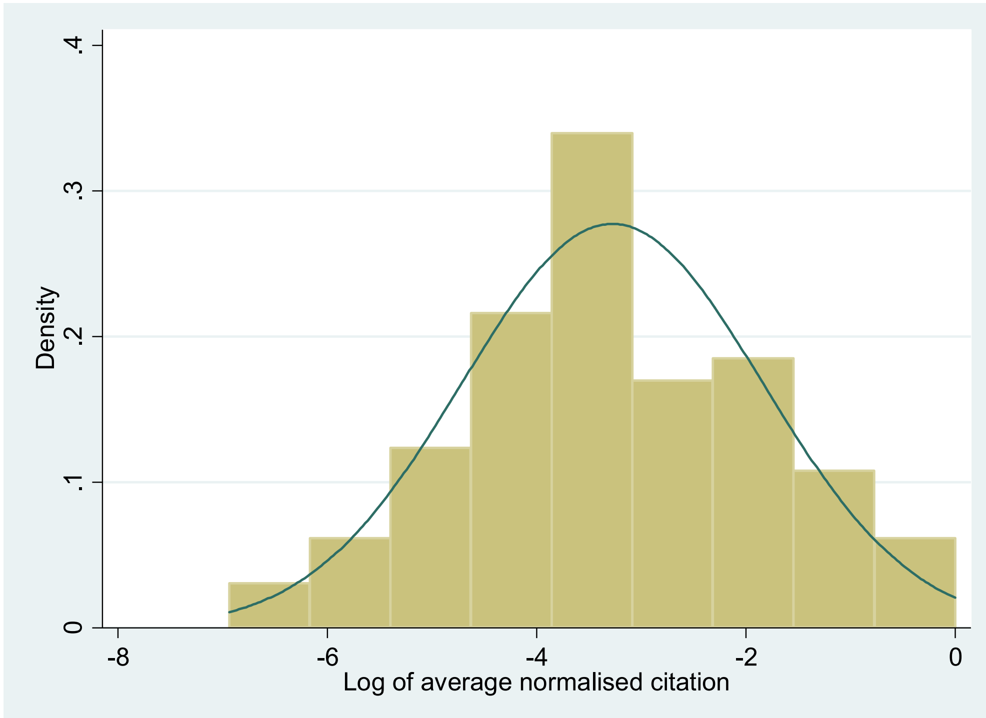


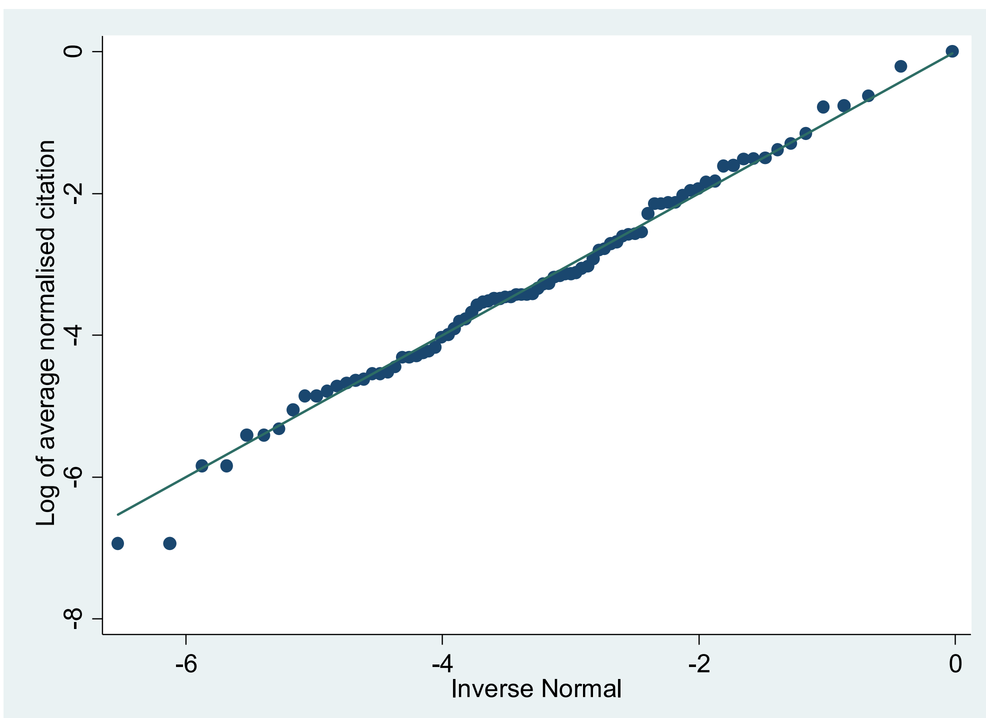
Average normalised citations (avenormcite) Skewness: 3.441709, Kurtosis: 16.50013





Log of average normalised citations (logavenormcite) Skewness: -0.068704, Kurtosis: 2.896712





Appendix D – 2 (Continued) Normality of distribution by variable

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
ajg	87	0.94214	4.255	3.188	0.00072
jif	87	0.90986	6.630	4.164	0.00002
wprod	87	0.93915	4.475	3.299	0.00049
aveprod	87	0.96994	2.211	1.746	0.04038
avenormcite	87	0.56161	32.243	7.646	0.00000
logwprod	86	0.69175	22.456	6.845	0.00000
logaveprod	86	0.63468	26.613	7.219	0.00000
logavenormcite	84	0.99153	0.605	-1.102	0.86484

Note: The normal approximation to the sampling distribution of W is valid for 4<=n<=2000.

Shapiro-Francia W' test for normal data

Variable	Obs	W'	V'	z	Prob>z
ajg	87	0.96914	2.506	1.799	0.03601
jif	87	0.90718	7.535	3.956	0.00004
wprod	87	0.93466	5.304	3.268	0.00054
aveprod	87	0.96998	2.437	1.745	0.04050
avenormcite	87	0.55922	35.782	7.007	0.00001
logwprod	86	0.67405	26.211	6.393	0.00001
logaveprod	86	0.61691	30.807	6.709	0.00001
logavenormcite	84	0.99297	0.554	-1.153	0.87552

Note: The normal approximation to the sampling distribution of W' is valid for 10<=n<=5000.

Appendix D – 3 Quantile regression estimates for average productivity across quantiles

	(1) Q(0.10)	(2) Q(0.20)	(3) Q(0.30)	(4) Q(0.40)	(5) Q(0.50)	(6) Q(0.60)	(7) Q(0.70)	(8) Q(0.80)	(9) Q(0.90)
Winner	0.0938	0.0990	0.1470*	0.1460*	0.0870	0.0691	0.0937	0.1610*	0.0815
	(0.0545)	(0.0544)	(0.0604)	(0.0559)	(0.0629)	(0.0539)	(0.0595)	(0.0651)	(0.0843)
Female	-0.0268	0.0039	0.0135	0.0148	-0.0014	-0.0153	-0.0198	-0.0263	-0.0357
	(0.0754)	(0.0667)	(0.0617)	(0.0527)	(0.0495)	(0.0508)	(0.0458)	(0.0495)	(0.0567)
Time	0.0058	0.0032	0.0051	-0.0114	-0.0030	0.0066	0.0042	0.0058	0.0011
	(0.0154)	(0.0137)	(0.0163)	(0.0135)	(0.0108)	(0.0102)	(0.0095)	(0.0116)	(0.0219)
Candidates	0.0058	0.0121	0.0346	0.0032	-0.0054	-0.0031	0.0043	0.0089	-0.0046
	(0.0517)	(0.0392)	(0.0309)	(0.0277)	(0.0258)	(0.0195)	(0.0178)	(0.0233)	(0.0366)
Teamsize	-0.0679	-0.0582	-0.0251	0.0087	0.0001	0.0038	0.0162	0.0026	0.0515
	(0.0495)	(0.0396)	(0.0391)	(0.0382)	(0.0318)	(0.0270)	(0.0240)	(0.0286)	(0.0396)
AM	0.0817	0.0801	0.1290	0.1420	0.1710	0.2060	0.1870	0.1620	0.1390
	(0.1412)	(0.1278)	(0.1464)	(0.1228)	(0.1193)	(0.1196)	(0.1111)	(0.1238)	(0.1465)
PSE	-0.0204	-0.0208	-0.0360	-0.0045	-0.0091	-0.0379	-0.0463	-0.1270	-0.1790
	(0.1215)	(0.0943)	(0.0789)	(0.0707)	(0.0619)	(0.0594)	(0.0801)	(0.1022)	(0.1381)
ESP	-0.0211	0.0934	0.0991	0.1210	0.1230	0.1090	0.1200	0.0507	0.0758
	(0.1143)	(0.1027)	(0.0994)	(0.0929)	(0.0782)	(0.0785)	(0.0840)	(0.1005)	(0.1112)
GE	0.1380	0.1190	0.0832	0.0171	0.0505	0.1210	0.1170	0.0439	-0.0402
	(0.1008)	(0.0971)	(0.0888)	(0.0795)	(0.0657)	(0.0783)	(0.0913)	(0.0977)	(0.0977)
EE	-0.0429	0.0875	0.1270	0.0772	0.0697	0.0372	0.0310	-0.0215	0.1800
	(0.1128)	(0.1066)	(0.1190)	(0.1007)	(0.0731)	(0.0743)	(0.0920)	(0.1170)	(0.1680)
ECE	0.0311	0.0217	0.0038	-0.0200	0.0141	0.0084	0.0481	-0.0907	-0.0996
	(0.0800)	(0.0890)	(0.1078)	(0.1035)	(0.1064)	(0.0980)	(0.0985)	(0.0988)	(0.1066)
BE	0.1960*	0.1740	0.1780	0.0946	0.1580	0.1480	0.1330	0.0661	0.0113
	(0.0972)	(0.0960)	(0.0926)	(0.0926)	(0.0947)	(0.0974)	(0.1043)	(0.1219)	(0.1366)
Constant	0.1860	0.1790	0.0626	0.2550	0.2980*	0.2800**	0.2560**	0.3320**	0.4270*
	(0.1764)	(0.1627)	(0.1613)	(0.1345)	(0.1169)	(0.0998)	(0.0885)	(0.1212)	(0.1792)
N	87	87	87	87	87	87	87	87	87

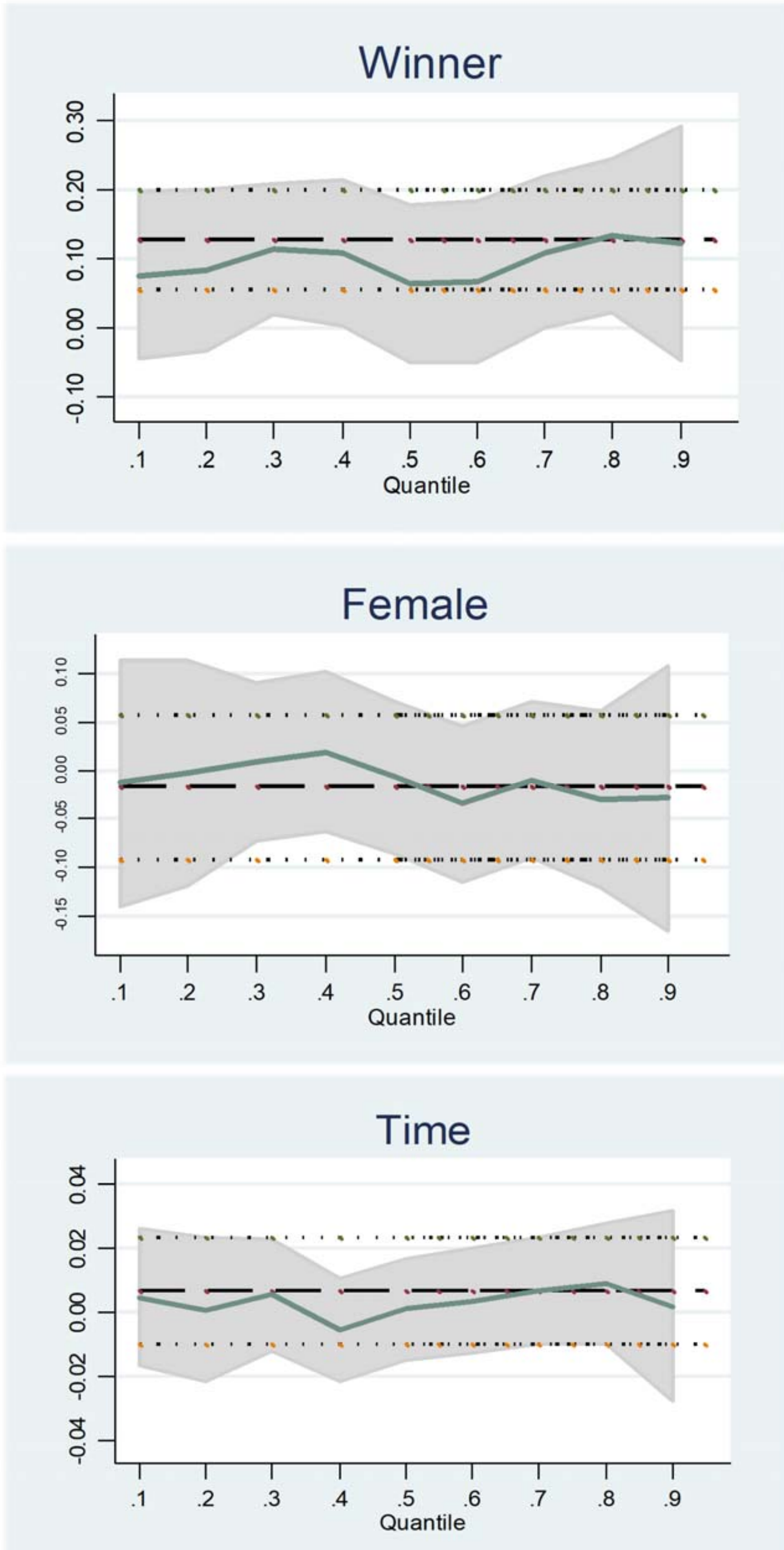
Notes: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001; Bootstrap data resampling with 50 repetitions

Appendix D – 4 Quantile regression estimates for log average normalised citations across quantiles

	(1) Q(0.10)	(2) Q(0.20)	(3) Q(0.30)	(4) Q(0.40)	(5) Q(0.50)	(6) Q(0.60)	(7) Q(0.70)	(8) Q(0.80)	(9) Q(0.90)
Winner	1.1660**	0.9060*	1.0240**	0.6000	0.5250	0.1200	0.0880	0.3450	0.7350
	(0.3984)	(0.3872)	(0.3773)	(0.4395)	(0.4928)	(0.5155)	(0.6006)	(0.6303)	(0.6478)
Female	-0.2350	-0.0584	-0.0701	-0.1160	-0.4360	-0.2650	-0.3200	-0.4060	0.1160
	(0.4835)	(0.4671)	(0.4434)	(0.4652)	(0.3360)	(0.3482)	(0.4201)	(0.4894)	(0.5677)
Time	0.1600	0.1850*	0.1090	0.1560	0.2130*	0.2030*	0.2350*	0.1640	0.0291
	(0.0966)	(0.0853)	(0.0940)	(0.1076)	(0.0929)	(0.0886)	(0.1043)	(0.1193)	(0.1468)
Candidates	-0.3160	-0.1410	0.1600	0.0195	0.0852	-0.2620	-0.1930	-0.0661	-0.1670
	(0.2831)	(0.3067)	(0.2997)	(0.2768)	(0.3082)	(0.2798)	(0.2564)	(0.2416)	(0.3673)
Teamsize	0.1720	0.2590	0.0702	0.0268	-0.0788	0.3860	0.3440	0.2840	0.4450
	(0.2842)	(0.3005)	(0.2654)	(0.2473)	(0.2858)	(0.2942)	(0.2719)	(0.2842)	(0.3232)
AM	0.7180	0.3590	0.1920	0.0973	-0.0170	0.5060	0.6040	0.2310	0.5050
	(1.1897)	(1.0772)	(1.0638)	(1.0299)	(1.0004)	(0.8719)	(0.7759)	(0.8804)	(0.9307)
PSE	0.6690	0.3220	-0.5910	-0.3610	-0.5010	-0.3890	-0.1640	-0.0767	0.1190
	(1.2817)	(1.2208)	(1.0211)	(0.8591)	(0.8204)	(0.6667)	(0.5885)	(0.8355)	(1.0088)
ESP	1.9830	1.3740	1.0720	1.0700	1.2700	0.9330	1.0940	1.0740	0.9910
	(1.1348)	(1.0195)	(0.8310)	(0.8866)	(0.8523)	(0.6980)	(0.6026)	(0.7031)	(0.6720)
GE	-1.0360	-1.1670	-0.7650	0.3770	1.0290	1.2500	1.2140	0.9110	1.1670
	(1.4778)	(1.4885)	(1.3691)	(1.5289)	(1.0448)	(0.7753)	(0.7374)	(0.7608)	(0.8894)
EE	1.3280	0.9080	0.5410	0.3870	0.5630	0.0268	0.0407	-0.2740	1.6250
	(1.2202)	(1.1013)	(0.9554)	(0.9635)	(0.9198)	(0.7863)	(0.8692)	(1.0819)	(1.2070)
ECE	0.4240	0.3500	-0.3230	1.7170	1.5860	2.0010	2.1970	1.6360	0.6490
	(1.5381)	(1.4296)	(1.4777)	(1.3935)	(1.4423)	(1.2039)	(1.1480)	(1.1755)	(1.1246)
BE	0.0650	-0.5550	-1.1460	-0.8930	-0.9230	-0.8450	-0.7980	-1.1700	-0.6720
	(1.1376)	(1.0488)	(0.9559)	(0.9395)	(0.9799)	(1.0347)	(1.0096)	(1.0053)	(0.9572)
Constant	-5.673***	-5.876***	-5.430***	-4.823***	-4.945***	-3.998***	-4.243***	-3.762**	-3.107*
	(1.3807)	(1.3837)	(1.3532)	(1.2890)	(1.3251)	(1.1025)	(1.1128)	(1.1361)	(1.5548)
N	84	84	84	84	84	84	84	84	84

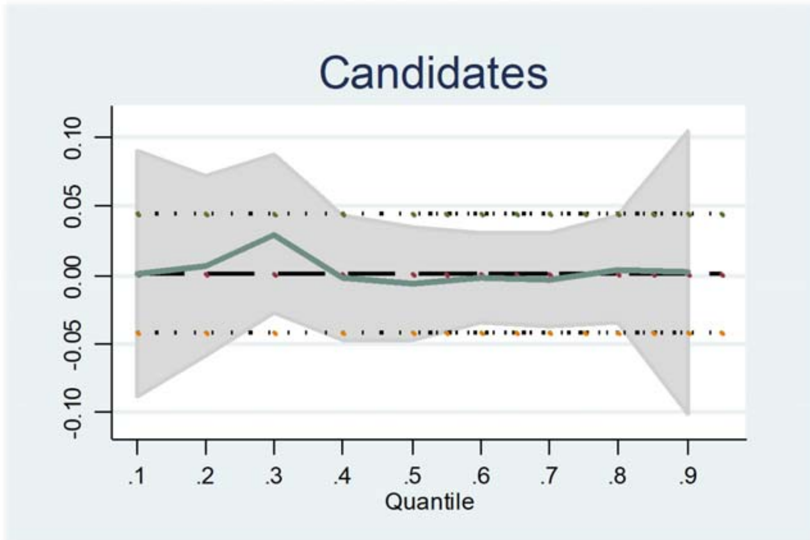
Notes: Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001; Bootstrap data resampling with 50 repetitions

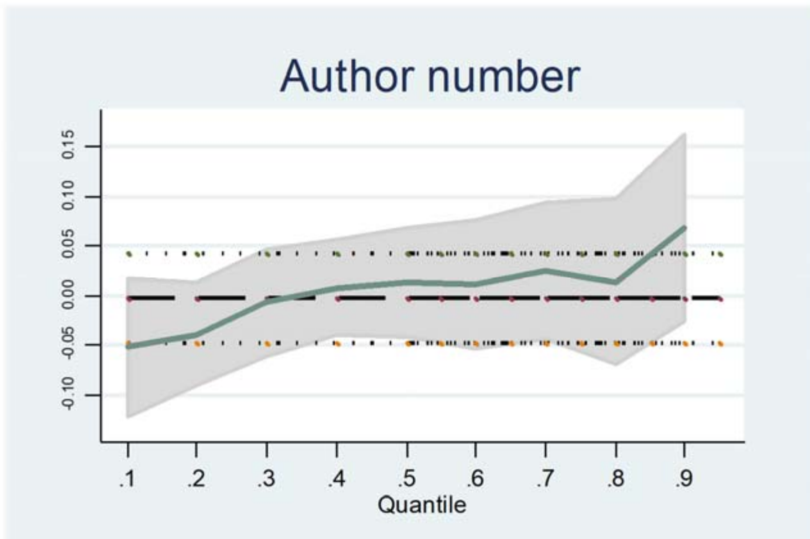
Appendix D – 5 Quantile coefficients for weighted productivity

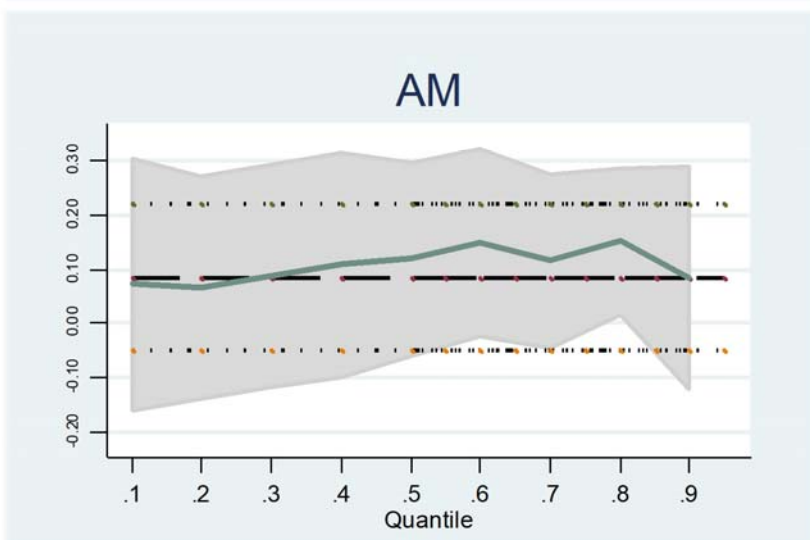


Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Appendix D – 5 (Continued) Quantile coefficients for weighted productivity

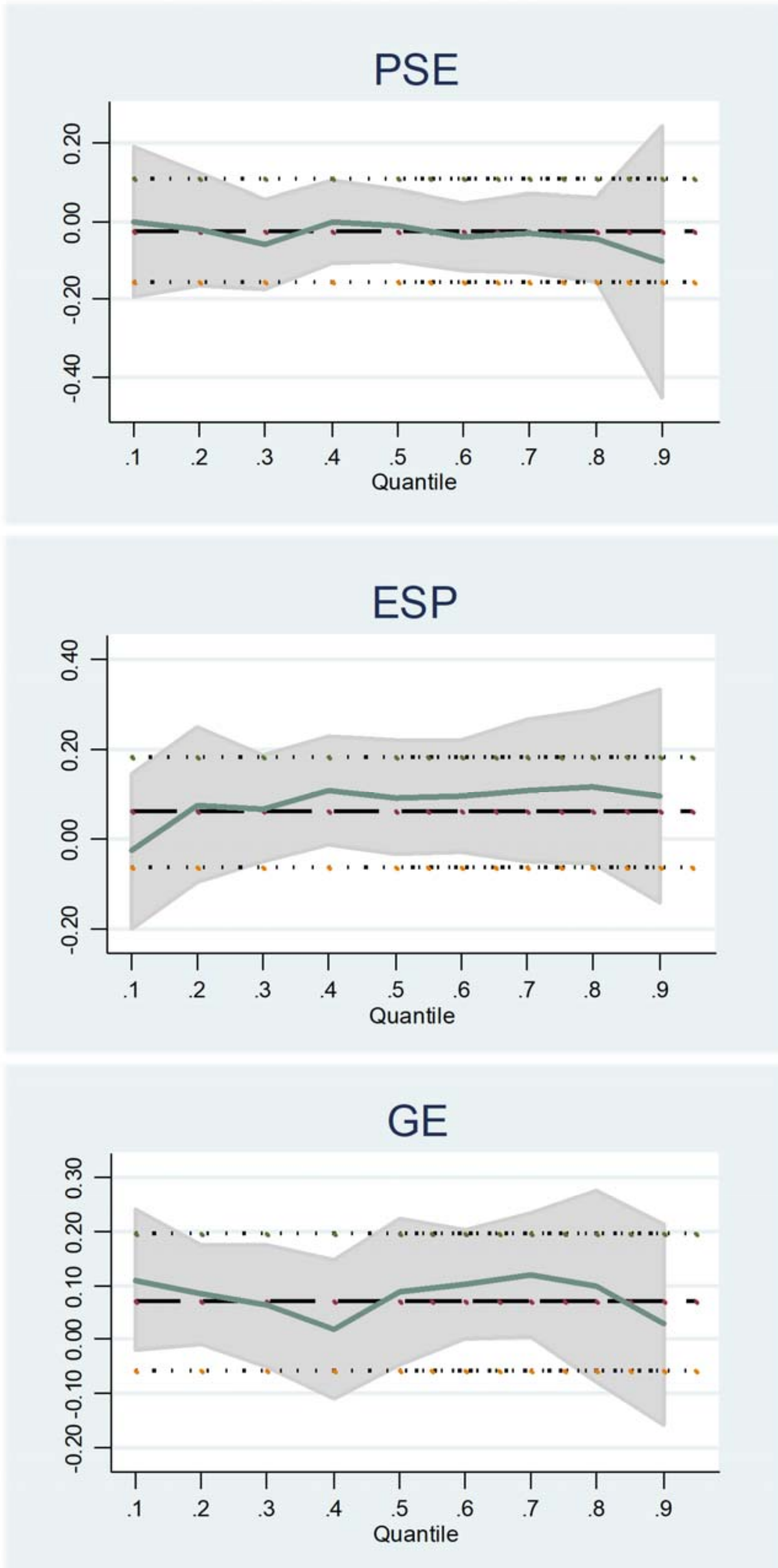






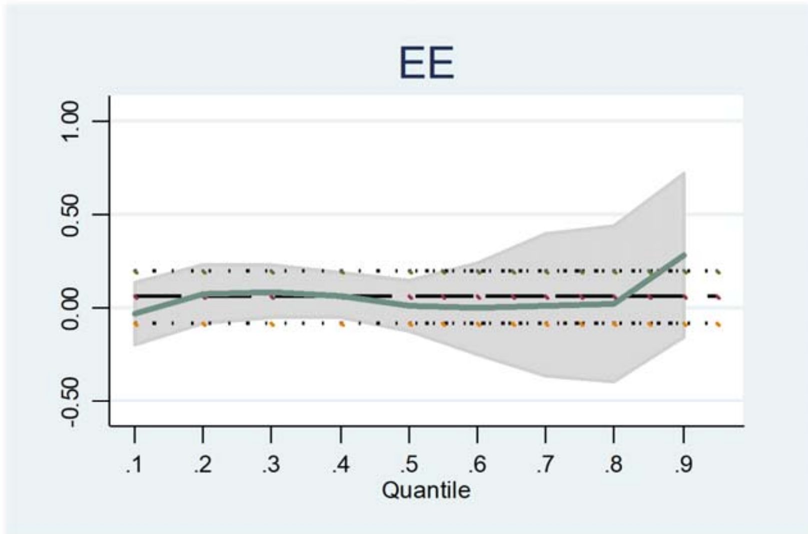
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

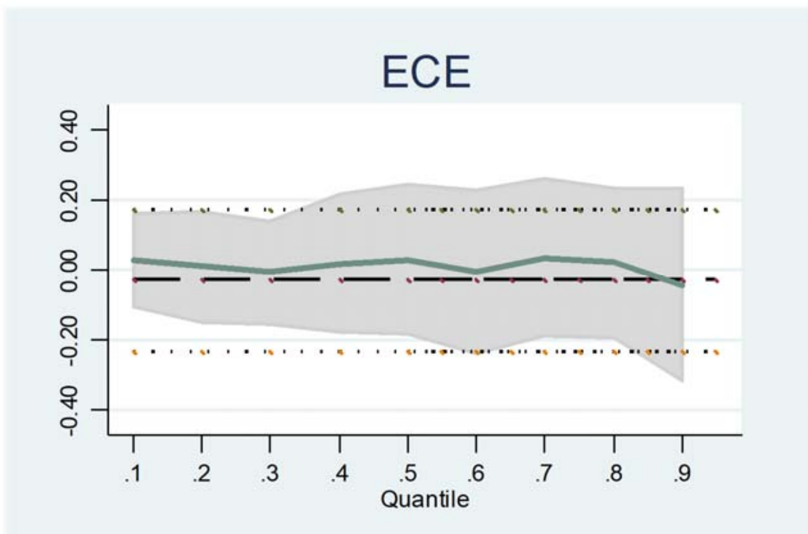
Appendix D – 5 (Continued) Quantile coefficients for weighted productivity

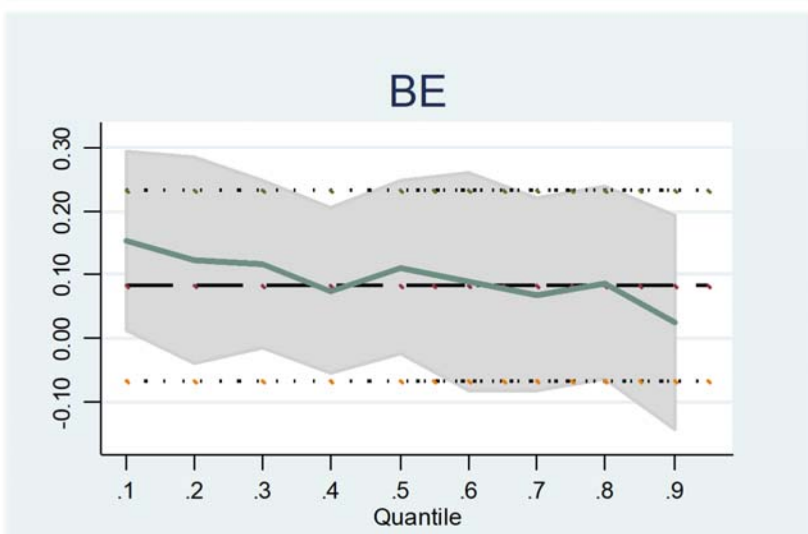


Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Appendix D – 5 (Continued) Quantile coefficients for weighted productivity

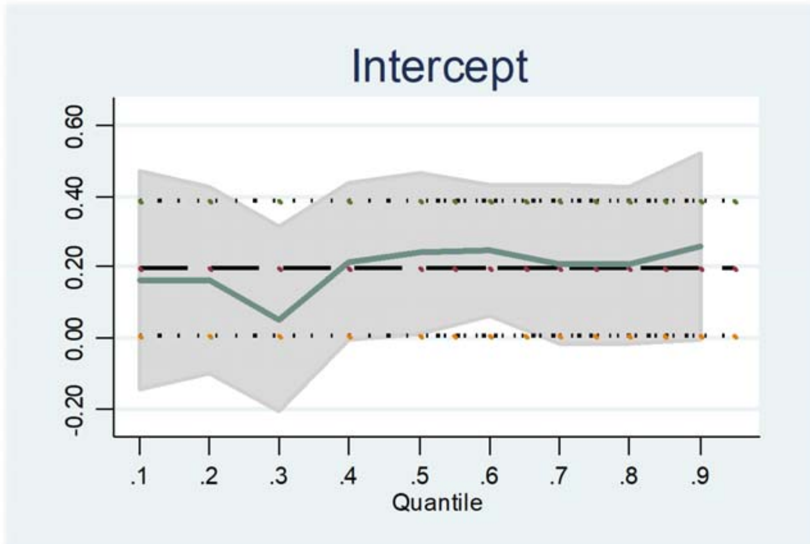






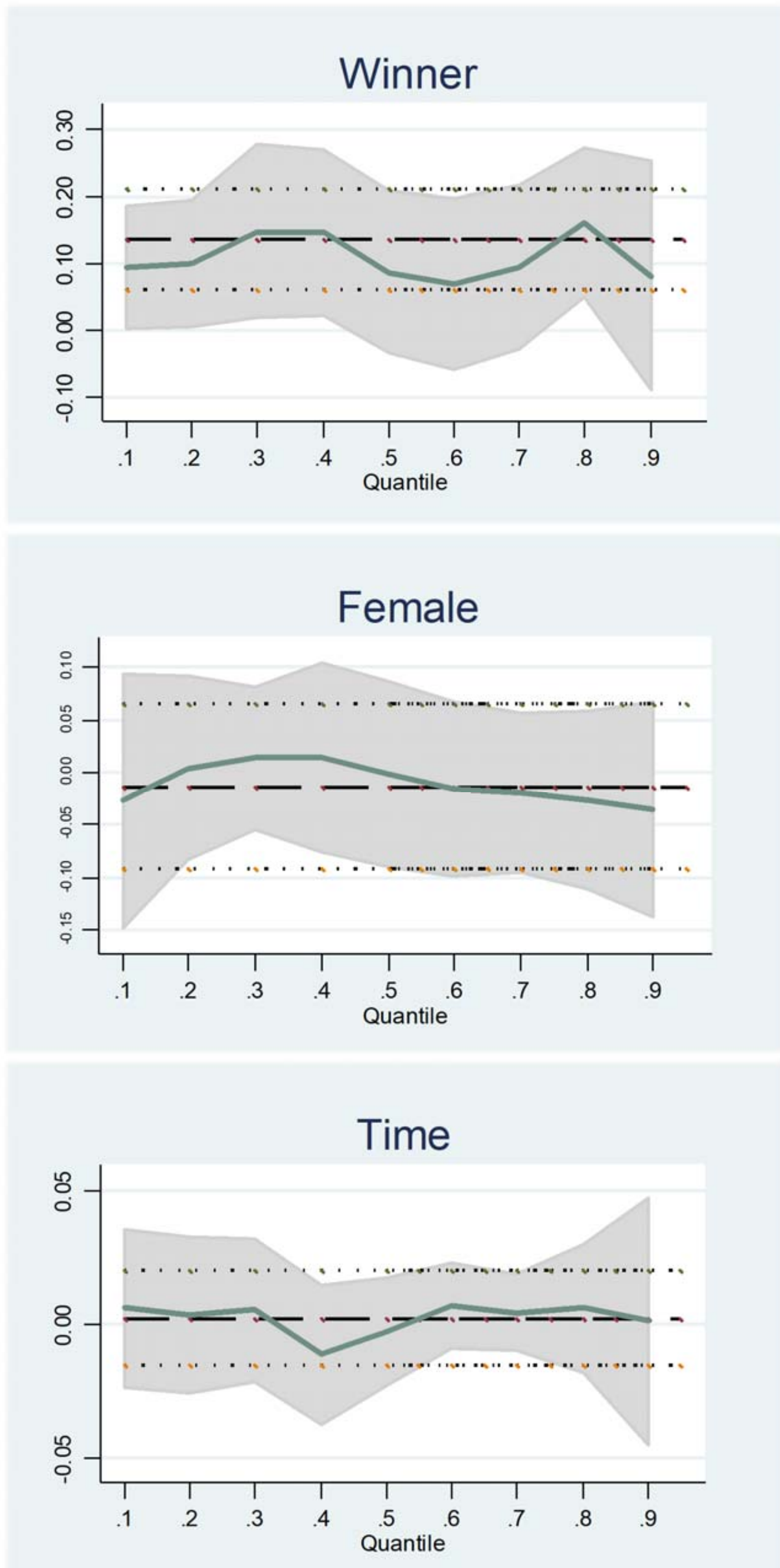
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Appendix D – 5 (Continued) Quantile coefficients for weighted productivity



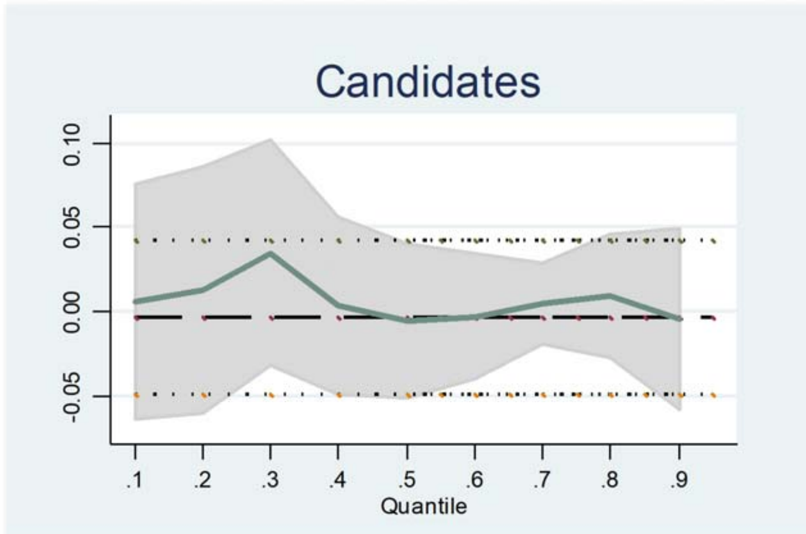
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

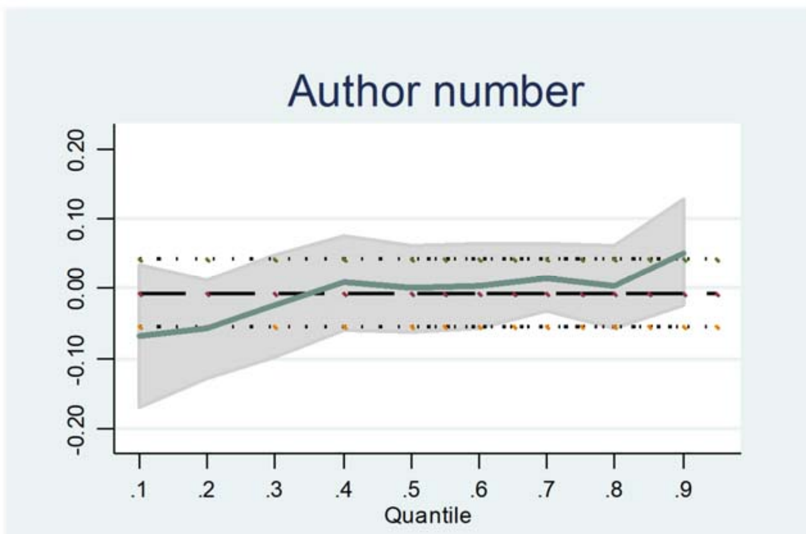
Appendix D – 6 Quantile coefficients for average productivity

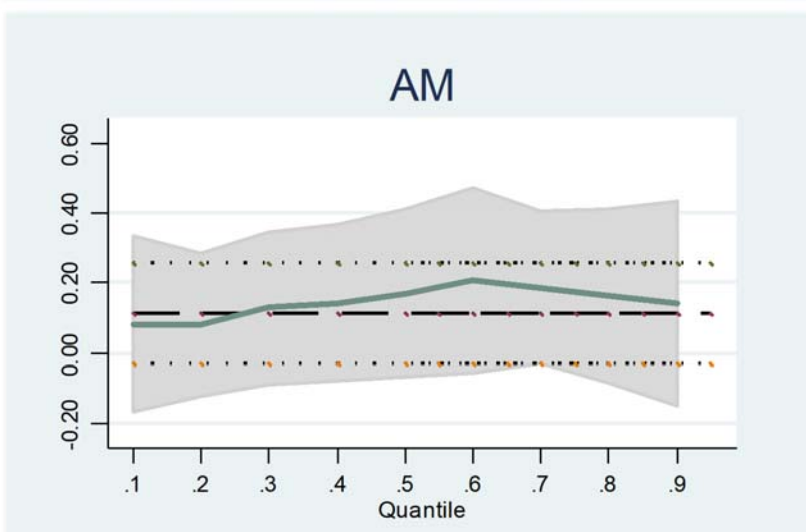


Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

Appendix D – 6 (Continued) Quantile coefficients for average productivity

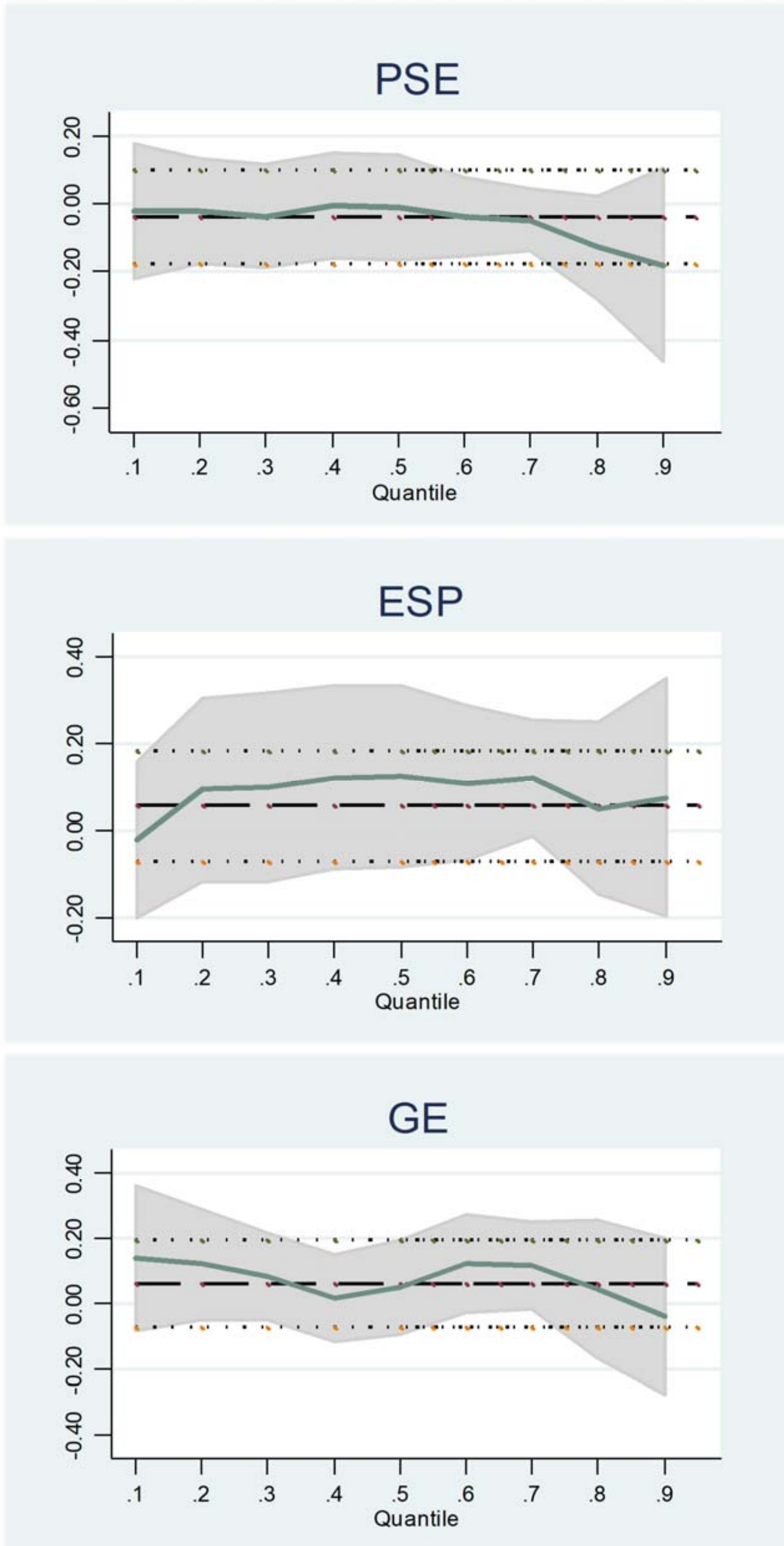






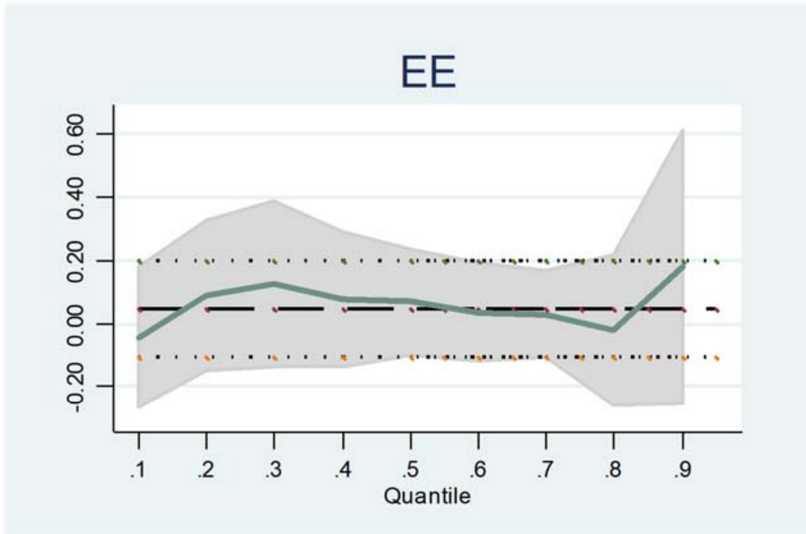
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

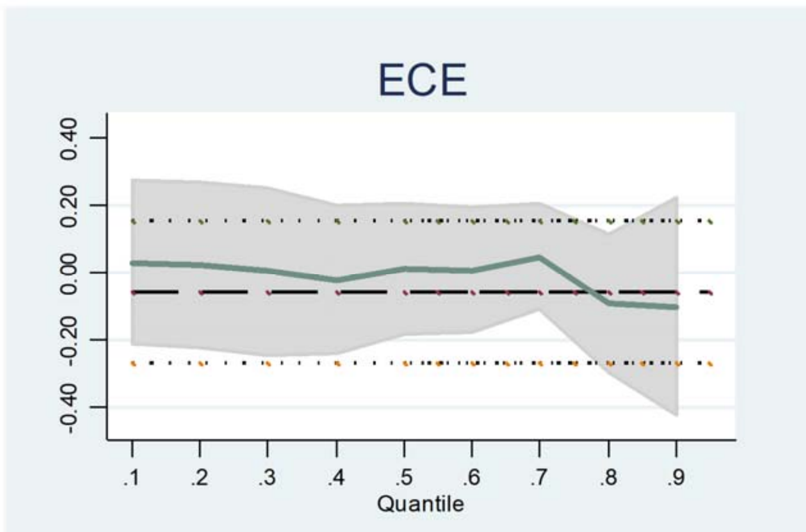
Appendix D – 6 (Continued) Quantile coefficients for average productivity

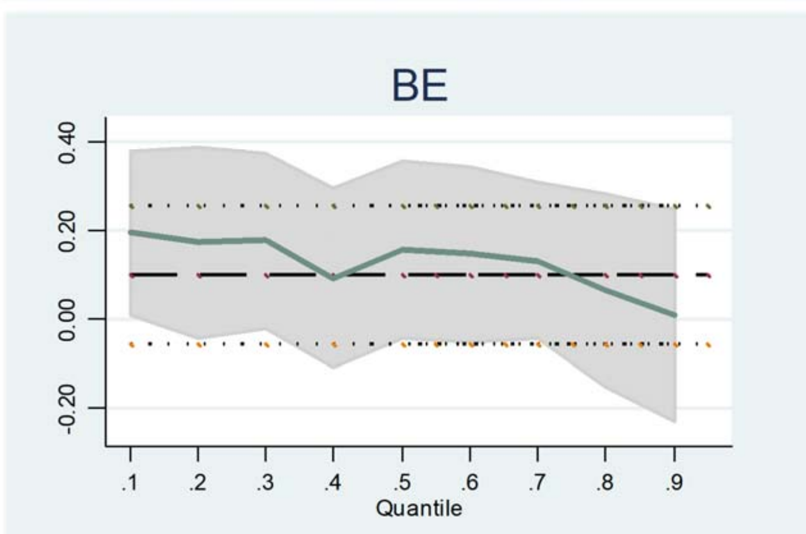


Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

Appendix D – 6 (Continued) Quantile coefficients for average productivity

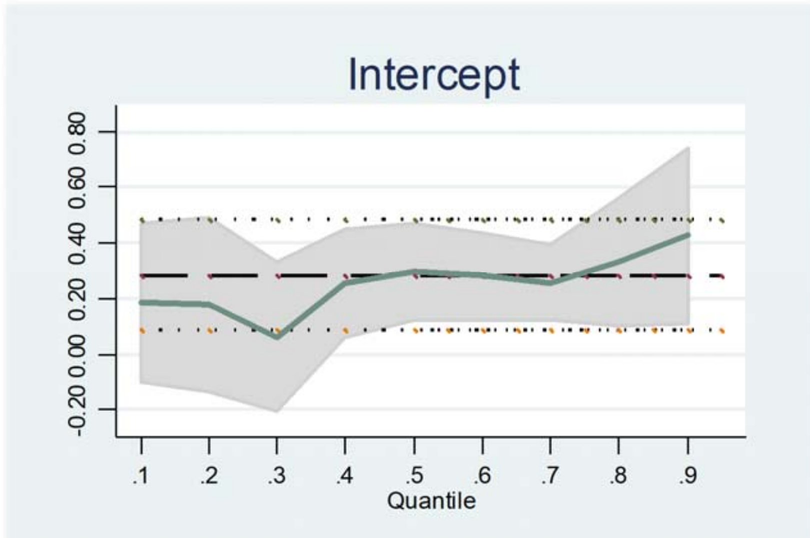






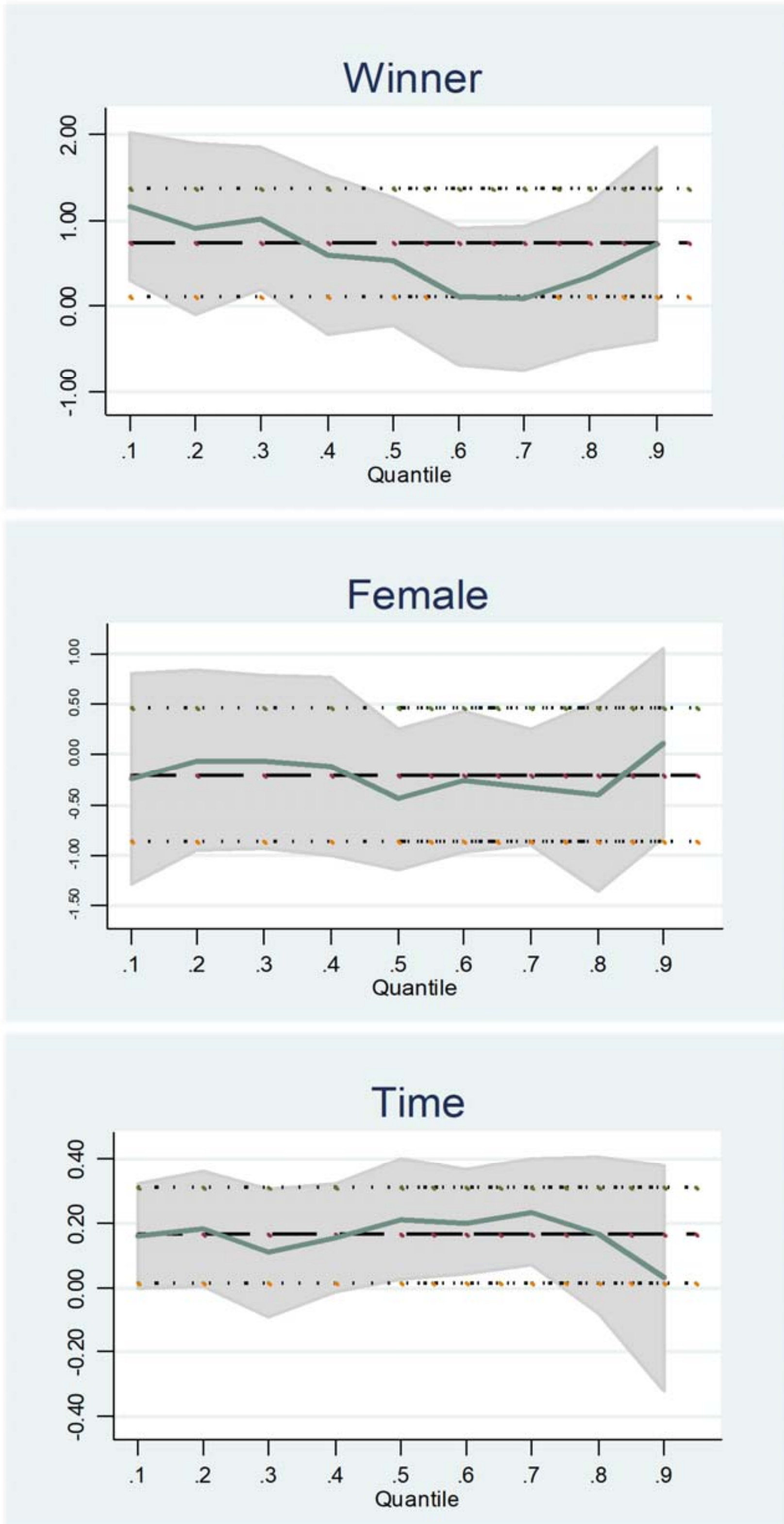
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

Appendix D – 6 (Continued) Quantile coefficients for average productivity



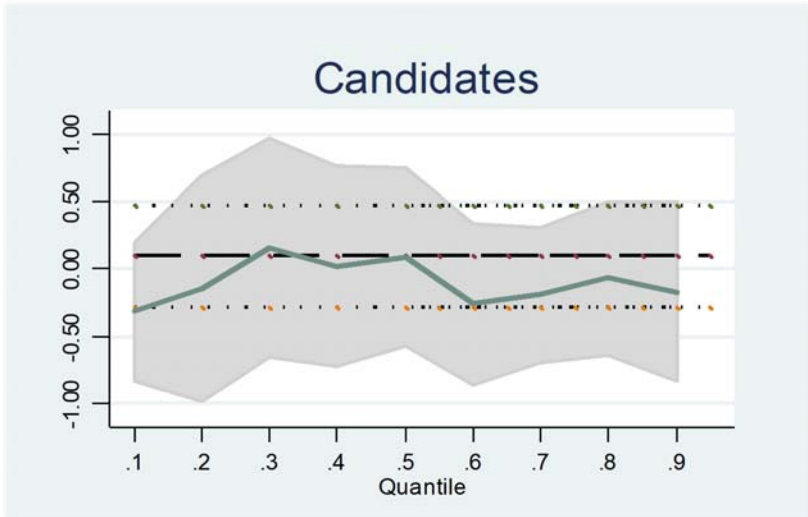
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

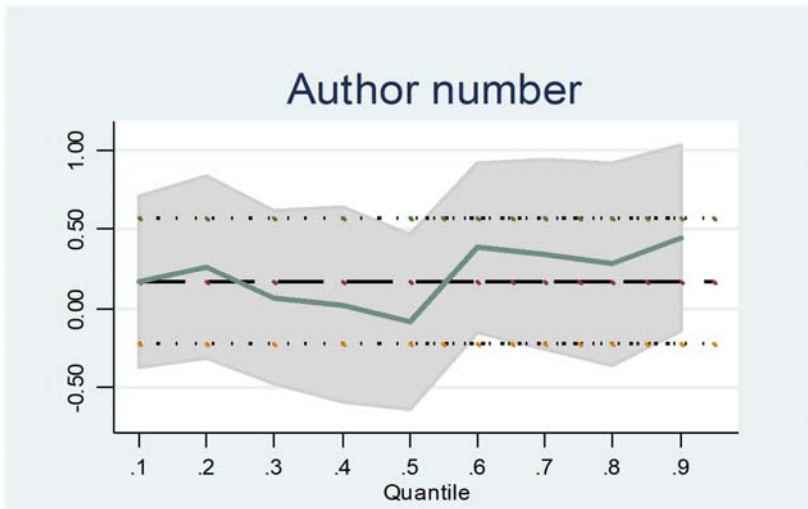
Appendix D – 7 Quantile coefficients for log average normalised citation

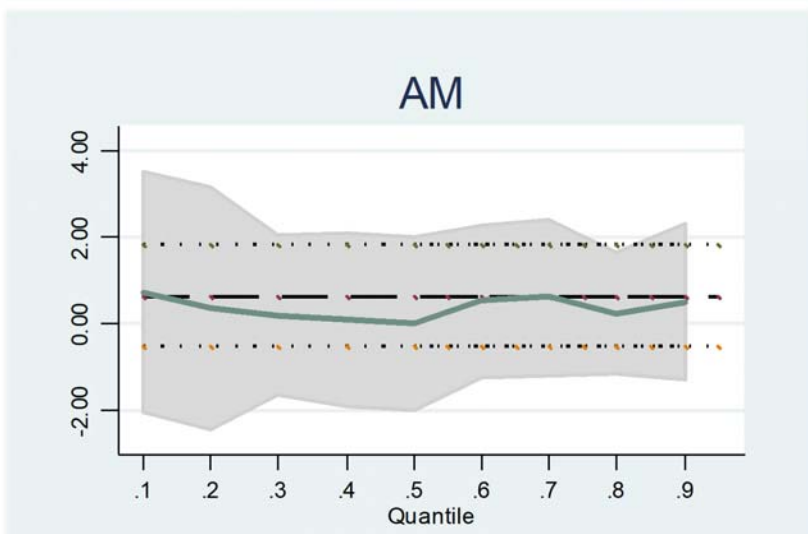


Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

Appendix D -7 (Continued) Quantile coefficients for log average normalised citation

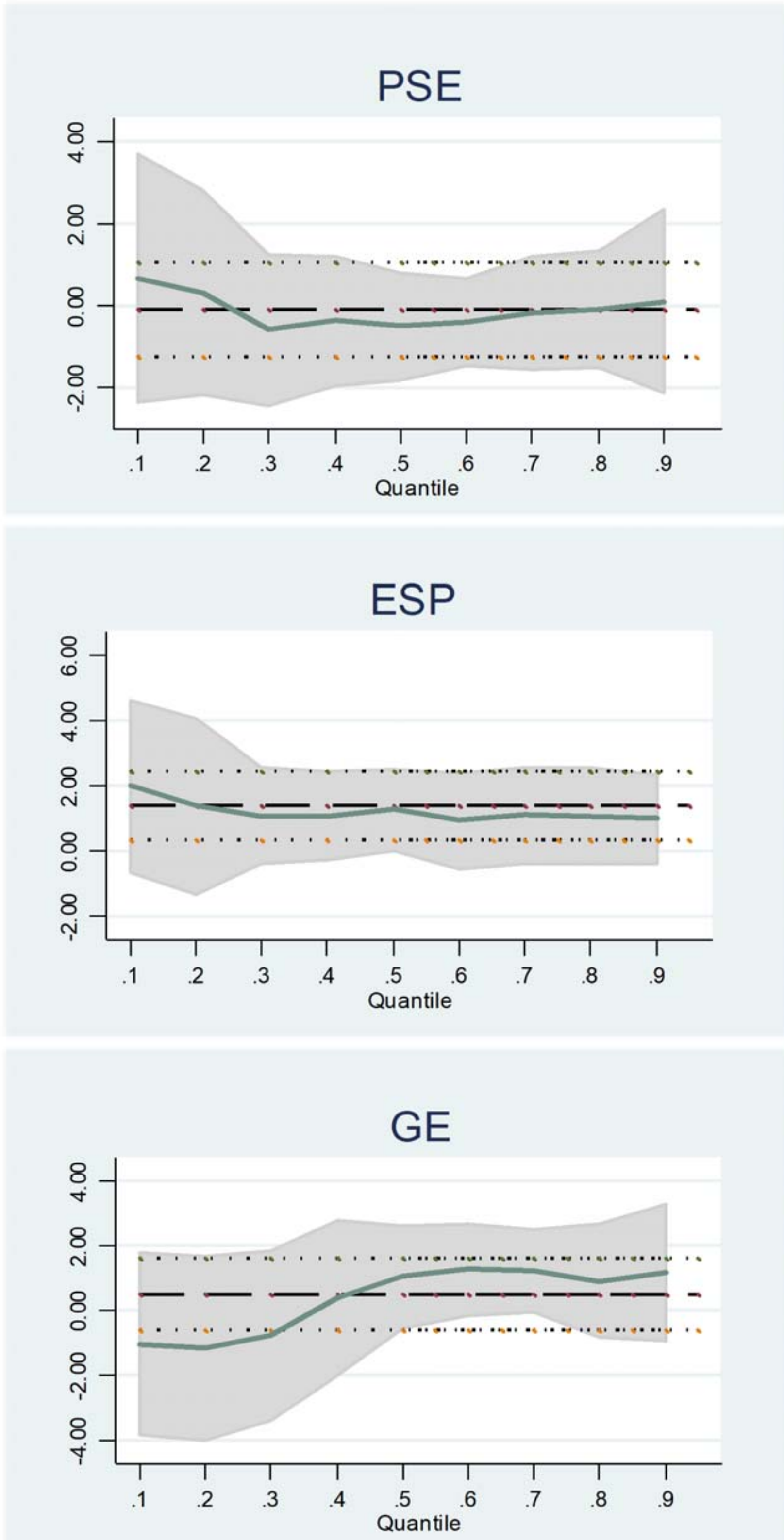






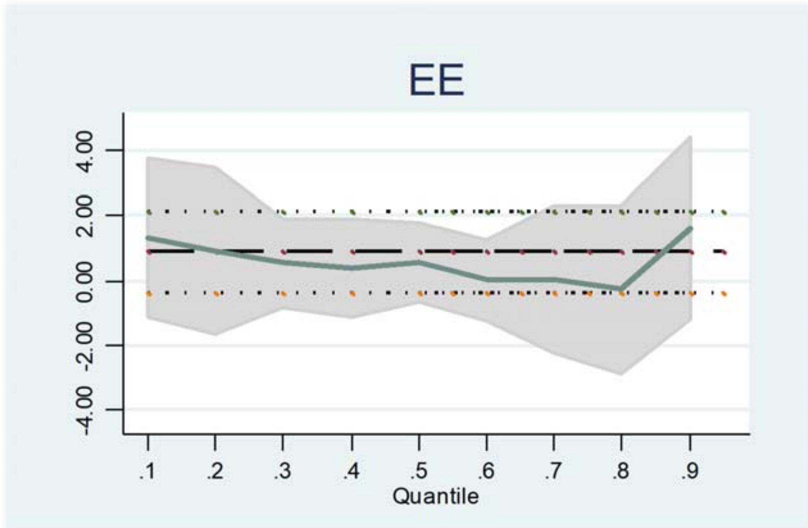
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

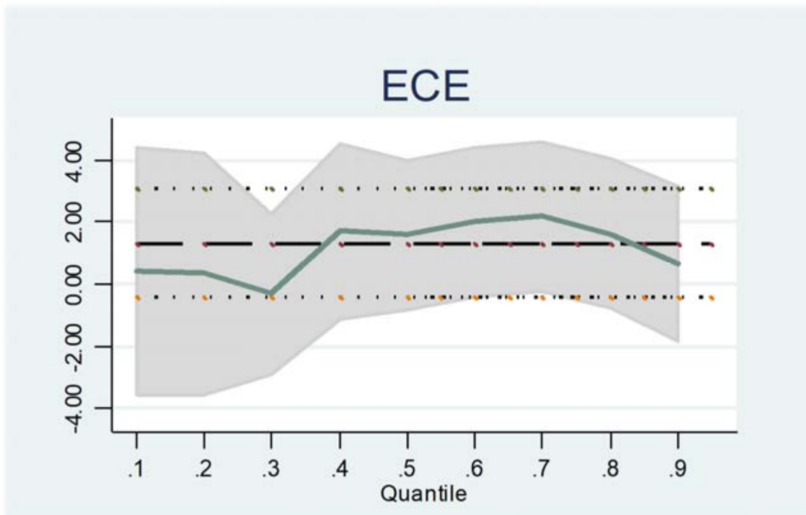
Appendix D – 7 (Continued) Quantile coefficients for log average normalised citation

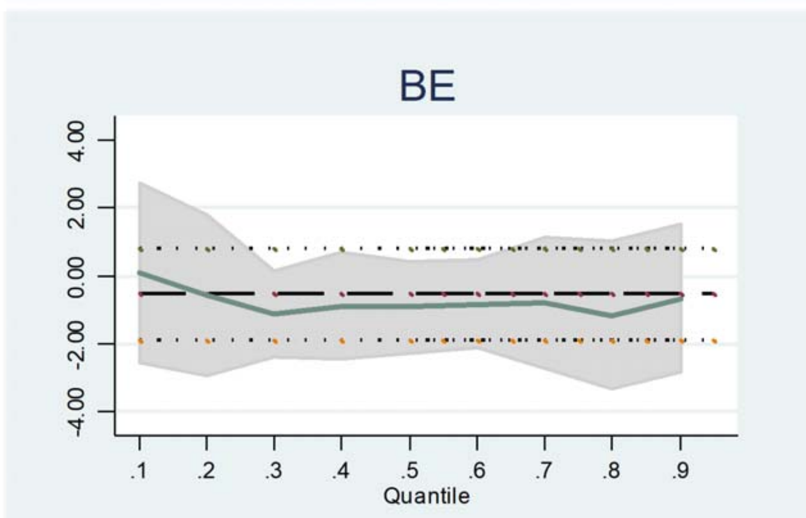


Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

Appendix D – 7 (Continued) Quantile coefficients for log average normalised citation

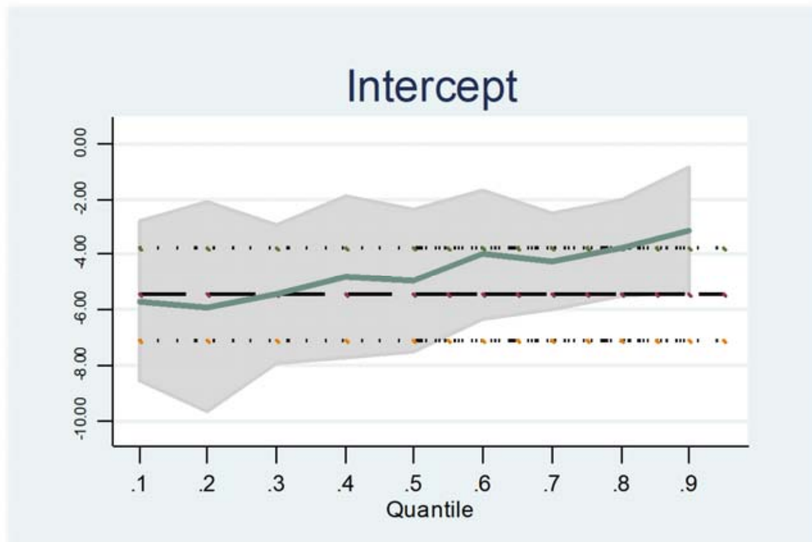






Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

Appendix D – 7 (Continued) Quantile coefficients for log average normalised citation



Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

CHAPTER SIX

CONCLUDING REMARKS

The process of knowledge production has fundamentally changed over the past few decades. Collaborative research teams increasingly dominate single authors in the research production and such collaboration increases across nearly all areas such as Arts and Humanities, Engineering, and Social Sciences (Wuchty *et al*., 2007). The previous studies show substantial evidence supporting that works produced by collaborative teams are more often cited than those from individual authors and that this pattern is increasing over time. It could be implied that collaborative teams tend to produce the exceptionally high-productive research. While collaboration is increasingly demanded in research production, it is generally more complex and less structured than those from solo authors. This is because an effective cooperation requires careful concentration to target, operate, and manage the differences among co-operators (Benda *et al*., 2002; Eigenbrode *et al*., 2007). This thesis attempts to provide evidence with regard to the collaboration as well as discrimination in academia particularly in scientific research production. The number of citations received is considered as a basic indicator for team productivity, which is obtained from Scopus and Google Scholar databases. Moreover, other metrics and sources of data such as journal impact factor and journal ranking should be applied for measuring the productivity of teams' outcome because the citation index only is inadequate to represent team productivity comprehensively (Stvilia *et al*., 2011).

This thesis contributes to collaboration and discrimination in three subjects. Firstly, we explore through the idea of the determinants of research productivity in economics (i.e., gender, nationality, seniority, academic rank, team size) and the extent to which those characteristics impact on productivity. Secondly, we investigate the effect of beauty, which is a form of appearance-based discrimination, on the research productivity. Then, we re-examine the role of physical attractiveness in another area, the Nobel Prize. Finally, we turn to examine another issue on inequality in scientific research which can be explained by the Matthew Effect.

Our analysis suggests that the characteristics of the authors, and collaborative teams, matters considerably for the subsequent success of academic publications. Some of the effects found are intuitive and expected, while others are rather surprising or even outright worrying. In Chapter 2, we find that larger teams and teams with greater share of senior authors get published in better journals and attract more citations. However, we also find that gender mixed and female dominated teams generally do worse. Given the economics continues to be a male-dominated field, this result is worrying. Further research should show whether this finding can be attributed to the relatively fragile footing that women have in the field of economics, or whether it results from open or inadvertent discrimination that they are subjected to. On the other hand, co-author teams that are mixed by rank or nationality do not seem disadvantaged. Given the increasing internationalisation of academia, this finding is reassuring.

We also find, somewhat unexpectedly, that physical attractiveness, or beauty, is related to academic success. At the level of regular academics (academic mortals), being attractive is associated with greater success in publishing and receiving citations. Among academic immortals, actual or potential Nobel Prize winners, the relationship is reversed. These two findings may suggest that attractive individuals are indeed more productive, possibly because physical features generally considered attractive are signs of greater intelligence and/or better health. If so, this effect holds for most of the distribution of academics, but not for those at the top of the distribution of productivity. For the very best of the best, attractiveness may even prove a hindrance, as the alternative opportunities and outside options that it brings (in personal or professional life) may distract researchers from their academic work. However, an alternative explanation rests on discrimination. In this case, attractive academics are favoured by their peers, their PhD supervisors, superiors, or members of hiring, funding and promotion committees. This discrimination, in turn, opens doors to resources and means that make them more productive and successful. The same relationship, however, need not hold at the top, where attractiveness does not fit our stereotypes of what a top scientist should look like.

Finally, our results show that winners of a best-paper competition, the Distinguished CESifo Affiliate prize awarded to junior researchers presenting their paper at CESifo area conferences is a signal of higher probability of future success with respect to publication quality and citations. Future analysis should show whether this confirms that the selection committees indeed tend to pick the best paper, or whether it reflects the additional advantage given to the winners in the shape of the boost to their career that this award bestows or the club goods associated with membership in the CESifo research network.

Nevertheless, we find some limitations in which to investigate the impact of teams' characteristics and research productivity. (1) There are some omitted variables, which should be included in the analysis for bringing about a better comprehension to this topic. For example, collaboration related factors such as degree of collaboration, or disagreement, within a team are overlooked. (2) The nature of academic collaboration is non-random: co-authors tend to form teams with their colleagues and peers so that many teams involve collaborators of the same nationality and often also rank. Moreover, one paper out of four in our sample is written by a single author and two out of three have no more than two co-authors so most of the author teams appear relatively homogenous which makes it difficult to explore the diversity. (3) As our measure of productivity is based on citations, some papers have not yet been cited or have received very few citations in the time since publication. (4) The norms, reasons, and motivations for citing have not been investigated and they may include factors other than the paper's quality. For example, some works can be cited due to an existing relationship (e.g., a supervisor-student relationship), or the cited author's academic status, such as journal editor and famous author (Baldi, 1998; Haslam and Koval, 2010).

There are some limitations with respect to the investigation of the appearance-based discrimination. (5) The results show correlation rather than causality and it is not possible to formally indicate what mechanism drives our findings in order to specify the emerging of the discrimination. (6) Regarding research productivity at the individual level, academics and practitioners show great interest in the citations as indicated in numerous studies recently. However, the norms of citing are different depending on discipline; for instance, papers from hard sciences (e.g., physics, biomedicine) are cited more than those from soft sciences (e.g., social sciences). Evaluation of the impact of individuals at the micro level requires an index which combines a measure of quantity and quality in a single indicator and measures separately by discipline (Costas and Bordons, 2007). (7) In regard to the winner effect, our sample using the data of the winners of the Distinguished CESifo Affiliate prize may be inadequate to identify the significant effect. (8) Other factors, for example, the prestige and proficiency of the corresponding authors of the papers, can also play a role and should not be neglected.

Therefore, the future research should: (1) employ interviews and in-depth surveys to further explore the perceptions of the team members as well as to observe and collect qualitative data such as motivations for participating in the team. (2) A more representative sample, which might be in different academic fields, should be used to investigate the relationship in the further studies. (3) A time period between the published year and cut-off date for citation counts should be left longer because this will provide enough time for some publications to receive more citation rates. (4) The interviews or in-depth surveys regarding the relationships between citing and cited authors are required to create a more precise model of research productivity. (5) The field experiments along with in-depth interviews as widely used in psychology papers can be applied to investigate the causality of the discrimination to understand the comprehensive views of the issue. (6) The further research in this area requires the careful application of the proper measurements, which is to reduce the misleading results and enhance its implication. In this case, H-index can be used as the suitable measurement for individual level.

In regard to the winner effect, (7) researchers who work on the inequality issue such as the Matthew effect should consider observing the data in other sources where abundant sample is provided. (8) More variables should be considered such as the prestige and proficiency of the corresponding authors of the papers to investigate the other factors that might effect.

These suggestions should help further studies produce an adequate and comprehensive model to understand the association of composition of teams and research productivity, the effect of physical attractiveness on research productivity and other areas, and the role of the winners towards the publication success. This thesis also extends the existing literature on discrimination in academia. Specifically, the findings break the new ground in labour economics through exploring the role of physical attractiveness in the context where there is no or limited face-to-face interaction such as academic publishing. We hope that further studies will shed more light on the issue of collaboration and discrimination either in academia or other areas.

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