Beautiful Minds: Physical Attractiveness and Research Productivity in Economics*

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Abstract

We study the impact of physical attractiveness of on productivity. Previous literature found a strong impact on wages and career progression, which can be either due to discrimination in favor of good-looking people or can reflect an association between attractiveness and productivity. We utilize a context where there is no or limited face-to-face interaction, academic publishing, so that scope for beauty-based discrimination should be limited. Using data on around 2,000 authors of journal publications in economics, we find a significantly positive effect of authors' attractiveness on both journal quality and citations. However, the impact on citations disappears after we control for journal quality.

Keywords: Attractiveness; productivity; discrimination; higher education.

JEL Codes: I20; J24; J70; O30

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1. Introduction

Economists have long been observing that wages depend on various characteristics. Some of these, for example education and experience, directly reflect workers' productivity (see, for example, the overview by Heckman, Lochner and Todd, 2006). Others, however, capture market returns to observable characteristics such as gender, ethnicity/race, age, or marital status that should have little bearing on productivity (the seminal contribution on the economics of discrimination is Becker, 1971). The latter include also the so-called 'halo effect' or 'physical attractiveness premium whereby beauty gets rewarded by higher wages. This observation was initially made by psychologists who argue that physical attractiveness serves as a signal for intelligence and sociable behavior (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 thought 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 has a positive return in the labor market. Physical attractiveness can play 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 labor market outcomes has been shown across all sectors, and holds both in high-visibility (high frequency of person-to-person interactions) occupations and in low-visibility occupations. We often see that jobs 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 occupations that require a low degree of public exposure (Cash *et al*., 1977; Watkins and Johnston, 2000).

Although most of the literature finds that attractiveness is beneficial in the labor market, some studies show the opposite effect. In particular, the reverse beauty bias was found for female job candidates applying for traditionally masculine jobs (Cash *et al*., 1977; Heilman and Saruwatari, 1979; Johnson *et al*., 2010). In contrast, male candidates tend to benefit from attractiveness irrespective of the occupation.[4]

[4] Johnson *et al*. (2010) conducted an experiment in which they asked participants to match photos of attractive and unattractive men and women with job descriptions. Attractive men were matched with all sorts of jobs. However,

Facial beauty seems to be a proxy for desirable behavior as beauty is associated with friendliness. Since people desire to interact with friendly and cooperative people, attractiveness conveys an advantage. Indeed, the preference for beauty appears innate: newborn 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 favor 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 rules concerning discrimination based on physical attractiveness (Watkins and Johnston, 2000). Apart from the labor market aspect, physical attractiveness 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).

In this paper, we address the role of physical attractiveness in beauty-neutral situations with no or limited face-to-face interaction: the publishing success and citations of academics. The decision on publication is made by editors who act upon advice of reviewers. Typically, neither meets the author in person as part of the review process. When the review process is double-blind, the reviewers do not even have any identifying information about the authors. The attractiveness of authors therefore presumably should not be linked with publication

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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). Instead, attractive women were matched with jobs such as receptionists and secretaries.

productivity; instead, factors such as intellectual ability and analytical and communicative 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 beauty bias in academic publishing. This question therefore forms the basis for this study: is there is a relationship between physical attractiveness and productivity in academic publishing, a context characteristic by low degree of face-to-face interaction? To this effect, we collect an extensive data set on around 2,000 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 introduces our data and methodology. Section 4 presents the results with an emphasis placed on the impact of beauty on research productivity. Finally, Section 5 concludes.

2. Returns to attractiveness: what do we know?

Under ideal circumstances, job applicants should have an equal opportunity to be hired regardless of non-job related factors such as gender, race, religion, and skin color. This is because these characteristics are irrelevant to labor productivity, which should the main factor considered when making decisions on hiring, promotion or wage rate. That is to say, an unattractive candidate with adequate educational qualifications and job experience should have the same opportunity to be hired as an attractive candidate. However, the literature is replete with evidence of discrimination in the labor market in a broad range of contexts. Minority groups often face discrimination in hiring: 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 generally non-whites in white societies (Riach and Rich, 2002; Carlsson and Rooth, 2007; McGinnity and Lunn, 2011). Other, health-related factors such as height and obesity, matter too. Harper (2000) finds evidence for a height premium in wages, while Harper (2000) and Rooth (2009) demonstrate the existence of an obesity penalty.

While economists tend to focus on the relationship between socio-economic characteristics and labor-market outcomes, the issue of physical attractiveness of an individual has been examined by psychologists widely. Laboratory studies explore the effect of beauty in different social interactions to determine why beauty is a desirable trait. These experiments show that attractive people are seen as more cooperative in the public goods game (Andreoni and Petrie, 2008), more trustworthy in the trust game (Wilson and Eckel, 2006), are offered higher wages (Mobius and Rosenblat, 2006), and receive higher negotiation offers in the ultimatum game (Solnick and Schweitzer, 1999) than unattractive ones. According to Eckel and Wilson (2004), physical attractiveness is often used as a clue when forming an opinion about the cooperativeness and trustworthiness of an unknown person. Andreoni and Petrie (2008), furthermore, find that the impact of beauty disappears when information about the actual job performance of the individual in question is available, though the perceived cooperativeness is still expected to boost the individual´s job performance. Moreover, attractive people are expected to be more intelligent than less attractive ones (Langlois *et al*., 2000; Zebrowitz *et al*., 2002; Kanazawa and Kovar, 2004). An experiment by Zebrowitz *et al*. (2002) finds that beauty is used as a proxy for intelligence: the more attractive an individual is found to be, the more intelligent he or she is assumed to be. Kanazawa and Kovar (2004) propose a theory that describes why intelligence positively corresponds to physical attractiveness. Accordingly, more intelligent men have greater possibility to attain higher socio-economic status than less intelligent ones. Higher-status individuals, in turn, fare better in the mating market, and therefore have a better change to pass on their intelligence and attractive genes to the next generation.

In contrast to the emphasis on the correlation between attractiveness and attitudes and skills (perceived or actual) in psychology, the study of the effects of beauty in economics began with its impact on labor-market outcomes. The general consensus is to agree that beauty discrimination exists in the labor market, both in recruitment (Watkins and Johnston, 2000; Dipboye and Dhahani, 2017) and wage determination (Frieze *et al*., 1991; Hamermesh and Biddle, 1994; Biddle and Hamermesh, 1998; Harper, 2000; Bowles *et al*., 2001; French, 2002; Mobius and Rosenblat, 2006; Fletcher, 2009; Scholz and Sicinski, 2015). Frieze, Olson and Russell (1991) investigate how physical attractiveness is associated with wages using longitudinal data of 737 MBA graduates. The results show that more attractive males have higher starting wages than unattractive males and the difference persists 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 ones. A follow-up paper by Biddle and Hamermesh (1998) extends their earlier study using a large sample of law school graduates by tracing their earnings over time. They also find a positive relationship between physical attractiveness and wages based on the rating of pre-graduation photos. After five years of experience, physically attractive attorneys earned more than others, and the difference increased with experience. Hamermesh (2011) confirm that physically attractive people earn more than average-looking people, and are also employed sooner, promoted more quickly, and tend to be appointed to higher ranking jobs.

Arunachalam and Shah (2012) offer an interesting perspective on the beauty premium in earnings by considering a profession where attractiveness is generally thought to play a very important role: prostitutes. Using data on earnings of a sample of sex workers in Mexico and Ecuador, they find, somewhat surprisingly, that the attractiveness premium in the oldest profession is approximately the same as in other occupations. Moreover, accounting for communication skills and personality features of the sex workers approximately halves the premium.

The findings concerning the effect of physical attractiveness on labor-market outcomes by gender are mixed. Some studies found no evidence of gender difference regarding the impact of beauty on earnings (Hamermesh and Biddle, 1994; Harper, 2000; Fletcher, 2009) while other studies reveal gender-specific effects. For instance, French (2002) found a beauty premium only for females while Roszell, Kennedy and Grabb (1989) and Rooth (2009) found beauty effects only for men. Similarly, some research suggests attractiveness premium and plainness penalty need not be both present at the same time. For instance, Harper (2000) finds evidence for the plainness penalty only while Robins, Homer and French (2011) find beauty premium only. Harper (2000) examines the effect of physical attractiveness of 7 and 11 year-olds on their labor market outcome after 26 and 22 years respectively, using British longitudinal data from the National Child Development Study (NCDS). He concludes that the importance of physical attractiveness for men was the same as it was for women. The plainness penalty for men (15%), however, was higher than for women (11%). The bias in favor of good-looking people goes beyond the labor market. Hamermesh (2011) even reveals that attractive people fare better with respect to getting loan applications approved and are offered lower interest rates than unattractive individuals with similar demographic characteristics (e.g., age, gender) or credit history.

Research has shown benefits of attractiveness in a wide range of socio-economic outcomes beyond the labor market. Hamermesh (2006) considers candidates' appearance on the ballots in the annual elections of officers of the American Economic Association between 1996 and 2004. Since the same candidate can participate multiple times, often with different pictures. The results indicate that an increase in beauty enhances the probability to be elected. Attractive people have the upper-hand also in politics. Berggren, Jordahl and Poutvaara (2010) confirm the existence of beauty advantage in local elections in Finland. Physical attractiveness had positive impact on the probability of being elected for non-incumbent candidates, both male and female. However, there was no significant impact of physical attractiveness for incumbent candidates. The difference between non-incumbent and incumbent candidates suggests that votes use attractiveness as a proxy for competence and trustworthiness of candidates whose have no track record of prior performance in office.

The relationship between beauty and performance seems to exist 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) discusses a study conducted by the New Scientist, indicating correlation between perceived attractiveness and athletic performance of professional male tennis players. The research team randomly picked 20 tennis players in the world top 100, with two players in each decile, based on the 2008 ranking. 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 athletic performance was measured by Association of Tennis Professionals (ATP) Tour ranking points in the 2008 season and the winning percentage in the 2008 season. The research suggests that the correlation between attractiveness and player's is not statistically significant. When using the percentage of matches each tennis player won in 2008, however, the result shows a weak but statistically significant correlation. The research team were undecided over which measurement is more accurate as a proxy for tennis player's performance. Ranking is a good measure for players who compete in many tournaments but is unfair to those with injuries. On the other hand, winning percentage provides a better measure of ability but reflects not only the player's own performance but also that of his opponents. Though this study was conducted informally and the measurement of athletic ability was ambiguous, the findings suggest that there may be a correlation between beauty and athletic performance.

Williams, Park and Wieling (2010) examine the correlation between attractiveness and performance of NFL quarterbacks, using passer score (completed passes, yardage gained, and touchdowns) as a measure of performance. The researchers asked 60 female university students in the Netherlands to rate pictures of quarterbacks who played in the 1997 season (30 photos), and those who played in 2007 season (58 photos). The results showed statistically significant correlation between good looks and the passer score. However, the effects were small. Postma (2014) collected 80 pre-race pictures of cyclists participating in the 2012 Tour de France. These were rated by volunteers for 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. Likeable cyclists were not more likely to win or were perceived as more masculine or attractive. However, there was a relationship between attractiveness and performance. The findings support the idea that attractiveness is a plausible factor of sports performance, at least for men.

Attractiveness also matters for student performance. Deryugina and Shurchkov (2015) find that attractive female university students tend to get better marks. This is confirmed by Hernández-Julián and Peters (2015), but only for the students participating in person; beauty makes no difference for those taking an online course.

Finally, physical attractiveness is also correlated with several other favorable outcomes: success in the mating market (Fisman *et al*., 2006; Jokela, 2009; Gangestad and Scheyd, 2005); happiness and mental health (Hamermesh and Abrevaya, 2013; Farina et al., 1977; Buddeberg-Fischer et al., 1999), physical health (Rhodes et al., 2003; Thornhill and Gangestad, 2006).

In summary, the aforementioned studies suggest two alternative explanations for the beauty premium. First, physical attractiveness can be a signal of higher productivity because it is correlated with (actual or perceived) desirable traits such as better physical and mental health, higher intelligence and sociability, trustworthiness and competence, and the like. Second, the beauty premium can be the result of taste-based discrimination in favor of attractive individuals. By focusing on a context in which merit and ability should play a crucial role and the potential for taste-based discrimination should be limited or non-existent, such as academic publishing, it should be possible to examine whether beauty indeed signals higher productivity or not. So far, the evidence of this kind is scarce. To the best of our knowledge, the only other study considering the impact of attractiveness on research productivity is Dilger, Lütkenhöner, and Müller (2015) who find that good looking academics publish in higher ranked journals and are also considered as more likeable and trustworthy. Their study, however, is only based on a small sample of 49 academics, who all attended the same conference. One might therefore question whether the results of such a small and selective sample could be generalized to academics in general. Our study, instead, is based on a diverse and large sample of some 2000 authors who published their research in a broad range of journals in economics.

3. Methodology

Data

The data for our analysis were collected from 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 to be broadly representative of the publication output of the profession of economists: both general and field journals are included, and the lists includes also journals that are associated with a particular geographical area (Europe, United Kingdom, and Germany). We collected information on all articles published in these journals in 2012, with the exception of special or conference issues. This resulted in a sample of 1,512 papers written by 2,800 authors. We also collected detailed information on the authors: their name, affiliation, gender, race, institution and country of undergraduate degree and PhD, the years of their undergraduate degree and PhD, academic rank, and photo (if available). This information was collected from multiple sources such as professional and/or personal webpage, curriculum vitae, and institutional website. Gender and ethnicity were coded by us based on the author’s picture (and name when picture was not available and the gender could be unambiguously inferred from the name). All of the information collected, including the author’s photo (if available), were in the public domain at the time of collection. Furthermore, we also collected article details: title of article, journal volume and issue, start page, end page, number of co-authors, citations, journal rank, and journal impact factor. The summary statistics are presented in Table 1.

Table 1 Summary statistics: Authors

Authors	**N**	**Mean**	**Std.Dev.**	**Min**	**Max**
No. of coauthors	2,800	2.535	1.002	1	8
Female	2,800	0.174		0	1
Ethnicity					
White	2,800	0.801		0	1
Black	2,800	0.011		0	1
South Asian	2,800	0.059		0	1
East Asian	2,800	0.114		0	1
Middle Eastern	2,800	0.015		0	1
Rank					
Assistant professor	2,800	0.203		0	1
Associate professor	2,800	0.194		0	1
Professor	2,800	0.399		0	1
Other	2,800	0.194		0	1
Rank N/A	2,800	0.009			
Country of UG degree					
Low income	2,800	0.036		0	1
Lower middle income	2,800	0.063		0	1
Upper middle income	2,800	0.069		0	1
High income	2,800	0.611		0	1
Country N/A	2,800	0.221			
UG year	1,953	1992	10.24	1956	2012
PhD year	2,343	1999	9.945	1960	2017
Work experience (after PhD)	2,322	12.94	9.936	0	52
Citations Scopus	2,800	5.676	9.579	0	94
Citations Google Scholar	2,800	29.21	58.09	0	616
Keele list rank	2,800	2.796	0.840	1	4
ERA list rank	2,800	3.379	0.615	2	4
Journal impact factor	2,800	1.368	1.087	0.404	5.278
Weighted productivity	2,800	0.260	0.148	0	0.886
Average productivity	2,800	0.299	0.173	0	0.924
Average normalized citations	2,800	0.054	0.095	0	0.968
Average beauty score	2,800	3.885	1.041	1.100	7.550

The authors in our sample are predominantly males: 82.6%, while females account for only 17.4%. 8.5% of all authors published more than once in the journals included in our sample, and several published 4 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%.[5] 83.7% of the authors hold a PhD degree and the working experience (defined as the difference between the

[5] For authors at universities that follow the British system of academic ranks, we classify both senior lecturers and readers as associate professors. The ‘other’ category includes postdocs at universities, as well as researchers at research institutions (which do not engage in teaching), and employees working for international organizations or government institutions.

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 (61.1% of authors in our sample), upper and lower middle income (6.9% and 6.3%, respectively), and low income countries (3.6%); the information on the country of undergraduate degree was not available for approximately one fifth of the authors. Work experience is computed as the number of years since the author has received their doctoral degree until the publication year (2012). The average author received their PhD in 1999 (and undergraduate degree in 1992), giving them some 13 years of post-PhD work experience.

Besides collecting some basic information on the authors, we also rated their attractiveness. To this effect, we circulated a number of online survey links to potential participants at Brunel University and elsewhere, using direct communication, email and social networks. Each online survey collected basic background information on the assessor (gender, age, ethnicity, highest education, and whether they are currently enrolled as a student) followed by 30 randomly-chosen and randomly-ordered photos, with each picture placed on a separate page. Each participant was asked to complete the survey just once; however, participants could participate in more than one survey (each survey had a separate link; since we collected no identifying information on the raters, we cannot distinguish those participating in more than one survey from those who participated only once). Each rater was asked to rate the attractiveness of the person in the photo on an 11-point scale, from 0 (unattractive) to 10 (very attractive). No information on the photographed individuals was provided and the raters were told that the survey studies the formation of perceptions of beauty. The raters were also asked whether they recognised the person in the picture, or whether the picture did not load properly: in such instances, their scores were excluded from the analysis. The average beauty score was 3.9, with the most attractive academic scoring 7.6 (Appendix J lists the three most attractive female and male researchers included in our analysis).

In total, 1,860 raters participated in the surveys, with each picture rated by at least 20 separate assessors. The summary statistics on the raters are reported in Table 2. The raters were approximately equally split across the two genders, with 44.8% being male and 55.2% female.

58.3% of all assessors are between 25 and 34. East Asians forms the biggest proportion (50.9%), followed whites (31.3%). 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). Given that many of them were recruited at a university, they tend to be relatively young: the vast majority of them are younger than 35. 45.2% of all assessors were 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, followed by 19.8% with a PhD.

Table 2 Summary statistics: Raters

	N	**Mean**
Age	1,860	
18 to 24	532	0.286
25 to 34	1085	0.583
35 to 44	207	0.111
45 to 54	26	0.014
55 to 64	8	0.004
65 to 74	2	0.001
75 or older	0	0
Female	1,860	0.552
Ethnicity	1,860	
White	583	0.313
Black	64	0.034
South Asian	152	0.082
East Asian	947	0.509
MENA	82	0.044
Other	32	0.017
Education	1,860	
Less than high school	18	0.010
High school or equivalent	248	0.133
Bachelor degree	604	0.325
Master degree	606	0.326
PhD	368	0.198
Other	16	0.009
Currently student	840	0.452

Methodology

Dependent variable

The outcome of interest in this research is the quality of publications. Research productivity is a crucial element of academic appraisal process such as academic hiring, decision on tenure and promotion, and funding proposal approval. This can be measured in several ways depending on the context. The amount of publications per researcher is to be the norm in bibliometrics as a gauge of individual research productivity. However, this measure fails to take account of quality. A number of other indicators and methods have been formulated to evaluate the quality of an individual author's publication output, such as the h-index, citation count, journal impact factor, and altmetrics. The h-index is an indicator that quantifies an individual's scientific research output using databases such as Web of Science, Scopus, and/or Google Scholar. However, there are drawbacks to using the h-index as it does not adjust for the number of co-authors and their relative contributions (Petersen *et al*., 2012). The citation analysis counts the number of times that article has been mentioned in other works. Various databases collect citation counts including Web of Science, Scopus, and Google Scholar. Citations can be used as a measure of both individual productivity and quality of specific publications. The journal impact factor, in turn, is a measure applied to journals, as it measures the average number of citations attained during a given year for articles published in that journal during the previous two years. A peculiar problem pertaining to both citation count and journal impact factor is that they can be manipulated by self-citation (at the level of individual authors, or journals). 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. Using a single bibliometric indicator as a sole measure cannot give a full picture of collaboration, impact and productivity. Consequently, applying multiple indicators with complementary is preferable. Since we measure the quality of individual papers, we combine measures that reflect the average quality of the journal in which the paper was published – journal rank and journal impact factor – with paper-specific citation counts.

Recall that all papers included in our analysis were published in the course of 2012. Citation counts were collected from the Scopus and Google Scholar databases in March 2015 so as to provide enough time for the articles to be cited. For journal rank, 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 ERA list is a list used by Australian government to evaluate the quality of research output of Australian universities, and to allocate research funds to them. The Keele list is a list compiled by faculty members at Keele University in the UK who sought to infer the ranking used by the UK government in its Research Assessment Exercise (subsequently replaced by the Research Excellence Framework). The Journal Impact Factor (JIF) is the average number of citations received during a given year by 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.

The ERA and Keele lists assign five values to journals, from 0 (lowest quality) to 4 (highest). Citation counts and journal impact factor, in principle, have no upper bounds. Scopus and Google Scholar (GS) count citations in other articles included in their respective databases. The bar for inclusion in GS is substantially lower than that for Scopus, which leads to GS citations being several fold higher than those reported by Scopus. To ensure that the various measures of research output that we use are comparable, all are normalized. We apply the Min-Max normalization to rescale the original values to the range [0,1]:

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

where x_i is the value pertaining to the research output in question and z_i is its normalized value.

We then calculate the average of normalized citation rates from both databases and also calculate the average of normalized journal ranking indexes from both lists. We then calculate the dependent variable as the average of normalized citations, normalized journal rankings, and the normalized 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 weighted productivity index and average normalized citation count. The weighted productivity, which we consider as our main dependent variable, combines normalized citations from Scopus and Google Scholar (together with a weight of 50%), normalized journal ranking from Excellence in Research for Australia (ERA) and the Keele list (together 30%), and normalized journal impact factor from Thomson Reuters Journal Citation Reports (20%). Hence, citations carry a weight of 50%

rather than one third. Finally, we also use the average normalized citations as a metric of research productivity pertaining specifically to individual papers.

The summary statistics on our measures of research output are also included in Table 1. The average author in our sample has 6 and 29 citations on Scopus and GS, respectively, and has published their paper in a journal ranked approximately 3 by both ERA and Keele and with an impact factor of 1.4.

Independent variables

Our main independent variable of interest is the average attractiveness score obtained by means of surveys (see above). The rest of control variables capture the authors' personal and professional background, and article characteristics. The only indicator pertaining to the article is the team size, indicating the number of authors of the article. The number of authors has been found to have a positive impact on citations (Sooryamoorthy, 2009; Gazni and Didegah, 2011). Bornmann (2015) finds that each additional author or each additional page of an article translate into 4% more citations. The author characteristics include gender, ethnicity, economic development in the country of their undergraduate degree, and professional rank. It is possible that physical attractiveness is of more importance for some ethnic groups than for others and/or that its effect differs by gender. Therefore, we also include interaction terms involving attractiveness and ethnicity/gender in the model.

Regression Strategy

The impact of physical attractiveness on labor market outcomes can be estimated using a broad range of different strategies. For example, much of the previous literature on the beauty premium in wages uses the earnings function (Harper, 2000; French, 2002; Fletcher, 2009). However, obtaining the pay of the authors used in our study would be all but impossible. Therefore, we instead estimate a productivity function, so that our results capture the impact of physical attractiveness on quality of publications and citations:

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

where *Productivity* denotes the research productivity (average, weighted-average, or citations); *Beauty* is the average beauty score; *Gender* equals 1 if the author is female and 0 otherwise; *Ethnicity* stands for a set of ethnicity dummies (with white left out as base category); *Country* refers to dummies for country classification according to their level of development (high-income being the omitted one); *Rank* is a set of dummies reflecting academic rank (with full professor being the base category); *TeamSize* captures the number of authors in the research team; *WorkExperience* denotes the accumulated years of work experience (years since obtaining the PhD degree), which we include as a linear term or quadratic polynomial; $Gender_i * Beauty_i$ and $Ethnicity_i * Beauty_i$ are interaction terms to capture whether beauty has a different effect across genders and/or ethnic groups; and, finally, α is the intercept.

Prior to running the regressions, we test whether parametric or non-parametric methods are suitable. The dependent variables (i.e., weighted productivity, average productivity, and average normalized citations) are found to be skewed with a long right tail (see Appendix B). Standard regression techniques are suitable only when the regression assumptions of homoscedasticity and normality are met (Koenker and Bassett Jr., 1978; Dimelis and Louri, 2002; Hao and Naiman, 2007). Therefore, we employ the quantile regression (Baum, 2013) which, as a non-parametric method, is more appropriate. Quantile regression relaxes the regression assumptions and offers a comprehensive view of the impact of independent variables on the central and non-central locations, shape, and scale of the distribution of the dependent variable. This technique, furthermore, is robust to outliers, unlike OLS, and 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). Because of this, in our discussion of the results, we focus on the estimates obtained with quantile regression, and report OLS results primarily for the sake of verifying their robustness.

4. <u>Results</u>

We report regression results for OLS and median (0.5^{th} quantile) regressions with the weighted productivity as the dependent variable in Table 3. First, we control for authors' physical attractiveness, 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 little, as the quadratic term is not statistically significant. Finally, we add interaction terms involving gender and beauty, and ethnicity and beauty (columns 5 and 6).

In all specifications, the effect of attractiveness on research productivity is positive and highly significant. Considering columns 5 and 6, the coefficient of the average beauty score in the median regression is 0.0389, which is slightly higher than the OLS coefficient, 0.302. Therefore, an increase in attractiveness by one point on the 11-point attractiveness scale would translate into an increase in weighted productivity by 0.0389, or approximately by 15% (given that the mean of the dependent variable is 0.260). Besides good looks, co-authors, experience, and economic development in the country of undergraduate degree also correlate with research productivity (both in OLS and median regressions). Each additional co-author increases weighted productivity by 0.0246, or 9.5%. Additional ten years of experience, in contrast, reduces productivity by 0.0157, or 6%: this may reflect the lower career pressure faced by more experienced researchers, as well as the fact that experienced researchers may face many additional demands on their time (such as administrative responsibilities) besides research. Finally, being from a country which is not a high-income economy has negative impact on research productivity. The size of this impact is inversely proportional to the level of economic development. It is greatest for low income countries, reduction of weighted productivity by 30% (-0.08/0.26) in the OLS model and by 32% (-0.833/0.26) in the median regression compared to high-income-country authors, followed by lower middle-income countries (-20% and -27% in the OLS and median models, respectively), and lowest for upper middle income countries (-14% and -23% in the OLS and median models, respectively).

The results obtained with average productivity, reported in Table 4, are very similar. The coefficient of the average beauty score in median regression 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% (given that the mean of average productivity is 0.299). The effects of the number of coauthors, work experience and economic development are also similar to those discussed above. However, work experience is not statistically significant in the median model while it is significant ($p<0.01$) with the negative effect on research productivity in the OLS model.

When using the average normalized citations as the dependent variable, we find that the constant of most models is not statistically significant (see Appendix C). It might be the effect of the right-skewed response variable, the average normalised citations (Appendix B).

To deal with this issue, we apply a log transformation on the response variable, in this case, the average normalized citations. After taking log transformation, the skewness changes from 4.81 to -0.38 and the kurtosis changes from 33.61 to 3.14, and the constant of all models is statistically significant. Table 5 column (5) shows that each additional point of the beauty score increases the average normalized citations by a factor of $e^{0.167} = 1.1817$, which indicates a 18.17% increase, in the OLS regression. The corresponding median-model (Table 5 column 6) shows a coefficient of 0.13, which indicates that each additional score of the average beauty score increases the average normalized citations by $e^{0.13} = 1.1388$, or a 13.88% increase. Therefore, the effects of average beauty score on average normalized citations are similar in magnitude to those on weighted and average productivity as reported above.

For team size, each additional author in the research team increases the average normalized citations by a factor of $e^{0.281} = 1.3245$, which indicates a 32.45% increase in the OLS model, and by a factor of $e^{0.318} = 1.3744$, a 37.44% increase, in the median regression. The coefficient of work experience is negative, -0.0152. The factor would be $e^{-0.0152} = 0.9849$, that is, a 1.5% decrease in average normalized citations for each additional year of experience under OLS. The corresponding median-model effect (Table 5 column 6) is -0.0113. The factor would be $e^{-0.0113} = 0.9888$, that is, a 1.12% decrease in average normalized citations for each additional year of work experience.

The reference category for the country development variable is high-income country. According to OLS results (Table 5 column 5), authors who obtained their undergraduate degree in a low-income country receive approximately half the citations of an author from a high-income country: the coefficient of -0.601 translates into a factor of $e^{-0.601} = 0.548$. The OLS coefficient for upper middle-income country is -0.356, or a factor of $e^{-0.356} = 0.700$, 30% less than high-income-country authors. The corresponding median-model effects (Table 5 column 6) are 60% ($e^{-0.892} = 0.41$) and 34% ($e^{-0.416} = 0.66$) lower citation counts for low-income and upper-middle-income country authors, respectively. Note that the effects of being from an upper-middle-income country are not significant in the regressions for citations.

Other variables, such as academic rank or ethnicity, are either insignificant or significant only inconsistently. The interactions with gender and ethnicity are likewise mainly insignificant, suggesting that the impact of beauty on research productivity is largely the same across both genders and all ethnic/racial groups.

Table 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***	0.0326***	0.0274***	0.0353***	0.0302***	0.0389***
	(0.0033)	(0.0053)	(0.0041)	(0.0036)	(0.0042)	(0.0066)
Female	-0.0230**	-0.0274	-0.0239*	-0.0306*	0.0420	0.0504
	(0.0076)	(0.0154)	(0.0104)	(0.0127)	(0.0334)	(0.0560)
Black	0.0191	0.0358	0.0207	0.0339	0.223	0.0961
	(0.0429)	(0.0555)	(0.0465)	(0.0461)	(0.1911)	(0.2714)
South Asian	0.0569***	0.0692*	0.0559***	0.0657*	0.0802	0.0671
	(0.0154)	(0.0343)	(0.0147)	(0.0319)	(0.0590)	(0.0936)
East Asian	-0.0270*	-0.0436**	-0.0267**	-0.0377*	-0.0630*	-0.0316
	(0.0130)	(0.0136)	(0.0100)	(0.0183)	(0.0313)	(0.0392)
MENA	0.00573	-0.0273	0.00581	-0.0189	0.136	0.0852
	(0.0232)	(0.0236)	(0.0245)	(0.0374)	(0.1600)	(0.1970)
Low income country	-0.0745***	-0.0878***	-0.0741***	-0.0876**	-0.0781***	-0.0833**
	(0.0211)	(0.0265)	(0.0190)	(0.0286)	(0.0204)	(0.0295)
Lower middle income country	-0.0503***	-0.0699***	-0.0497***	-0.0764***	-0.0518***	-0.0699**
	(0.0116)	(0.0179)	(0.0108)	(0.0189)	(0.0131)	(0.0213)
Upper middle income country	-0.0356**	-0.0641**	-0.0359**	-0.0710***	-0.0354**	-0.0606***
	(0.0111)	(0.0196)	(0.0117)	(0.0207)	(0.0108)	(0.0170)
Assistant professor	-0.0225*	-0.0136	-0.0152	0.00128	-0.0223*	-0.00995
	(0.0108)	(0.0199)	(0.0127)	(0.0201)	(0.0100)	(0.0137)
Associate professor	-0.0283**	-0.0156	-0.0264*	-0.0146	-0.0282**	-0.0171
	(0.0102)	(0.0162)	(0.0107)	(0.0197)	(0.0098)	(0.0141)
Other occupations	-0.0331**	-0.0266	-0.0280	-0.0145	-0.0333**	-0.0230
	(0.0113)	(0.0203)	(0.0144)	(0.0204)	(0.0117)	(0.0196)
Teamsize	0.0234***	0.0236**	0.0229***	0.0240**	0.0232***	0.0246***
	(0.0057)	(0.0085)	(0.0053)	(0.0079)	(0.0054)	(0.0067)
Work experience	-0.00150**	-0.00156	0.000506	0.00258	-0.00151**	-0.00157*
	(0.0005)	(0.0009)	(0.0012)	(0.0019)	(0.0005)	(0.0007)
Work experience squared			-0.0000490	-0.000104*		
			(0.0000)	(0.0001)		
Female*Average beauty score					-0.0145*	-0.0175
					(0.0073)	(0.0134)
Black*Average beauty score					-0.0629	-0.0154
					(0.0531)	(0.0874)
South Asian*Average beauty score					-0.00597	0.000965
					(0.0169)	(0.0268)
East Asian*Average beauty score					0.00999	-0.00335
					(0.0083)	(0.0094)
MENA*Average beauty score					-0.0396	-0.0307
					(0.0462)	(0.0558)
Constant	0.162***	0.138***	0.146***	0.0956**	0.151***	0.109**
	(0.0228)	(0.0413)	(0.0297)	(0.0346)	(0.0260)	(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 4 The 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	0.291	0.152
	(0.0640)	(0.0576)	(0.0552)	(0.0636)	(0.2605)	(0.2737)
South Asian	0.0731***	0.0982*	0.0721**	0.0920**	0.0906	-0.00438
	(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	0.181	0.0924
	(0.0310)	(0.0326)	(0.0298)	(0.0203)	(0.1704)	(0.2448)
Low income country	-0.0910**	-0.115***	-0.0905***	-0.116***	-0.0951***	-0.116***
	(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	0.00751	-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	-0.00173**	-0.00157	0.000530	0.00371	-0.00175**	-0.00163
	(0.0006)	(0.0011)	(0.0014)	(0.0023)	(0.0007)	(0.0012)
Work experience squared			-0.0000552	-0.000137*		
			(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					-0.00392	0.0290
					(0.0173)	(0.0343)
East Asian*Average beauty score					0.0120	-0.00299
					(0.0127)	(0.0123)
MENA*Average beauty score					-0.0513	-0.0350
					(0.0460)	(0.0694)
Constant	0.187***	0.144***	0.169***	0.0988*	0.172***	0.115*
	(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

Table 5 The 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	0.162***	0.128**	0.164***	0.123**	0.167***	0.130**
	(0.0390)	(0.0450)	(0.0369)	(0.0404)	(0.0485)	(0.0483)
Female	-0.229*	-0.176	-0.231*	-0.167	-0.0909	0.0665
	(0.0937)	(0.1210)	(0.0994)	(0.1053)	(0.4172)	(0.4831)
Black	-0.130	-0.00287	-0.126	0.00298	1.772	2.322
	(0.4399)	(0.5120)	(0.3349)	(0.4325)	(1.7550)	(1.7451)
South Asian	0.334	0.468*	0.332*	0.470*	0.340	0.504
	(0.1959)	(0.2162)	(0.1575)	(0.2348)	(0.6104)	(0.5182)
East Asian	-0.300*	-0.425**	-0.299**	-0.440**	-0.637	-1.029
	(0.1388)	(0.1485)	(0.1140)	(0.1475)	(0.4277)	(0.5515)
MENA	0.0454	0.167	0.0445	0.165	1.733*	0.965
	(0.1864)	(0.2433)	(0.1951)	(0.1905)	(0.7867)	(1.2706)
Low income country	-0.565*	-0.824**	-0.564**	-0.846***	-0.601**	-0.892**
	(0.2636)	(0.2526)	(0.1868)	(0.2449)	(0.2284)	(0.3113)
Lower middle income country	-0.126	-0.235	-0.125	-0.251	-0.129	-0.271
	(0.1402)	(0.1700)	(0.1515)	(0.1531)	(0.1134)	(0.1609)
Upper middle income country	-0.357**	-0.454***	-0.357**	-0.449***	-0.356**	-0.416**
	(0.1129)	(0.1254)	(0.1127)	(0.1341)	(0.1250)	(0.1331)
Assistant professor	-0.322**	-0.236	-0.304**	-0.268	-0.323***	-0.248*
	(0.1099)	(0.1306)	(0.1135)	(0.1628)	(0.0949)	(0.1178)
Associate professor	-0.278**	-0.138	-0.273**	-0.165	-0.281**	-0.154
	(0.0995)	(0.1128)	(0.0988)	(0.1114)	(0.0894)	(0.1127)
Other occupations	-0.174	-0.138	-0.161	-0.176	-0.179	-0.139
	(0.1139)	(0.1523)	(0.1202)	(0.1528)	(0.0982)	(0.1578)
Teamsize	0.282***	0.323***	0.281***	0.327***	0.281***	0.318***
	(0.0359)	(0.0518)	(0.0388)	(0.0493)	(0.0288)	(0.0439)
Work experience	-0.0151***	-0.0109	-0.0102	-0.0172	-0.0152***	-0.0113*
	(0.0045)	(0.0058)	(0.0122)	(0.0128)	(0.0041)	(0.0053)
Work experience squared			-0.000120	0.000134		
			(0.0003)	(0.0003)		
Female*Average beauty score					-0.0316	-0.0442
					(0.0886)	(0.1024)
Black*Average beauty score					-0.585	-0.679
					(0.5063)	(0.5727)
South Asian*Average beauty score					0.00547	0.00310
					(0.1628)	(0.1561)
East Asian*Average beauty score					0.0921	0.182
					(0.1094)	(0.1468)
MENA*Average beauty score					-0.510*	-0.239
					(0.2516)	(0.3955)
Constant	-4.509***	-4.418***	-4.549***	-4.347***	-4.519***	-4.402***
	(0.2434)	(0.2537)	(0.2325)	(0.2287)	(0.2473)	(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

Individual Conditional Quantiles

We are also interested in the other quantiles of distribution of productivity in addition to the median. For example, the advantage 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 6. We can see that the impact of average beauty score on research productivity in the center and right tail of the productivity distribution is greater than on the left tail, suggesting that the physical attractiveness matters little for relatively unproductive individuals while it is important for intermediately and highly productive researchers.

Table 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	0.00372 (0.0030)	0.00773** (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)	0.00233 (0.0198)	0.0328 (0.0318)	0.118* (0.0561)	0.0504 (0.0560)	0.0787 (0.0503)	0.0374 (0.0325)	0.0451 (0.0442)	0.0283 (0.0886)
Black	0.268 (0.2751)	0.248 (0.2024)	0.0977 (0.2602)	0.277 (0.2835)	0.0961 (0.2714)	0.0943 (0.2934)	0.00178 (0.3693)	0.171 (0.3662)	0.338 (0.3802)
South Asian	0.0292 (0.0397)	0.00705 (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)	0.110 (0.0859)
East Asian	-0.0306 (0.0477)	0.00101 (0.0139)	-0.00655 (0.0295)	-0.0165 (0.0329)	-0.0316 (0.0392)	-0.0513 (0.0657)	-0.111 (0.0621)	-0.104 (0.0587)	-0.101 (0.0850)
MENA	0.0209 (0.0993)	0.0458 (0.0860)	0.0978 (0.1057)	0.225 (0.1490)	0.0852 (0.1970)	0.166 (0.2433)	0.283 (0.2279)	0.431 (0.2348)	0.581 (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)	-0.102* (0.0436)
Lower middle income country	-0.0343* (0.0168)	-0.00882 (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)	-0.00995 (0.0137)	-0.0158 (0.0106)	-0.0230 (0.0150)	-0.0356 (0.0184)	-0.0247 (0.0214)
Associate professor	-0.00679 (0.0063)	-0.00824 (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	0.00233 (0.0031)	0.00355 (0.0021)	0.00699* (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)	-0.00101** (0.0003)	-0.0018*** (0.0004)	-0.0021*** (0.0005)	-0.00157* (0.0007)	-0.00120** (0.0005)	-0.00136* (0.0005)	-0.00186* (0.0008)	-0.00106 (0.0009)
Female*Average beauty score	-0.00449 (0.0061)	-0.00137 (0.0051)	-0.00960 (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)	0.00469 (0.1078)	-0.0445 (0.1015)	-0.0942 (0.1030)
South Asian* Average beauty score	0.000717 (0.0144)	0.00213 (0.0104)	0.00427 (0.0160)	0.000330 (0.0238)	0.000965 (0.0268)	0.00418 (0.0235)	-0.00246 (0.0199)	-0.00396 (0.0207)	-0.0135 (0.0201)
East Asian* Average beauty score	0.00725 (0.0111)	-0.00220 (0.0039)	-0.00372 (0.0088)	-0.00267 (0.0091)	-0.00335 (0.0094)	0.00116 (0.0178)	0.0251 (0.0164)	0.0210 (0.0146)	0.0190 (0.0230)
MENA*Average beauty score	0.00333 (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)	-0.136* (0.0618)	-0.159 (0.0977)
Constant	0.141*** (0.0174)	0.128*** (0.0131)	0.132*** (0.0230)	0.0896* (0.0358)	0.109** (0.0413)	0.171*** (0.0331)	0.209*** (0.0281)	0.256*** (0.0373)	0.259*** (0.0428)
N	1926	1926	1926	1926	1926	1926	1926	1926	1926

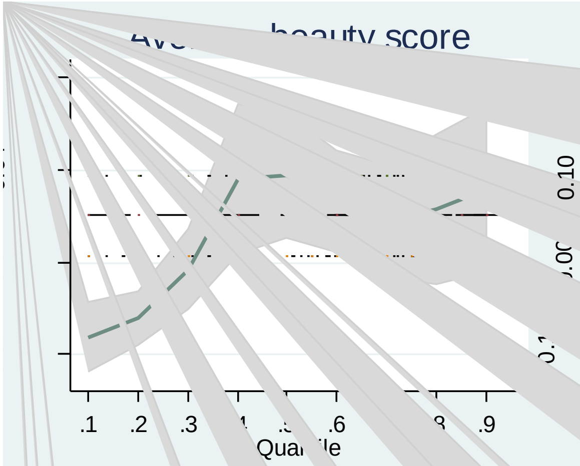
Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

The effect of economic development in the country of origin also changes across the quantiles. Coming from a low-income country has a negative effect in the middle and upper quantiles. Being from a lower middle-income country has a negative impact on research productivity across all quantiles, and constitutes a particularly strong disadvantage in the middle of the range. Upper-middle-income country researchers face a disadvantage especially in the middle quantiles. Associate professors face a negative effect only in the upper quantiles. The size of the research team has a positive effect across all quantiles except the 0.1^{th} and 0.2^{th} quantile, and the size of the effect increases in the higher quantiles: having more authors in the team significantly improves the chance of producing high-quality publications while it matters little for low-quality research. The negative effect of work experience, finally, mainly pertains to the lower and middle quantiles: either because top researchers continue producing high-quality research also later in their career, or because established and well-known academics find it easier to publish their work.

Figures 1a to 1c depict the quantile effects graphically for the main variables of interest: average beauty score, number of authors, and work experience (full sets of graphs for all covariates are summarized in Appendix D, F, and H for weighted productivity, average productivity and log average citations, respectively). The graphs depict the variable impact for each quantile as well as the 95% confidence interval based on bootstrap estimates with 50 repetitions. Figure 1a presents the effect of attractiveness as an upward-sloping line: insignificant at the beginning, then significantly positive and increasing until the 0.4^{th} quantile, and subsequently leveling off. Figure 1b illustrates the effect of the team size, which is significantly positive except for the lowest two quantiles. The effect of each additional co-author is therefore increasing across the quantiles. Finally, the effect of work experience, depicted in Figure 1c, fluctuates and becomes insignificant repeatedly.

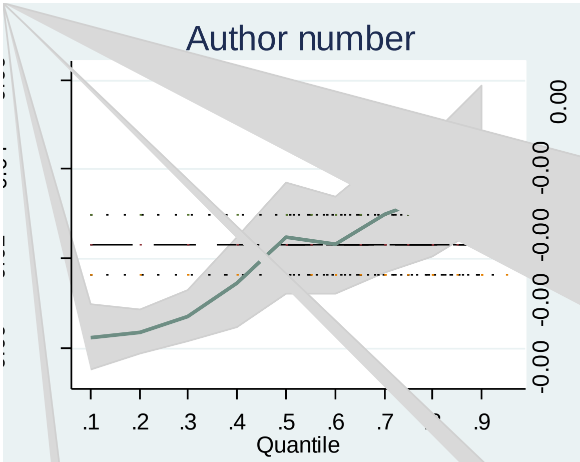
The effect on the average productivity and the log average normalized citations across quantiles are reported in Appendixes E and G, respectively. The results are generally in line with those reported in Table 6, with only small differences in the effects and significance levels of covariates. The impact 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.

Figure 1a Quantile coefficients for weighted productivity



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

Figure 1b Quantile coefficients for weighted productivity



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

Figure 1c Quantile coefficients for weighted productivity

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

5. Robustness

In this section, we test the robustness of the positive relationship between physical attractiveness and research productivity. We first test whether the beauty effect depends on authors' age, then consider only one author per paper, and, finally, re-estimate the impact of beauty on citations while controlling for the quality of the journal in which the article was published.

A plausible reason for the positive association between beauty and research productivity is the possibility that the raters tend to find young authors more attractive. If young authors are more productive (for example, because they face greater career pressure while being in a tenure-track position), then this could explain the positive effect of beauty. If so, then the coefficient of average attractiveness would effectively pick up the effect of authors' age. Therefore, we re-estimate our results for young authors only: since we do not have their exact age, we define young authors as those with up to 10 years of post-PhD work experience. 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 OLS and median regression results are presented in Tables 7-9 for weighted productivity, average productivity and log normalized citations (the results across all quantiles are in Appendix I).

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 of (log of) normalized 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.

Next, we re-estimate the analysis with only one author per paper. Given that most papers included in our analysis have multiple authors, we are effectively including each paper's publication quality and citations several times as dependent variables, explaining them with the individual characteristics of the different co-authors, including their attractiveness. This could, potentially, lead to a bias (for example, if attractive authors are more likely to be matched with similarly attractive co-authors). Therefore, we next consider only the first author of each paper, so as to have exactly one author per paper. The results, reported in Table 10, are again very similar to the baseline findings: the effects of both average beauty score and other variables remain essentially unchanged.

As a final test, we take a closer look at the impact of beauty on citations: while editors and referees may know the identity (and be familiar with the attractiveness) of the authors, and their judgement may therefore be influenced by the authors looks, it is unlikely that citations are driven by similar effects. On the other hand, papers published in better journals tend to reach more readers. Therefore, we next consider the effect of beauty on citations, while controlling for the average journal quality (taking the average of journal rank and impact factor). Table 11 reports the results. The coefficient of the average journal quality (normalized again to range between 0 and 1) is very high and strongly significant: on average, an author publishing in a top journal gets 14 times (median regression) to 17 times (OLS) as many citation as one publishing in a journal with the lowest possible quality. The striking result, however, is the fact that the positive effect of beauty disappears in these regressions. This implies that attractive authors tend to publish in better journals, but do not seem to receive any more citations than less good-looking authors who published in the same or similar journals.

Table 7 The 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***	0.0264***	0.0243***	0.0257***	0.0272***	0.0272***
	(0.0038)	(0.0048)	(0.0048)	(0.0056)	(0.0047)	(0.0072)
Female	-0.0204	-0.0109	-0.0204	-0.0103	0.0697	0.105
	(0.0147)	(0.0184)	(0.0106)	(0.0155)	(0.0435)	(0.0748)
Black	-0.0162	0.0330	-0.0156	0.0331	0.255	0.258
	(0.0370)	(0.0523)	(0.0482)	(0.0526)	(0.1617)	(0.2568)
South Asian	0.0489*	0.0337	0.0485*	0.0350	0.00667	-0.0545
	(0.0194)	(0.0296)	(0.0216)	(0.0300)	(0.0523)	(0.0920)
East Asian	-0.0199	-0.0428	-0.0198	-0.0418*	-0.0850*	-0.0929
	(0.0144)	(0.0220)	(0.0130)	(0.0198)	(0.0399)	(0.0643)
MENA	-0.0182	-0.0357	-0.0173	-0.0362	0.242	0.122
	(0.0285)	(0.0299)	(0.0252)	(0.0432)	(0.2725)	(0.3253)
Low income country	-0.0823***	-0.0972***	-0.0825***	-0.0991***	-0.0862***	-0.0973***
	(0.0220)	(0.0237)	(0.0226)	(0.0285)	(0.0218)	(0.0283)
Lower middle income country	-0.0481**	-0.0785***	-0.0484**	-0.0780***	-0.0491**	-0.0731***
	(0.0150)	(0.0179)	(0.0150)	(0.0218)	(0.0151)	(0.0196)
Upper middle income country	-0.0273	-0.0488	-0.0276	-0.0497	-0.0274*	-0.0566
	(0.0154)	(0.0307)	(0.0160)	(0.0350)	(0.0132)	(0.0347)
Assistant professor	-0.0119	-0.000874	-0.0128	-0.00254	-0.0130	-0.00486
	(0.0150)	(0.0215)	(0.0146)	(0.0217)	(0.0174)	(0.0232)
Associate professor	-0.0173	-0.00410	-0.0173	-0.00418	-0.0174	-0.00990
	(0.0156)	(0.0295)	(0.0161)	(0.0210)	(0.0188)	(0.0243)
Other occupations	-0.0518**	-0.0477	-0.0515**	-0.0487	-0.0544***	-0.0612*
	(0.0197)	(0.0298)	(0.0175)	(0.0255)	(0.0163)	(0.0282)
Teamsize	0.0227***	0.0272**	0.0229***	0.0267***	0.0223***	0.0266***
	(0.0053)	(0.0102)	(0.0056)	(0.0066)	(0.0061)	(0.0080)
Work experience	0.00134	0.00142	0.00418	0.00200	0.000886	0.000892
	(0.0016)	(0.0024)	(0.0071)	(0.0080)	(0.0020)	(0.0026)
Work experience squared			-0.000278	-0.0000536		
			(0.0007)	(0.0008)		
Female*Average beauty score					-0.0194*	-0.0236
					(0.0092)	(0.0153)
Black*Average beauty score					-0.0850	-0.0966
					(0.0528)	(0.0836)
South Asian*Average beauty score					0.0135	0.0206
					(0.0137)	(0.0277)
East Asian*Average beauty score					0.0169	0.0132
					(0.0100)	(0.0153)
MENA*Average beauty score					-0.0769	-0.0517
					(0.0848)	(0.0923)
Constant	0.156***	0.134**	0.150***	0.137**	0.150***	0.141**
	(0.0264)	(0.0480)	(0.0302)	(0.0419)	(0.0298)	(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 8 The impact of beauty on average productivity, OLS and median regression, authors with less than 10 years of working experience

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**QR(0.5)**	**OLS**	**QR(0.5)**	**OLS**	**QR(0.5)**
Average beauty score	0.0298***	0.0309***	0.0298***	0.0307***	0.0335***	0.0351***
	(0.0045)	(0.0064)	(0.0050)	(0.0075)	(0.0044)	(0.0091)
Female	-0.0236	-0.00984	-0.0236	-0.00825	0.0889	0.135
	(0.0164)	(0.0276)	(0.0125)	(0.0257)	(0.0503)	(0.0831)
Black	-0.00960	0.0465	-0.00874	0.0475	0.345	0.357
	(0.0482)	(0.0681)	(0.0492)	(0.0603)	(0.6375)	(0.2598)
South Asian	0.0627*	0.0579	0.0621*	0.0575	0.00224	-0.0434
	(0.0248)	(0.0355)	(0.0297)	(0.0360)	(0.0703)	(0.1024)
East Asian	-0.0203	-0.0462	-0.0202	-0.0464	-0.0923	-0.0883
	(0.0138)	(0.0255)	(0.0170)	(0.0276)	(0.0574)	(0.0711)
MENA	-0.0231	-0.0393	-0.0218	-0.0384	0.292	0.169
	(0.0339)	(0.0496)	(0.0340)	(0.0471)	(0.3815)	(0.7408)
Low income country	-0.102***	-0.131***	-0.102***	-0.130***	-0.107***	-0.127***
	(0.0263)	(0.0339)	(0.0271)	(0.0343)	(0.0311)	(0.0334)
Lower middle income country	-0.0607***	-0.0947***	-0.0611***	-0.0863***	-0.0618***	-0.0880***
	(0.0169)	(0.0268)	(0.0172)	(0.0247)	(0.0185)	(0.0230)
Upper middle income country	-0.0320*	-0.0531	-0.0323	-0.0565	-0.0319*	-0.0715
	(0.0128)	(0.0409)	(0.0176)	(0.0339)	(0.0149)	(0.0383)
Assistant professor	-0.0203	-0.00391	-0.0214	-0.00292	-0.0217	0.00107
	(0.0222)	(0.0336)	(0.0185)	(0.0353)	(0.0208)	(0.0290)
Associate professor	-0.0263	-0.00379	-0.0263	-0.00182	-0.0265	-0.00555
	(0.0231)	(0.0318)	(0.0187)	(0.0364)	(0.0221)	(0.0317)
Other occupations	-0.0671**	-0.0634	-0.0668**	-0.0606	-0.0704***	-0.0600
	(0.0227)	(0.0347)	(0.0228)	(0.0359)	(0.0203)	(0.0407)
Teamsize	0.0244***	0.0280**	0.0247***	0.0285**	0.0240***	0.0287**
	(0.0056)	(0.0096)	(0.0062)	(0.0106)	(0.0057)	(0.0100)
Work experience	0.00201	0.00199	0.00574	0.00367	0.00143	0.00149
	(0.0022)	(0.0026)	(0.0056)	(0.0110)	(0.0023)	(0.0035)
Work experience squared			-0.000365	-0.000123		
			(0.0005)	(0.0010)		
Female*Average beauty score					-0.0242*	-0.0297
					(0.0101)	(0.0184)
Black*Average beauty score					-0.111	-0.127
					(0.2015)	(0.0847)
South Asian*Average beauty score					0.0192	0.0230
					(0.0201)	(0.0314)
East Asian*Average beauty score					0.0187	0.0108
					(0.0158)	(0.0184)
MENA*Average beauty score					-0.0929	-0.0669
					(0.1204)	(0.2313)
Constant	0.181***	0.157**	0.174***	0.150*	0.173***	0.140*
	(0.0289)	(0.0574)	(0.0403)	(0.0677)	(0.0329)	(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 9 The impact of beauty on log average normalized citations, OLS and median regression, authors with less than 10 years of working experience

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**QR(0.5)**	**OLS**	**QR(0.5)**	**OLS**	**QR(0.5)**
Average beauty score	0.156**	0.147*	0.155***	0.148**	0.151***	0.131*
	(0.0482)	(0.0641)	(0.0446)	(0.0486)	(0.0422)	(0.0614)
Female	-0.192	-0.196	-0.192	-0.193	0.0329	0.0917
	(0.1333)	(0.1463)	(0.1180)	(0.1298)	(0.5191)	(0.4779)
Black	-0.362	-0.152	-0.353	-0.148	0.853	0.556
	(0.4487)	(0.3463)	(0.5167)	(0.5746)	(2.1536)	(2.3104)
South Asian	0.397	0.481	0.391	0.493*	0.583	0.608
	(0.3430)	(0.2819)	(0.3095)	(0.2284)	(0.9918)	(0.9047)
East Asian	-0.395**	-0.440**	-0.394**	-0.433*	-1.051*	-1.318*
	(0.1531)	(0.1613)	(0.1358)	(0.1942)	(0.4437)	(0.5623)
MENA	-0.128	-0.0837	-0.114	-0.0813	0.317	-0.876
	(0.3503)	(0.4465)	(0.3913)	(0.3602)	(13.0127)	(5.4077)
Low income country	-0.303	-0.357	-0.307	-0.353	-0.338	-0.317
	(0.3017)	(0.2994)	(0.3052)	(0.2875)	(0.3638)	(0.3709)
Lower middle income country	-0.00171	-0.222	-0.00650	-0.223	-0.0133	-0.275
	(0.1387)	(0.1964)	(0.1634)	(0.2032)	(0.1490)	(0.1968)
Upper middle income country	-0.233	-0.441*	-0.237	-0.456*	-0.238	-0.440*
	(0.1702)	(0.1904)	(0.1213)	(0.1923)	(0.1700)	(0.1804)
Assistant professor	-0.285*	-0.194	-0.298*	-0.233	-0.280*	-0.183
	(0.1271)	(0.1903)	(0.1394)	(0.2327)	(0.1382)	(0.1656)
Associate professor	-0.185	-0.0419	-0.185	-0.0585	-0.182	-0.0529
	(0.1488)	(0.1726)	(0.1388)	(0.1643)	(0.1493)	(0.1797)
Other occupations	-0.335	-0.308	-0.333*	-0.344	-0.337	-0.276
	(0.1786)	(0.2376)	(0.1421)	(0.1863)	(0.1726)	(0.1856)
Teamsize	0.313***	0.348***	0.316***	0.349***	0.312***	0.344***
	(0.0506)	(0.0529)	(0.0514)	(0.0447)	(0.0409)	(0.0508)
Work experience	-0.0103	-0.00229	0.0307	0.00579	-0.0108	0.00426
	(0.0210)	(0.0262)	(0.0660)	(0.0789)	(0.0179)	(0.0181)
Work experience squared			-0.00401	-0.00124		
			(0.0062)	(0.0074)		
Female*Average beauty score					-0.0478	-0.0527
					(0.1025)	(0.1018)
Black*Average beauty score					-0.383	-0.180
					(0.6972)	(0.7822)
South Asian*Average beauty score					-0.0500	-0.0548
					(0.2579)	(0.2371)
East Asian*Average beauty score					0.172	0.244
					(0.1066)	(0.1415)
MENA*Average beauty score					-0.134	0.199
					(3.2747)	(1.7235)
Constant	-4.614***	-4.629***	-4.688***	-4.612***	-4.586***	-4.586***
	(0.3144)	(0.3709)	(0.3499)	(0.2816)	(0.2333)	(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 10 The impact of beauty on research productivity: first authors

	Weighted Productivity		Average Productivity		Log Norm Citations	
	OLS	**QR(0.5)**	**OLS**	**QR(0.5)**	**OLS**	**QR(0.5)**
Average beauty score	0.0240***	0.0313***	0.0291***	0.0380***	0.198***	0.115
	(0.0041)	(0.0071)	(4.32)	(4.29)	(0.0532)	(0.0744)
Female	-0.0283*	-0.0358	-0.0316*	-0.0401	-0.340**	-0.320
	(0.0144)	(0.0214)	(-2.20)	(-1.59)	(0.1314)	(0.1863)
Black	-0.00880	0.00526	0.00191	0.0276	-0.387	-0.277
	(0.0429)	(0.0668)	(0.04)	(0.35)	(0.3671)	(0.4986)
South Asian	0.0262	-0.0000676	0.0367	-0.00782	-0.00836	0.231
	(0.0254)	(0.0412)	(1.25)	(-0.14)	(0.2664)	(0.3315)
East Asian	-0.0409**	-0.0544**	-0.0466**	-0.0542*	-0.477**	-0.551***
	(0.0145)	(0.0200)	(-2.95)	(-2.00)	(0.1480)	(0.1518)
MENA	0.0154	-0.0225	0.0246	-0.0328	0.172	0.00954
	(0.0355)	(0.0554)	(0.57)	(-0.63)	(0.2116)	(0.3104)
Low income country	-0.0482*	-0.0321	-0.0624	-0.0420	-0.248	-0.652
	(0.0244)	(0.0483)	(-1.81)	(-0.66)	(0.2619)	(0.4262)
Lower middle income country	-0.0503***	-0.0663***	-0.0632***	-0.0850***	-0.0233	-0.153
	(0.0121)	(0.0156)	(-3.86)	(-3.98)	(0.1605)	(0.1826)
Upper middle income country	-0.0344*	-0.0533*	-0.0389*	-0.0695*	-0.338*	-0.498**
	(0.0167)	(0.0266)	(-2.30)	(-2.48)	(0.1419)	(0.1600)
Assistant professor	-0.00398	0.00689	-0.00306	0.0122	-0.215	-0.0966
	(0.0149)	(0.0238)	(-0.19)	(0.50)	(0.1390)	(0.1832)
Associate professor	-0.0208	-0.0135	-0.0227	-0.0213	-0.159	0.0251
	(0.0132)	(0.0210)	(-1.49)	(-0.91)	(0.1307)	(0.1021)
Other occupations	-0.0215	-0.00968	-0.0243	-0.00768	-0.139	-0.146
	(0.0164)	(0.0287)	(-1.58)	(-0.21)	(0.1579)	(0.1637)
Teamsize	0.0189**	0.0219*	0.0206**	0.0256*	0.244***	0.239***
	(0.0060)	(0.0099)	(2.61)	(2.11)	(0.0522)	(0.0648)
Work experience	-0.00111	-0.000971	-0.00125	-0.000911	-0.00866	-0.000390
	(0.0006)	(0.0013)	(-1.84)	(-0.54)	(0.0055)	(0.0079)
Constant	0.167***	0.124*	0.189***	0.129*	-4.727***	-4.400***
	(0.0255)	(0.0487)	(6.05)	(1.99)	(0.2893)	(0.3533)
N	975	975	975	975	933	933

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

Table 11 The impact of beauty on log average normalized citations, OLS and median regression, controlling for journal quality

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**QR(0.5)**	**OLS**	**QR(0.5)**	**OLS**	**QR(0.5)**
Average beauty score	0.0438	0.0584*	0.0426	0.0577	0.0276	0.0502
	(0.0337)	(0.0272)	(0.0323)	(0.0313)	(0.0291)	(0.0435)
Female	-0.157	-0.121	-0.155	-0.119	-0.415	-0.356
	(0.0847)	(0.0752)	(0.0816)	(0.0818)	(0.2906)	(0.3660)
Black	-0.172	0.111	-0.176	0.113	0.804	2.012
	(0.4283)	(0.3355)	(0.4539)	(0.3410)	(1.9894)	(1.4370)
South Asian	0.0647	0.109	0.0669	0.116	-0.0620	0.0746
	(0.1841)	(0.2046)	(0.1872)	(0.1891)	(0.5325)	(0.4612)
East Asian	-0.204	-0.164	-0.205*	-0.157	-0.342	-0.150
	(0.1141)	(0.1316)	(0.0975)	(0.1309)	(0.3127)	(0.3887)
MENA	-0.0238	-0.132	-0.0228	-0.124	0.712	1.325
	(0.1688)	(0.3255)	(0.1864)	(0.2907)	(0.8033)	(1.8951)
Low income country	-0.212	-0.158	-0.213	-0.162	-0.234	-0.334
	(0.2098)	(0.3088)	(0.2510)	(0.3292)	(0.2177)	(0.3403)
Lower middle income country	0.145	-0.0740	0.143	-0.0827	0.152	-0.0909
	(0.1189)	(0.1391)	(0.1059)	(0.1271)	(0.1328)	(0.1381)
Upper middle income country	-0.197*	-0.199*	-0.196*	-0.197	-0.198**	-0.213*
	(0.0910)	(0.0998)	(0.0939)	(0.1177)	(0.0747)	(0.1030)
Assistant professor	-0.217*	-0.258*	-0.236*	-0.252	-0.220**	-0.262*
	(0.0962)	(0.1067)	(0.1068)	(0.1490)	(0.0781)	(0.1103)
Associate professor	-0.179*	-0.217*	-0.184*	-0.216	-0.183*	-0.219*
	(0.0893)	(0.0951)	(0.0811)	(0.1224)	(0.0737)	(0.1090)
Other occupations	-0.00656	-0.0327	-0.0196	-0.0280	-0.0103	-0.0493
	(0.0784)	(0.1113)	(0.0981)	(0.1256)	(0.0855)	(0.1083)
Teamsize	0.225***	0.228***	0.226***	0.229***	0.225***	0.225***
	(0.0289)	(0.0373)	(0.0257)	(0.0422)	(0.0269)	(0.0387)
Work experience	-0.00831*	-0.00965	-0.0135	-0.00929	-0.00846*	-0.0101*
	(0.0040)	(0.0054)	(0.0114)	(0.0135)	(0.0036)	(0.0047)
Work experience squared			0.000128	-0.00000569		
			(0.0003)	(0.0003)		
Average Journal Quality	2.844***	2.672***	2.847***	2.670***	2.844***	2.628***
	(0.1105)	(0.1557)	(0.1213)	(0.1381)	(0.0894)	(0.1777)
Female*Average beauty score					0.0559	0.0569
					(0.0625)	(0.0764)
Black*Average beauty score					-0.300	-0.575
					(0.5508)	(0.4770)
South Asian*Average beauty score					0.0402	0.0440
					(0.1421)	(0.1203)
East Asian*Average beauty score					0.0367	-0.000883
					(0.0778)	(0.0990)
MENA*Average beauty score					-0.224	-0.354
					(0.2558)	(0.5485)
Constant	-5.627***	-5.433***	-5.586***	-5.438***	-5.560***	-5.363***
	(0.1801)	(0.2628)	(0.1939)	(0.2942)	(0.1456)	(0.2595)
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

6. Conclusions

We revisit the role of physical attractiveness in the labor market: many previous studies found that good looks have positive returns with respect to both higher wages and faster career progression. However, what causes these returns remains unclear: they can be either due to discriminatory preferences in favor of attractive people, or can be driven by workers' intrinsic qualities such as better physical and mental health, trustworthiness, or competence, for which perceived beauty serves as a signal. This study extends this research by investigating the role of physical attractiveness in academic publishing. This is a context in which physical attractiveness should play only very limited role: the peer-review process is, as a rule, free of face-to-face interactions. We collect detailed information on authors who published their papers in 2012 in 16 economics journals, together with their photos. We had these photos rated for attractiveness by survey participants, with 20 raters assessing each photo. We examine the extent to which physical attractiveness correlates with research productivity as measured by a combined index of journal rank, journal impact factor and citations, as well as citations alone. Our results suggest that being more attractive strongly increases the probability to produce high-quality publications: attractive researchers publish in better journals and also get more citations. This result is obtained with OLS and quantile regression alike. The latter technique suggests that beauty matters especially for authors of intermediate and high productivity, while its impact is limited or none for the least productive authors. Another strong factor of publication quality is the number of coauthors: papers with more authors tend to be published in better journals and attract more citations; the effect of team size. Economic development in the country of origin (proxied in our analysis as the country in which the author obtained their undergraduate degree) is also an important predictor of research productivity: authors from low and middle-income countries are at a distinct disadvantage relative to their peers from high-income countries.

Our findings are robust to only looking at relatively young academics and to only considering one author per paper instead of including all authors in the analysis. However, the positive effect of beauty on citations disappears once we control for journal quality: attractive authors tend to publish their research in better journals, but once their work is published, it does not attract more citations than other papers published in the same journal by less good-looking authors. This last result suggests that attractive academics have an advantage at gaining access to better outlets for their work, but do not produce research of higher intrinsic quality.

Given the crucial role that publication play in determining career outcomes of academics, we thus confirm the previous literature's finding that beauty plays a significant role in driving labor-market outcomes, even in an area of low degree of person-to-person contact such as publication process. The channel behind this effect, however, should be investigated further. One possible explanation is that beauty is a proxy for intelligence (Langlois *et al*., 2000; Zebrowitz *et al*., 2002; Kanazawa and Kovar, 2004). An alternative explanation would be one of discrimination: the fact that attractive researchers do not receive more citations than their less attractive colleagues who publish in similar journals would be consistent with this explanation. Attractive researchers may be accepted into better graduate schools, get paired up with better PhD supervisors, and get hired into higher-ranked and more prestigious universities and research institutions. Their institutional affiliation, which would be known to editors and possibly also referees, may have an important marginal impact on the publication decision. Good-looking authors also probably have wider social and professional networks, giving them better access to invitations to research seminars and conferences, and higher probability that their work will be refereed by someone who knows them.

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Appendix (not for publication)

Appendix A 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)

Appendix A Example of the online survey (continued)

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 A Example of the online survey (continued)

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

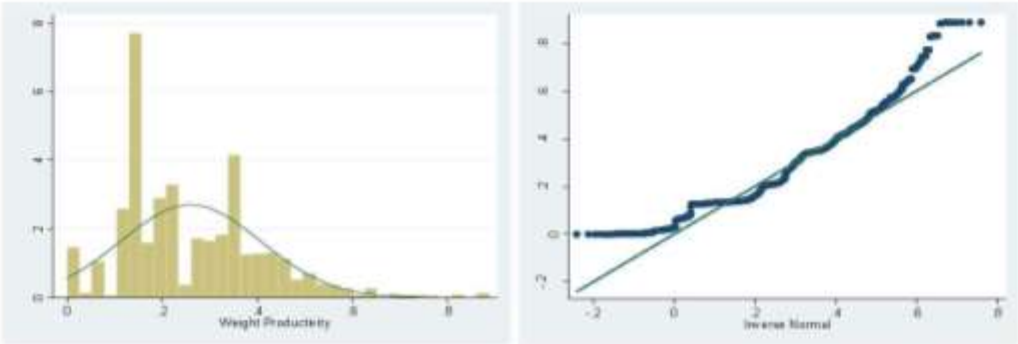
See how easy it is to create a survey.

Note: Photo has been anonymised due to privacy issues

Appendix B Normality of distribution by variable

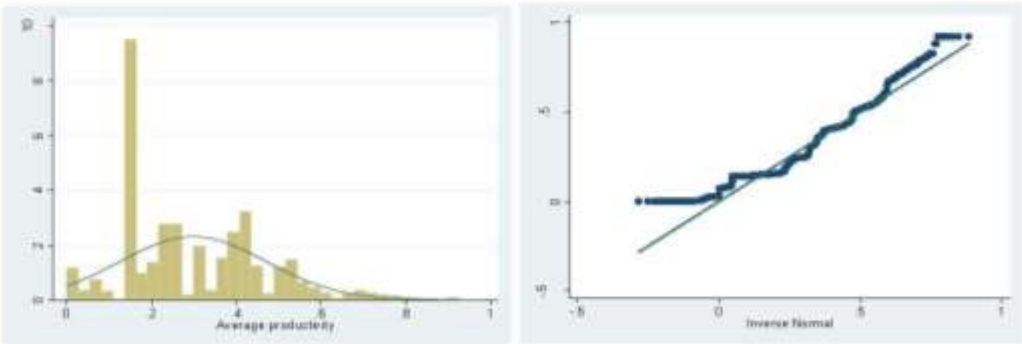
Weight productivity (wprod)

Skewness: 0.8650315, Kurtosis: 4.087823



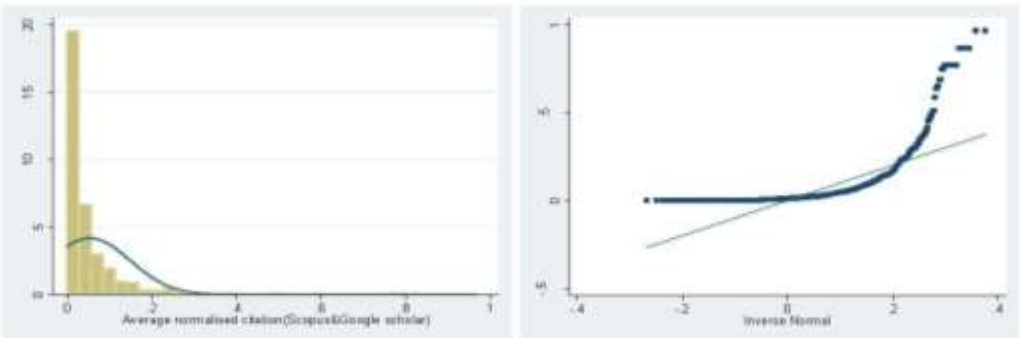
Average productivity (aveprod)

Skewness: 0.7108023, Kurtosis: 3.187089



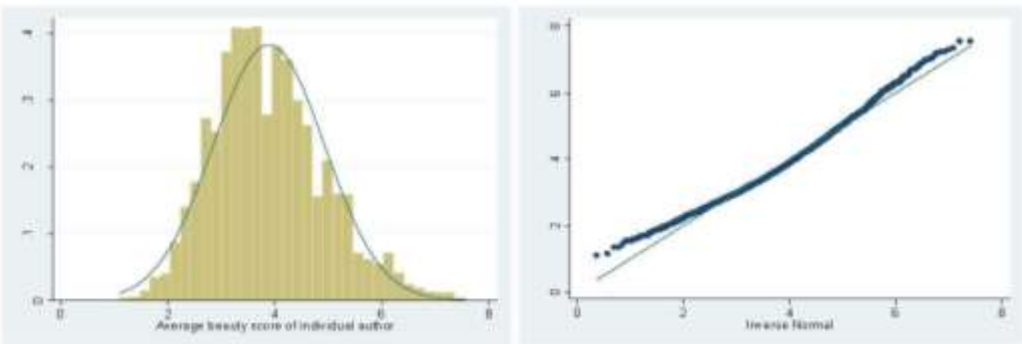
Average normalised citations (avenormcite)

Skewness: 4.810407, Kurtosis: 33.61025



Average beauty score of individuals (avebeauty)

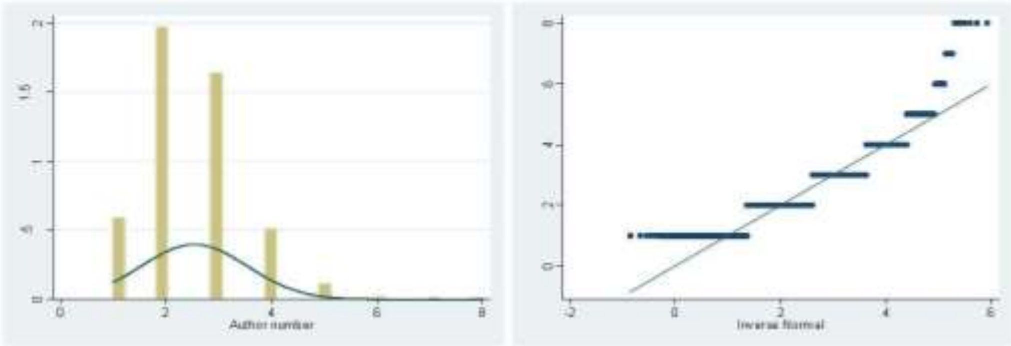
Skewness: 0.4790202, Kurtosis: 3.089837



Appendix B (Continued) Normality of distribution by variable

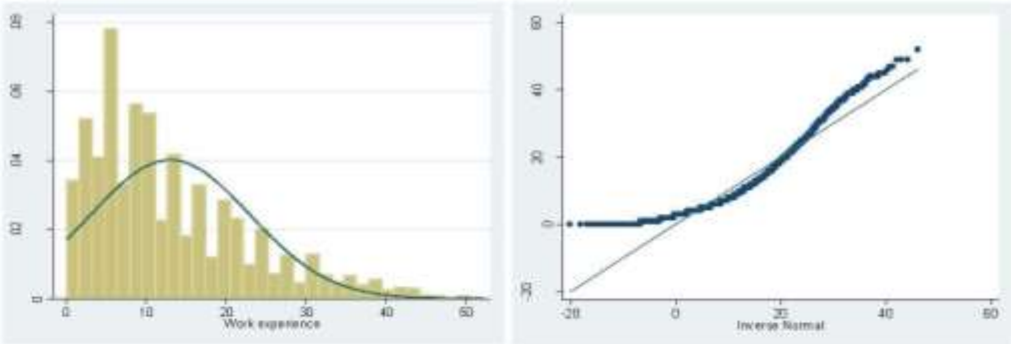
Author number (teamsize)

Skewness: 0.9778917, Kurtosis: 5.788467



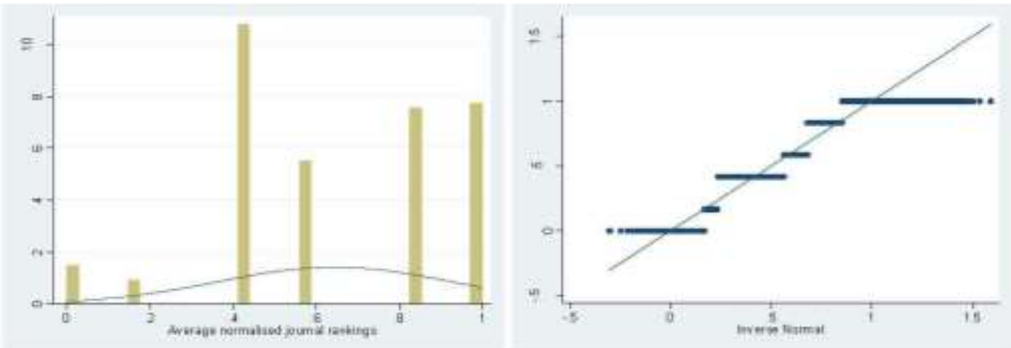
Work experience (workexp)

Skewness: 1.077584, Kurtosis: 3.69367



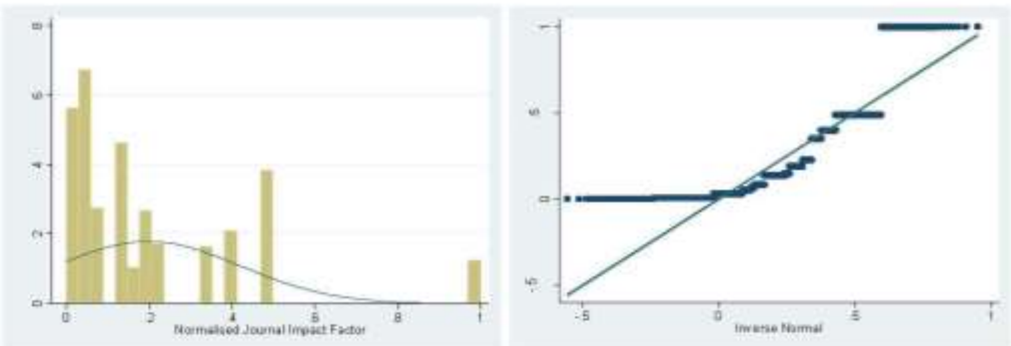
Average normalised journal rankings (avenormrank)

Skewness: -0.3061057, Kurtosis: 2.248191



Normalised Journal Impact Factor (norma_jif)

Skewness: 1.814065, Kurtosis: 6.631405



Appendix B (Continued) Normality of distribution by variable

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
wprod	2,800	0.93971	97.04	11.778	0.00000
aveprod	2,800	0.94276	92.123	11.644	0.00000
avenormcite	2,800	0.52364	766.67	17.099	0.00000
avebeauty	2,800	0.98534	23.599	8.138	0.00000
teamsize	2,800	0.97019	47.978	9.965	0.00000
workexp	2,322	0.91325	117.832	12.198	0.00000
avenormrank	2,800	0.98529	23.675	8.147	0.00000
norma_jif	2,800	0.79466	330.484	14.933	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	103.076	11.332	0.00001
aveprod	2,800	0.94287	97.656	11.2	0.00001
avenormcite	2,800	0.52496	812.038	16.378	0.00001
avebeauty	2,800	0.98542	24.917	7.861	0.00001
teamsize	2,800	0.9722	47.525	9.439	0.00001
workexp	2,322	0.91585	121.129	11.592	0.00001
avenormrank	2,800	0.98583	24.221	7.792	0.00001
norma_jif	2,800	0.79436	351.524	14.331	0.00001

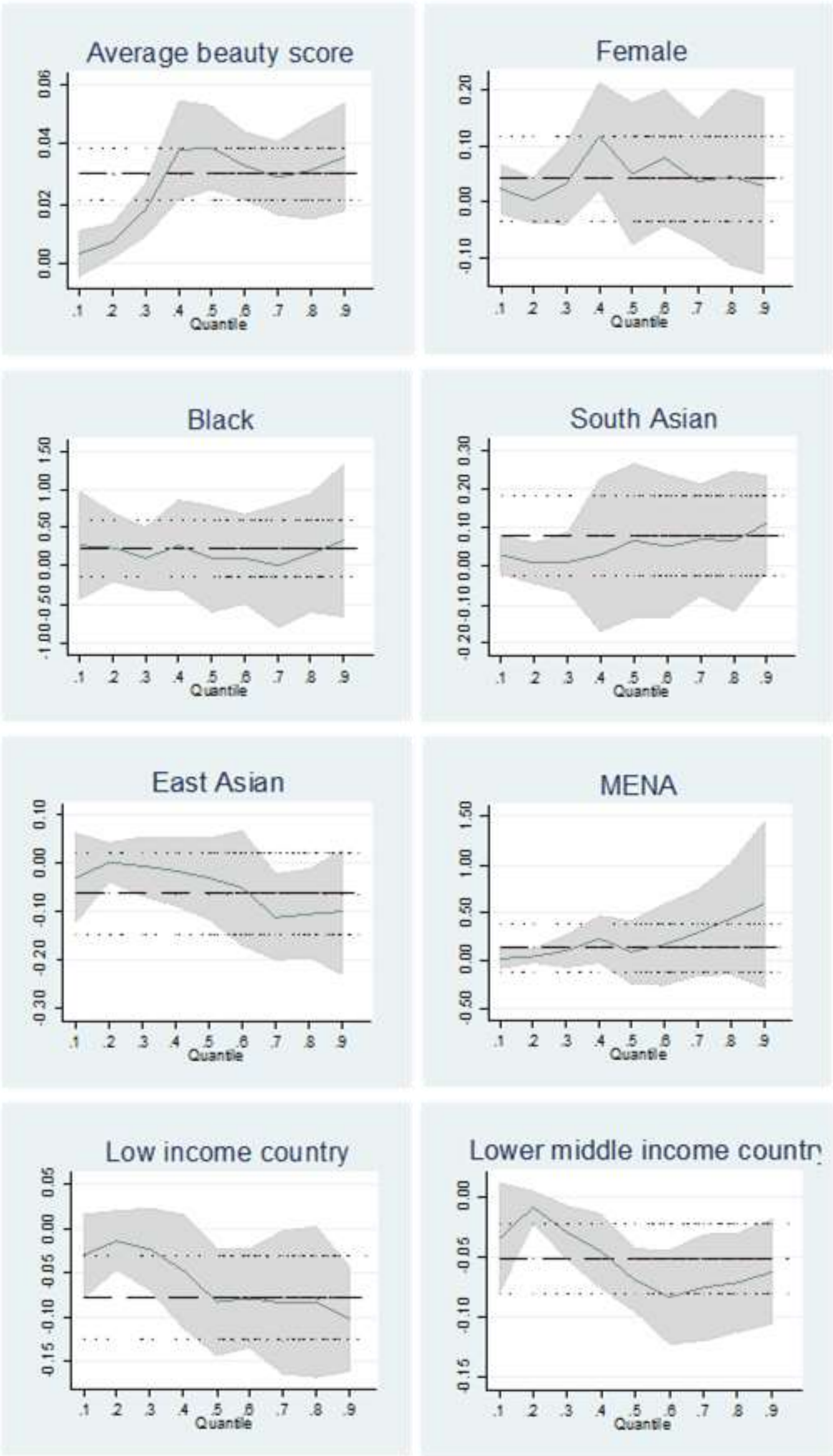
Note: The normal approximation to the sampling distribution of W' is valid for 10<=n<=5000.

Appendix C The impact of beauty on average normalized 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***	0.00391***	0.0106***	0.00401**	0.0107**	0.00419**
	(0.00249)	(0.00118)	(0.00258)	(0.00125)	(0.00327)	(0.00158)
Female	-0.0127*	-0.00593*	-0.0131*	-0.00605*	-0.0116	0.00126
	(0.00632)	(0.00280)	(0.00626)	(0.00255)	(0.02174)	(0.01283)
Black	0.00709	0.00620	0.00788	0.00497	0.0904	0.0576
	(0.01827)	(0.00988)	(0.01817)	(0.01051)	(0.07057)	(0.04095)
South Asian	0.0156*	0.0123	0.0152	0.0134	0.0298	0.0154
	(0.00774)	(0.00789)	(0.00855)	(0.00845)	(0.02821)	(0.01975)
East Asian	-0.0178***	-0.00917***	-0.0177***	-0.00870**	-0.0224	-0.0193
	(0.00461)	(0.00276)	(0.00497)	(0.00289)	(0.01986)	(0.01204)
MENA	-0.0148*	0.00280	-0.0147*	0.00307	0.0161	0.0138
	(0.00643)	(0.00480)	(0.00689)	(0.00424)	(0.03405)	(0.02989)
Low income country	-0.0298***	-0.0206*	-0.0296***	-0.0204*	-0.0321***	-0.0226*
	(0.00743)	(0.00911)	(0.00738)	(0.00848)	(0.00949)	(0.00891)
Lower middle income country	-0.0129*	-0.00633	-0.0126	-0.00630	-0.0132*	-0.00739*
	(0.00552)	(0.00359)	(0.00733)	(0.00350)	(0.00612)	(0.00377)
Upper middle income country	-0.0139	-0.00978***	-0.0141	-0.00974**	-0.0140	-0.00978***
	(0.00711)	(0.00292)	(0.00860)	(0.00302)	(0.00737)	(0.00295)
Assistant professor	-0.00709	-0.00473	-0.00360	-0.00625	-0.00720	-0.00499
	(0.00798)	(0.00389)	(0.00771)	(0.00449)	(0.00883)	(0.00463)
Associate professor	-0.0191***	-0.00154	-0.0182**	-0.00233	-0.0194**	-0.00248
	(0.00545)	(0.00368)	(0.00574)	(0.00364)	(0.00660)	(0.00355)
Other occupations	-0.00796	-0.00383	-0.00553	-0.00405	-0.00808	-0.00435
	(0.00729)	(0.00496)	(0.01005)	(0.00449)	(0.00881)	(0.00303)
Teamsize	0.0241***	0.00888***	0.0239***	0.00911***	0.0240***	0.00931***
	(0.00473)	(0.00178)	(0.00396)	(0.00175)	(0.00474)	(0.00149)
Work experience	-0.000498	-0.000290	0.000464	-0.000599	-0.000502	-0.000354*
	(0.00029)	(0.00016)	(0.00108)	(0.00039)	(0.00031)	(0.00017)
Work experience squared			-0.0000234	0.00000659		
			(0.00002)	(0.00001)		
Female*Average beauty score					-0.000223	-0.00168
					(0.00527)	(0.00281)
Black*Average beauty score					-0.0254	-0.0153
					(0.01985)	(0.01120)
South Asian*Average beauty score					-0.00386	-0.000265
					(0.00907)	(0.00532)
East Asian*Average beauty score					0.00131	0.00315
					(0.00523)	(0.00337)
MENA*Average beauty score					-0.00940	-0.00257
					(0.01013)	(0.00974)
Constant	-0.0207	0.00206	-0.0284*	0.00378	-0.0216	0.00128
	(0.01751)	(0.00779)	(0.01399)	(0.00775)	(0.02126)	(0.00732)
N	1926	1926	1926	1926	1926	1926

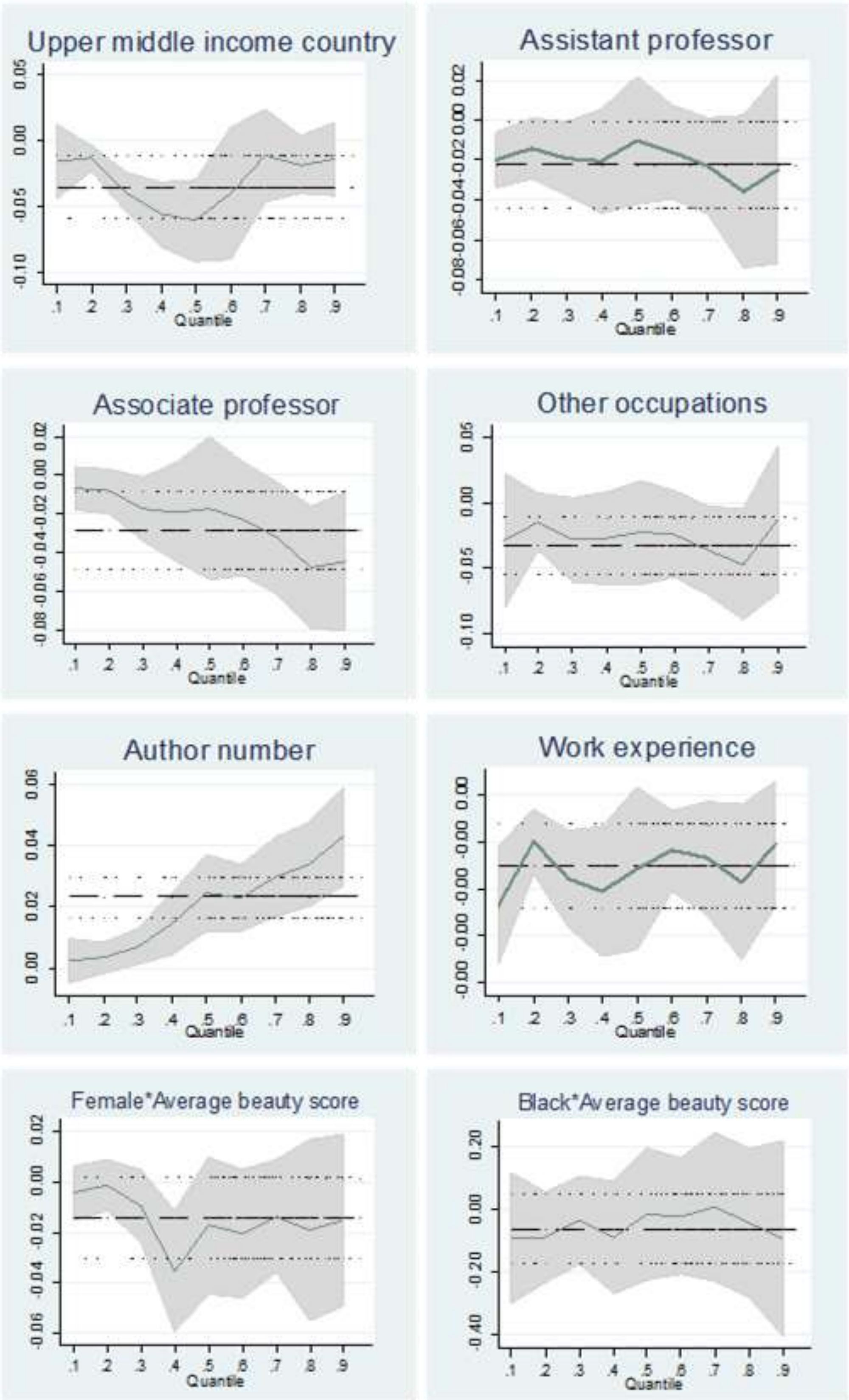
Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Appendix D Quantile coefficients for weighted productivity



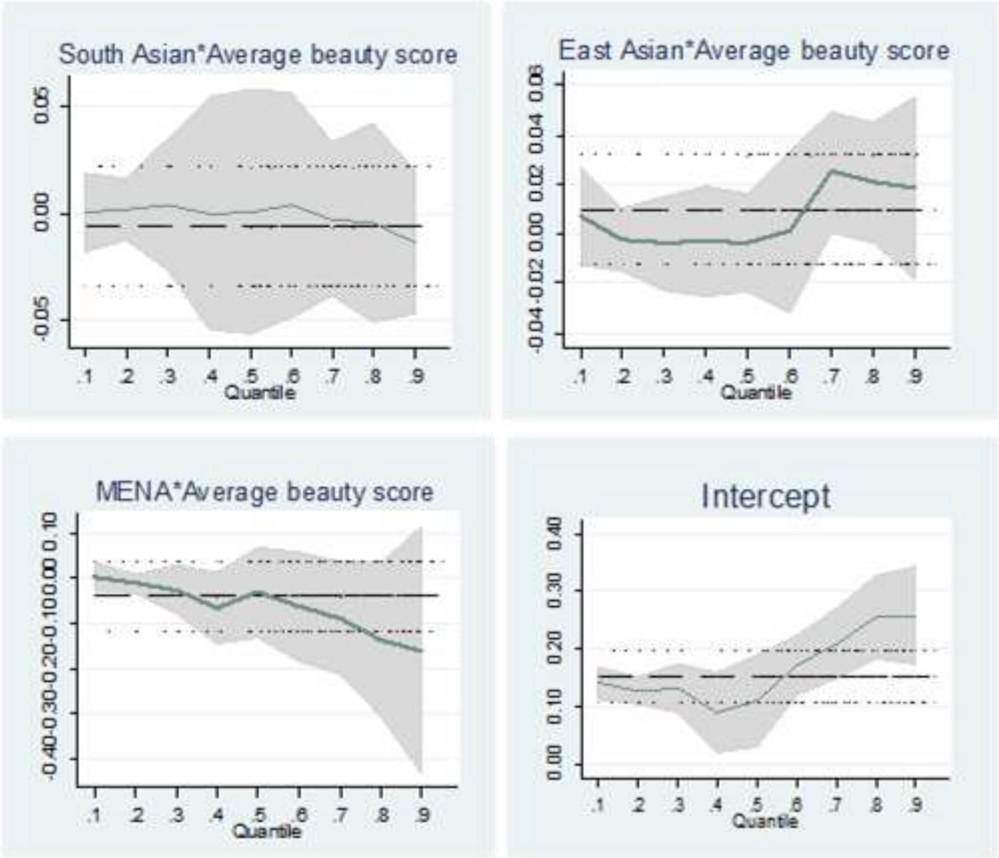
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

AppendixD (Continued) Quantile coefficients for weighted productivity



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

Appendix D (Continued) Quantile coefficients for weighted productivity



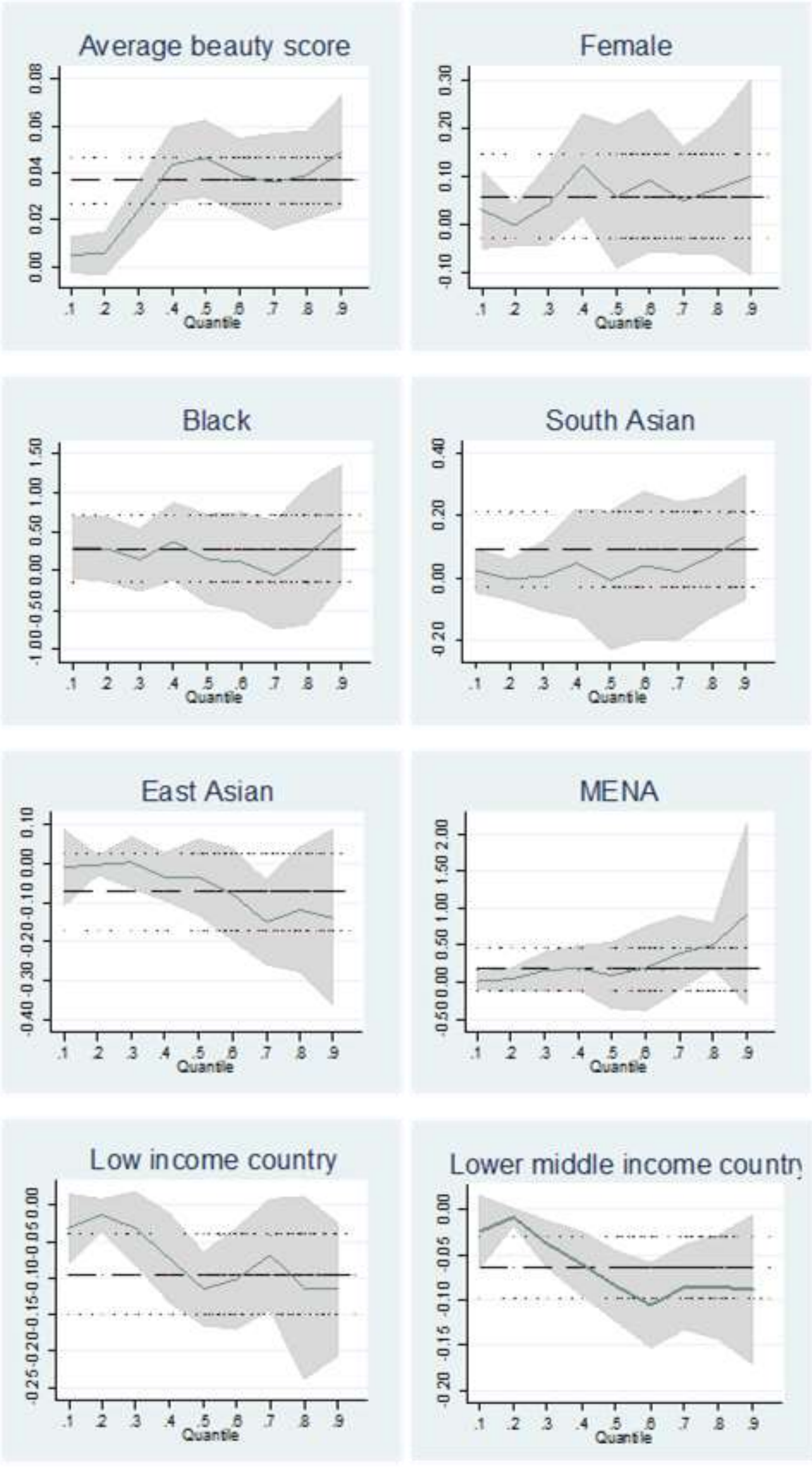
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (weighted productivity)

Appendix E 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	0.00537 (0.0044)	0.00606 (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)	0.049*** (0.0103)
Female	0.0322 (0.0273)	-0.00066 (0.0222)	0.0418 (0.0436)	0.124* (0.0606)	0.0583 (0.0710)	0.0922 (0.0632)	0.0506 (0.0541)	0.0758 (0.0664)	0.0991 (0.0879)
Black	0.306 (0.2298)	0.280 (0.1947)	0.145 (0.1766)	0.381 (0.2493)	0.152 (0.2737)	0.122 (0.3895)	-0.0522 (0.5141)	0.207 (0.5438)	0.595 (0.5393)
South Asian	0.0243 (0.0486)	-0.00277 (0.0315)	0.00830 (0.0500)	0.0482 (0.0824)	-0.00438 (0.1235)	0.0408 (0.1161)	0.0225 (0.0948)	0.0714 (0.1196)	0.133 (0.0999)
East Asian	-0.0119 (0.0397)	-0.00424 (0.0156)	0.00263 (0.0355)	-0.0346 (0.0392)	-0.0358 (0.0532)	-0.0782 (0.0715)	-0.151* (0.0687)	-0.118* (0.0563)	-0.140 (0.0845)
MENA	0.0218 (0.1260)	0.0421 (0.1220)	0.161 (0.1353)	0.202 (0.2209)	0.0924 (0.2448)	0.190 (0.2617)	0.396 (0.2554)	0.501 (0.3579)	0.923 (0.5108)
Low income country	-0.0329 (0.0287)	-0.0139 (0.0152)	-0.0324 (0.0198)	-0.0729* (0.0353)	-0.116*** (0.0313)	-0.102** (0.0371)	-0.0682 (0.0480)	-0.113 (0.0667)	-0.115* (0.0471)
Lower middle income country	-0.0236 (0.0184)	-0.00745 (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)	-0.00768 (0.0285)	-0.00889 (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)	-0.00430 (0.0213)	-0.0213 (0.0225)	-0.0354 (0.0230)	-0.0261 (0.0302)
Associate professor	-0.00498 (0.0074)	-0.00619 (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	0.00249 (0.0033)	0.00225 (0.0028)	0.00702 (0.0046)	0.0160** (0.0059)	0.0289*** (0.0073)	0.0248*** (0.0070)	0.0312*** (0.0084)	0.0374*** (0.0081)	0.047*** (0.0075)
Work experience	-0.00263*** (0.0007)	-0.00085 (0.0004)	-0.00209*** (0.0005)	-0.0024** (0.0008)	-0.00163 (0.0012)	-0.00114 (0.0008)	-0.00148 (0.0008)	-0.00218* (0.0010)	-0.00149 (0.0011)
Female* Average beauty score	-0.00633 (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	-0.107 (0.0756)	-0.103 (0.0677)	-0.0531 (0.0637)	-0.123 (0.0853)	-0.0249 (0.0901)	-0.0315 (0.1239)	0.0136 (0.1568)	-0.0476 (0.1644)	-0.153 (0.1597)
South Asian* Average beauty score	0.00166 (0.0159)	0.00563 (0.0132)	0.00627 (0.0194)	0.00242 (0.0262)	0.0290 (0.0343)	0.0113 (0.0328)	0.00933 (0.0236)	0.00600 (0.0290)	-0.0132 (0.0237)
East Asian* Average beauty score	0.00306 (0.0093)	-0.00038 (0.0045)	-0.00720 (0.0094)	0.00242 (0.0113)	-0.00299 (0.0123)	0.00637 (0.0173)	0.0325 (0.0171)	0.0256 (0.0132)	0.0267 (0.0227)
MENA*Average beauty score	0.000446 (0.0381)	-0.0107 (0.0376)	-0.0452 (0.0388)	-0.0578 (0.0632)	-0.0350 (0.0694)	-0.0753 (0.0739)	-0.125 (0.0696)	-0.163 (0.0947)	-0.242 (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

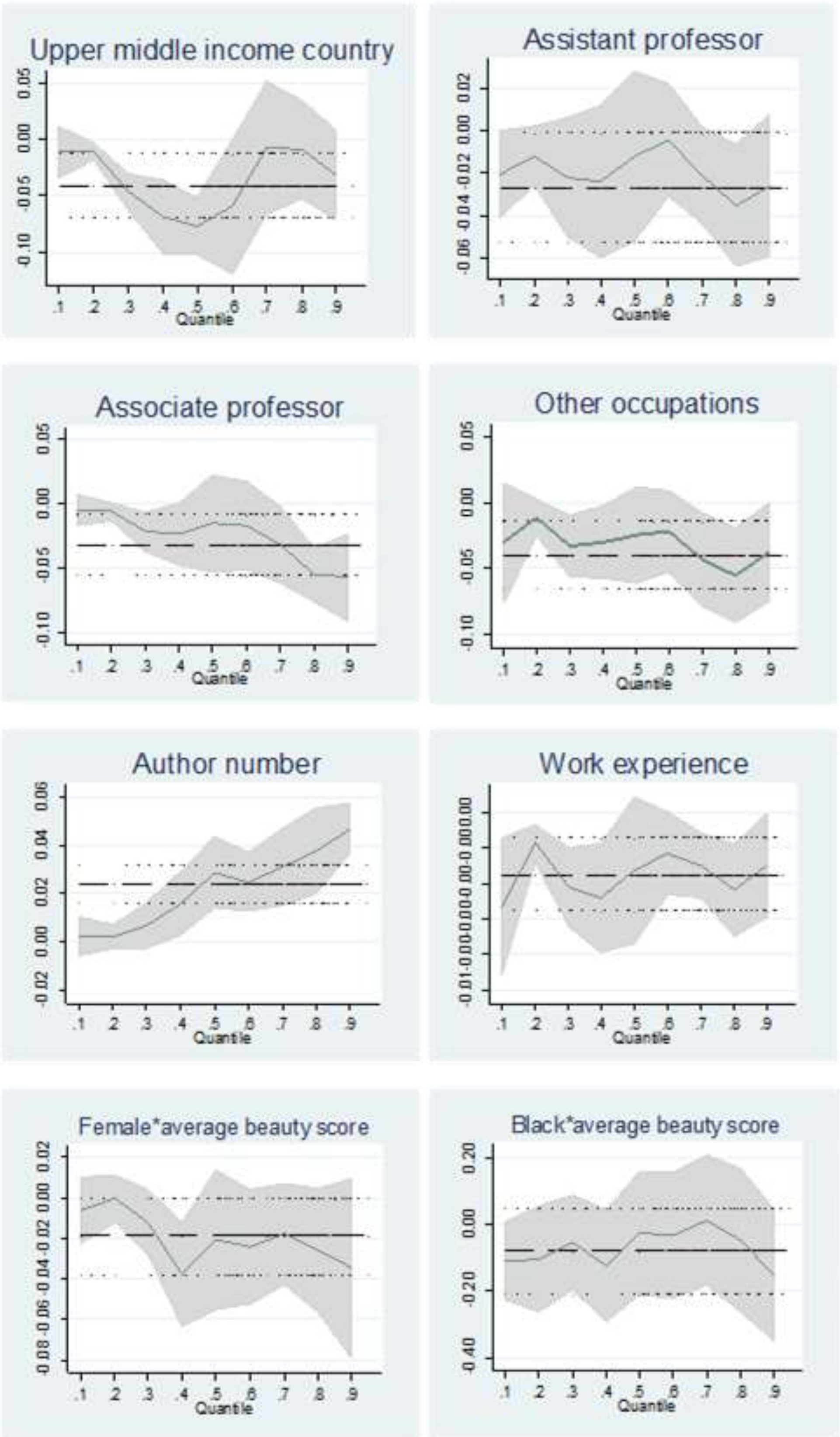
Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Appendix F Quantile coefficients for average productivity



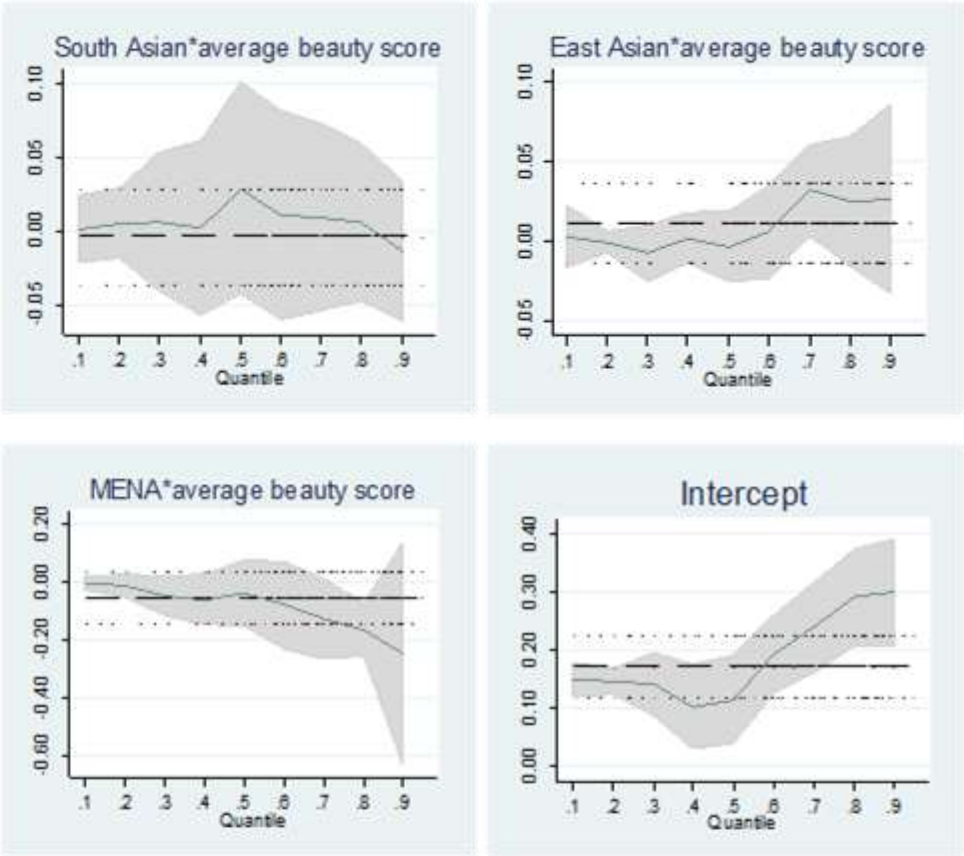
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

Appendix F (Continued) Quantile coefficients for average productivity



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

Appendix F (Continued) Quantile coefficients for average productivity



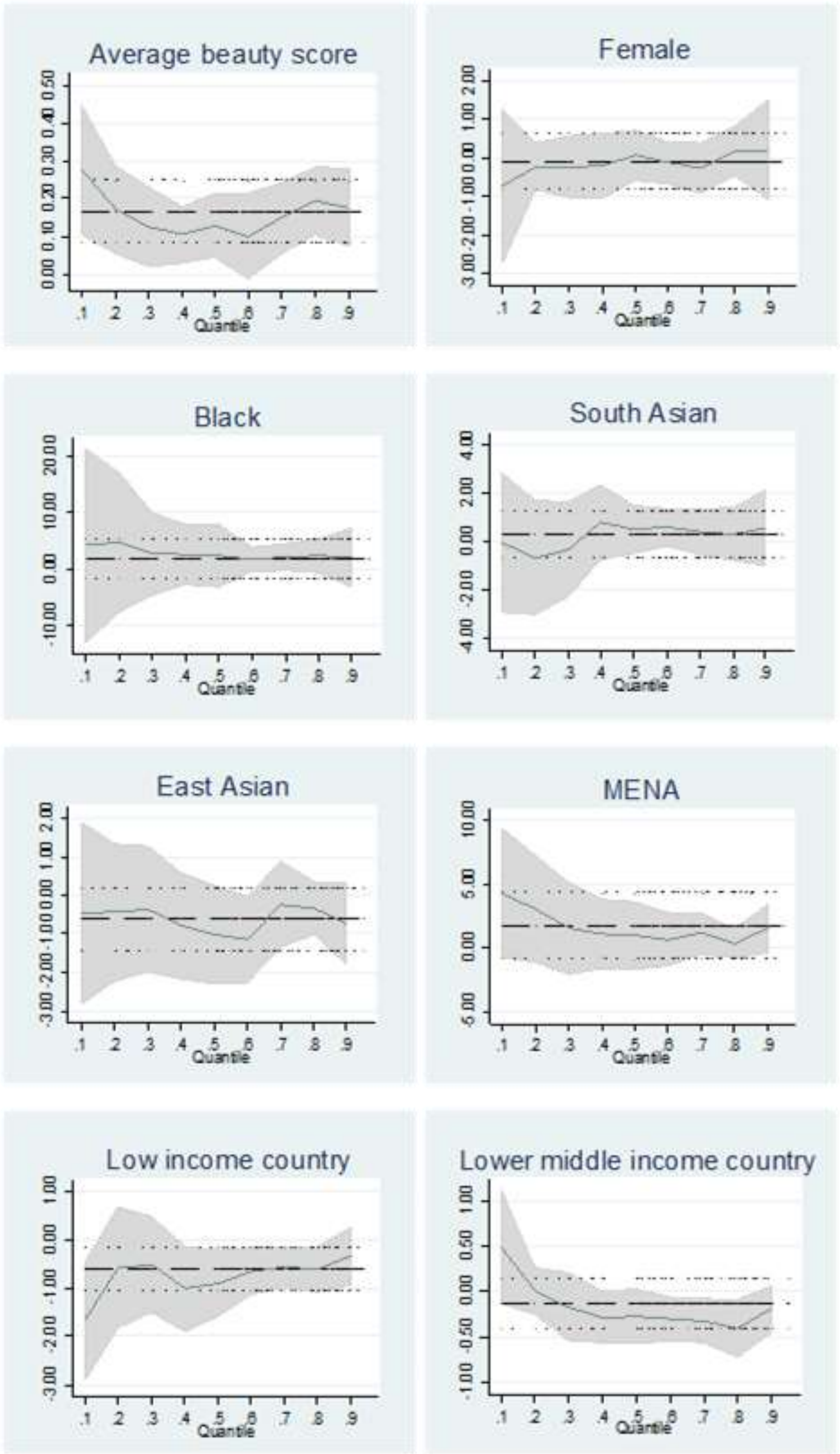
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (average productivity)

Appendix G Quantile regression estimates for log average normalized 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	0.276**	0.172**	0.126*	0.105*	0.130**	0.101	0.150***	0.195***	0.177*
	(0.1067)	(0.0553)	(0.0616)	(0.0519)	(0.0483)	(0.0538)	(0.0434)	(0.0396)	(0.0782)
Female	-0.730	-0.229	-0.229	-0.196	0.0665	-0.119	-0.262	0.177	0.209
	(1.3522)	(0.4508)	(0.5073)	(0.5750)	(0.4831)	(0.3803)	(0.4475)	(0.5350)	(0.6031)
Black	4.106	4.594	2.594	2.483	2.322	1.589	1.974	2.332	1.958
	(7.0096)	(4.7612)	(3.1493)	(2.3442)	(1.7451)	(1.5171)	(1.5214)	(2.0779)	(3.3030)
South Asian	-0.0331	-0.664	-0.305	0.806	0.504	0.594	0.406	0.322	0.590
	(2.0805)	(1.2412)	(0.9664)	(0.8199)	(0.5182)	(0.4166)	(0.4707)	(0.6047)	(1.1083)
East Asian	-0.480	-0.454	-0.366	-0.794	-1.029	-1.146	-0.246	-0.345	-0.737
	(0.9503)	(0.5413)	(0.6509)	(0.5517)	(0.5515)	(0.6108)	(0.6370)	(0.5544)	(0.6898)
MENA	4.304*	3.091	1.522	1.138	0.965	0.678	1.178	0.390	1.524
	(2.0777)	(1.6641)	(1.2823)	(1.2323)	(1.2706)	(1.0177)	(1.0859)	(0.7904)	(1.0826)
Low income country	-1.663*	-0.569	-0.511	-1.010**	-0.892**	-0.645*	-0.563*	-0.606**	-0.334
	(0.7380)	(0.6324)	(0.4609)	(0.3867)	(0.3113)	(0.2507)	(0.2566)	(0.2264)	(0.3061)
Lower middle income country	0.493	0.0124	-0.162	-0.285	-0.271	-0.301*	-0.319*	-0.399**	-0.187
	(0.2926)	(0.1903)	(0.1924)	(0.1573)	(0.1609)	(0.1225)	(0.1274)	(0.1428)	(0.1599)
Upper middle income country	-0.675	-0.270	-0.308*	-0.426**	-0.416**	-0.440***	-0.457***	-0.442***	-0.347
	(0.4010)	(0.2269)	(0.1416)	(0.1317)	(0.1331)	(0.1125)	(0.1126)	(0.1217)	(0.2190)
Assistant professor	-0.716**	-0.652***	-0.454***	-0.369**	-0.248*	-0.213	-0.216	-0.238*	0.0175
	(0.2712)	(0.1971)	(0.1309)	(0.1340)	(0.1178)	(0.1114)	(0.1404)	(0.1169)	(0.1940)
Associate professor	-0.309	-0.221	-0.168	-0.146	-0.154	-0.212*	-0.247*	-0.447***	-0.440**
	(0.2867)	(0.1187)	(0.1306)	(0.1367)	(0.1127)	(0.0969)	(0.1069)	(0.0888)	(0.1434)
Other occupations	-0.293	-0.250	-0.183	-0.228	-0.139	-0.147	-0.222	-0.298*	0.0975
	(0.2847)	(0.1593)	(0.1432)	(0.1474)	(0.1578)	(0.1130)	(0.1219)	(0.1226)	(0.1645)
Teamsize	0.322***	0.323***	0.283***	0.303***	0.318***	0.306***	0.294***	0.312***	0.246***
	(0.0873)	(0.0605)	(0.0521)	(0.0520)	(0.0439)	(0.0368)	(0.0472)	(0.0359)	(0.0318)
Work experience	-0.0315*	-0.0222**	-0.0171**	-0.0138**	-0.0113*	-0.0122***	-0.0108**	-0.0171***	-0.00686
	(0.0126)	(0.0074)	(0.0059)	(0.0052)	(0.0053)	(0.0036)	(0.0036)	(0.0046)	(0.0074)
Female* Average beauty score	0.0704	0.00929	0.00156	0.0280	-0.0442	-0.00624	0.00616	-0.110	-0.0486
	(0.2905)	(0.1028)	(0.1057)	(0.1188)	(0.1024)	(0.0830)	(0.0914)	(0.1180)	(0.1249)
Black*Average beauty score	-1.010	-1.463	-0.913	-0.630	-0.679	-0.546	-0.667	-0.861	-0.552
	(2.0468)	(1.5156)	(0.9490)	(0.7590)	(0.5727)	(0.5095)	(0.4440)	(0.6217)	(0.9447)
South Asian* Average beauty score	0.326	0.351	0.198	0.00564	0.00310	-0.0762	-0.00103	0.0111	-0.0861
	(0.5994)	(0.3380)	(0.2239)	(0.1868)	(0.1561)	(0.1248)	(0.1443)	(0.1691)	(0.3093)
East Asian* Average beauty score	0.0445	0.0147	0.0325	0.158	0.182	0.188	-0.00465	0.0508	0.116
	(0.2337)	(0.1586)	(0.1761)	(0.1523)	(0.1468)	(0.1530)	(0.1540)	(0.1443)	(0.1815)
MENA*Average beauty score	-1.096	-0.847	-0.433	-0.246	-0.239	-0.224	-0.373	-0.141	-0.590
	(0.6981)	(0.5656)	(0.4144)	(0.3764)	(0.3955)	(0.3079)	(0.3407)	(0.2582)	(0.3326)
Constant	-6.577***	-5.498***	-4.908***	-4.599***	-4.402***	-3.949***	-3.804***	-3.532***	-3.098***
	(0.5972)	(0.3330)	(0.3008)	(0.2836)	(0.2506)	(0.2492)	(0.2120)	(0.2165)	(0.3288)
N	1851	1851	1851	1851	1851	1851	1851	1851	1851

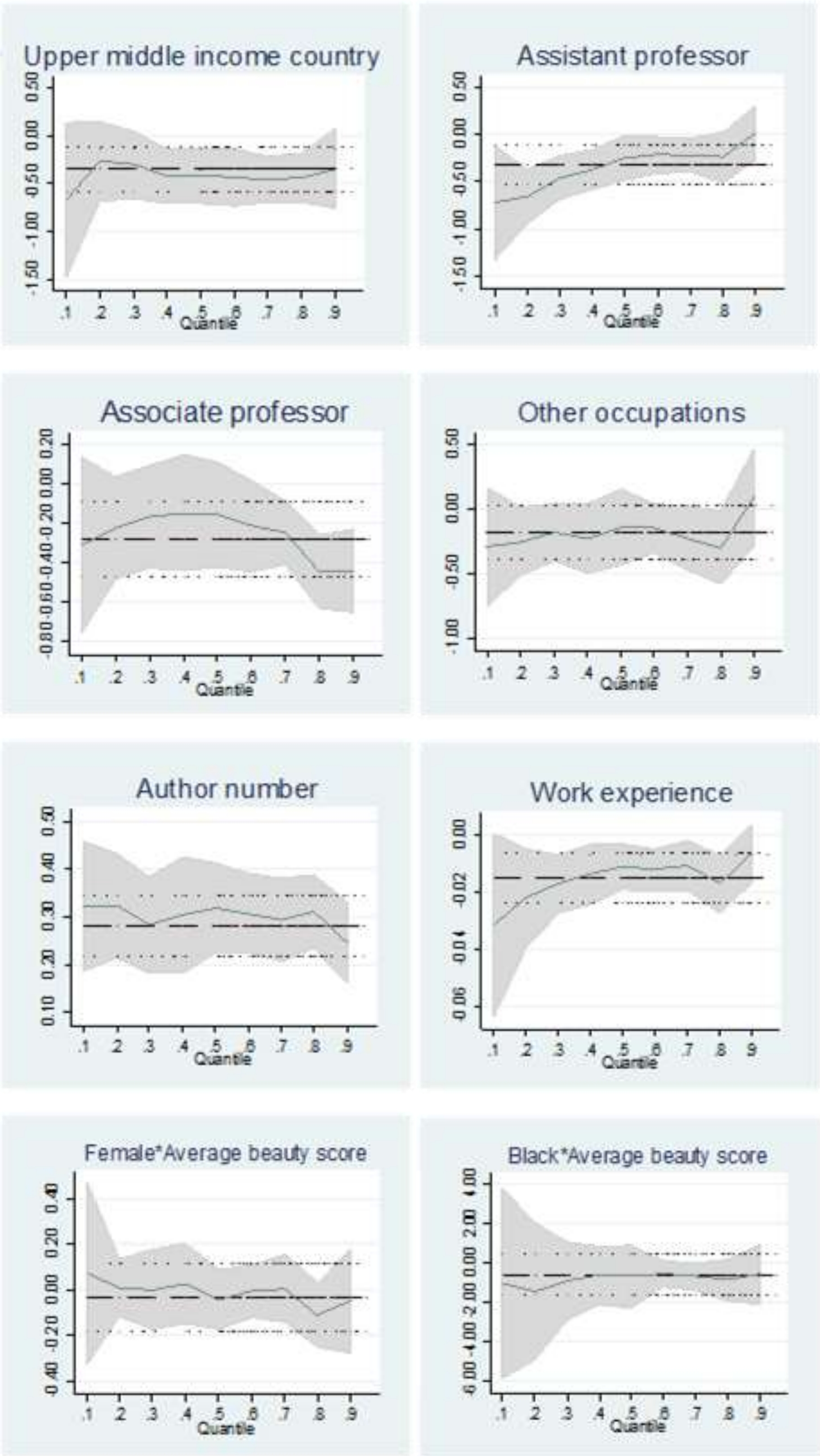
Notes: Standard errors are in parentheses; Bootstrap data resampling with 50 repetitions; * p<0.05, ** p<0.01, *** p<0.001

Appendix H Quantile coefficients for log average normalized citation



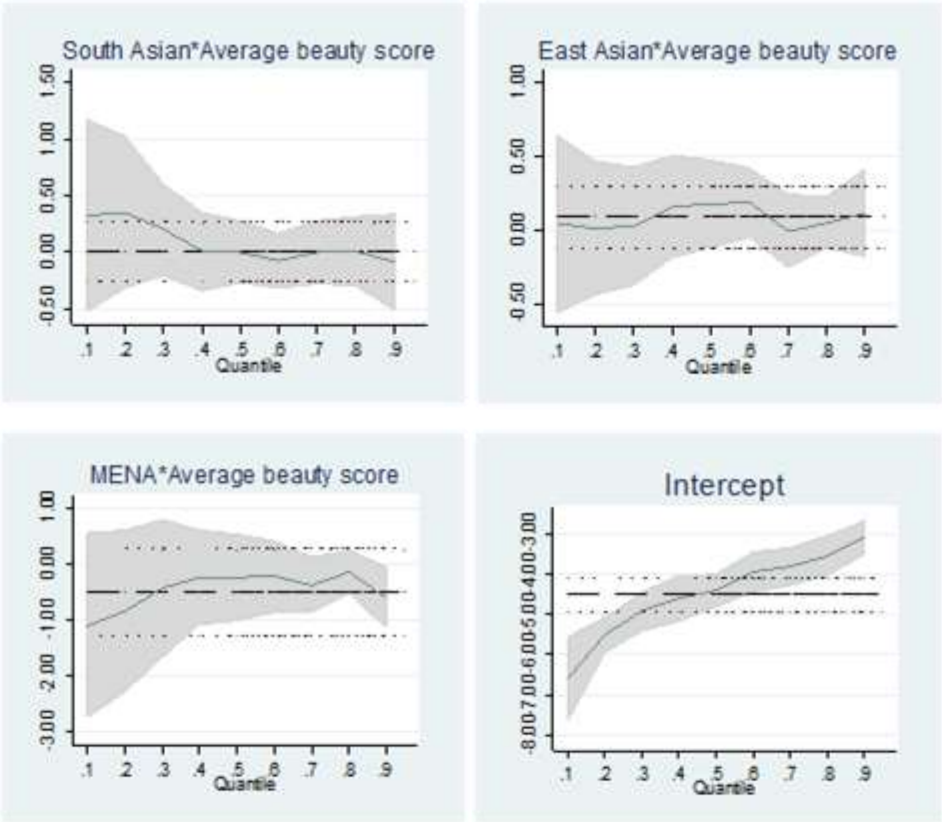
Note: Bootstrap 95% Confidence Interval of Quantile-Regression Estimates: Research Productivity (log of average normalised citation)

Appendix H (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 H (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 I 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	0.00346 (0.0031)	0.00970* (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)	0.105 (0.0908)	0.0783 (0.0763)	0.0969 (0.0648)	0.129 (0.0905)	0.0894 (0.1224)
Black	0.278 (0.1638)	0.265 (0.1948)	0.120 (0.1925)	0.189 (0.2284)	0.258 (0.2296)	0.0554 (0.2275)	0.120 (0.2651)	0.218 (0.3058)	0.403 (0.3512)
South Asian	-0.00165 (0.0606)	0.00434 (0.0663)	-0.0124 (0.0718)	0.00350 (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)	-0.101* (0.0503)	-0.0929 (0.0820)	-0.0906 (0.0853)	-0.115 (0.0975)	-0.0944 (0.0958)	-0.0516 (0.0966)
MENA	0.0371 (0.1970)	0.119 (0.1776)	0.194 (0.4643)	0.173 (0.4513)	0.122 (0.3649)	0.219 (0.2937)	0.234 (0.2824)	0.207 (0.3094)	0.287 (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)	-0.117*** (0.0253)	-0.117*** (0.0339)	-0.113* (0.0443)	-0.0763 (0.0412)
Lower middle income country	-0.00818 (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	-0.00857 (0.0174)	-0.0194* (0.0095)	-0.0387** (0.0139)	-0.0613* (0.0255)	-0.0566 (0.0389)	-0.0229 (0.0314)	0.00352 (0.0226)	-0.00814 (0.0211)	-0.0136 (0.0213)
Assistant professor	-0.0168 (0.0131)	-0.0172 (0.0116)	0.000841 (0.0163)	0.0115 (0.0300)	-0.00486 (0.0258)	-0.00270 (0.0211)	-0.0309 (0.0285)	-0.0301 (0.0305)	-0.0329 (0.0300)
Associate professor	0.00413 (0.0145)	-0.00408 (0.0131)	0.00232 (0.0139)	-0.00646 (0.0313)	-0.00990 (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	0.00538 (0.0052)	0.00222 (0.0045)	0.00721 (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	-0.00320 (0.0025)	-0.00199 (0.0022)	-0.0000821 (0.0023)	0.00393 (0.0039)	0.000892 (0.0031)	0.000673 (0.0023)	0.00148 (0.0027)	0.000186 (0.0028)	-0.0000533 (0.0039)
Female* Ave rage beauty score	-0.00505 (0.0112)	-0.00320 (0.0092)	-0.00592 (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)	-0.124 (0.1149)
South Asian* Average beauty score	0.00979 (0.0156)	0.00502 (0.0172)	0.0112 (0.0216)	0.00716 (0.0276)	0.0206 (0.0353)	0.0446 (0.0331)	0.0418 (0.0289)	0.0245 (0.0236)	-0.00755 (0.0222)
East Asian* Average beauty score	0.00499 (0.0153)	0.00225 (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)	0.00762 (0.0272)
MENA* Average beauty score	-0.00566 (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)	-0.108 (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

Appendix I (continued) 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	0.00386 (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)	0.112 (0.0943)	0.135 (0.0928)	0.124 (0.0863)	0.136 (0.0828)	0.171* (0.0848)	0.111 (0.1463)
Black	0.295 (0.2314)	0.321 (0.2379)	0.203 (0.2287)	0.279 (0.2668)	0.357 (0.2997)	0.145 (0.3266)	0.126 (0.3278)	0.376 (0.4734)	0.808 (0.5066)
South Asian	0.00582 (0.0982)	-0.00799 (0.0996)	0.0291 (0.1081)	0.0102 (0.1265)	-0.0434 (0.1129)	-0.101 (0.0846)	-0.0889 (0.1014)	-0.0369 (0.1352)	0.103 (0.1395)
East Asian	-0.0158 (0.0555)	-0.00446 (0.0440)	-0.0929 (0.0494)	-0.105 (0.0589)	-0.0883 (0.0711)	-0.119 (0.0961)	-0.163 (0.1085)	-0.118 (0.1099)	-0.110 (0.1138)
MENA	0.0561 (2.1396)	0.125 (2.1971)	0.212 (2.1752)	0.240 (2.0285)	0.169 (1.8091)	0.326 (1.8592)	0.277 (1.7053)	0.282 (1.6394)	0.350 (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)	-0.133* (0.0551)	-0.120 (0.0710)	-0.0681 (0.0463)
Lower middle income country	-0.00510 (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	-0.00724 (0.0130)	-0.0179 (0.0127)	-0.0538** (0.0199)	-0.0693** (0.0228)	-0.0715 (0.0378)	-0.0351 (0.0361)	0.00618 (0.0231)	0.000226 (0.0210)	-0.0326 (0.0211)
Assistant professor	-0.0134 (0.0125)	-0.0281 (0.0181)	0.00653 (0.0216)	0.0170 (0.0330)	0.00107 (0.0245)	0.00320 (0.0256)	-0.0334 (0.0331)	-0.0367 (0.0337)	-0.0437 (0.0491)
Associate professor	0.00617 (0.0110)	-0.0120 (0.0143)	0.00234 (0.0193)	-0.00266 (0.0300)	-0.00555 (0.0242)	-0.00196 (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)	-0.111 (0.0653)
Teamsize	0.00464 (0.0036)	0.00217 (0.0044)	0.00690 (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	-0.00294 (0.0027)	-0.00226 (0.0027)	0.000127 (0.0026)	0.00412 (0.0046)	0.00149 (0.0037)	0.000166 (0.0030)	0.00233 (0.0032)	0.00197 (0.0042)	0.00269 (0.0053)
Female*Average beauty score	-0.00572 (0.0103)	-0.00416 (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	-0.105 (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)	-0.111 (0.1464)	-0.240 (0.1623)
South Asian* Average beauty score	0.00667 (0.0249)	0.0103 (0.0264)	0.000547 (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	0.00400 (0.0132)	0.00113 (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)	-0.108 (0.6197)	-0.0943 (0.5711)	-0.102 (0.5502)	-0.130 (0.5402)
Constant	0.143*** (0.0138)	0.152*** (0.0260)	0.124** (0.0430)	0.0660 (0.0487)	0.140** (0.0443)	0.220*** (0.0395)	0.252*** (0.0486)	0.286*** (0.0630)	0.331** (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

Appendix I (continued) 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	0.265* (0.1157)	0.163* (0.0810)	0.0794 (0.0713)	0.0755 (0.0735)	0.131* (0.0664)	0.0759 (0.0685)	0.121* (0.0576)	0.153** (0.0557)	0.138* (0.0586)
Female	-0.481 (1.1743)	0.123 (0.6956)	0.0535 (0.8946)	0.128 (0.7296)	0.0917 (0.5973)	-0.226 (0.5358)	-0.226 (0.4884)	0.0767 (0.8381)	0.423 (0.8464)
Black	3.585 (9.9420)	5.620 (5.6726)	5.293 (5.2925)	3.058 (3.6450)	0.556 (3.0516)	-0.0645 (2.3836)	1.035 (1.8904)	0.762 (1.9492)	-1.861 (2.1088)
South Asian	0.495 (3.0319)	0.994 (2.3618)	0.257 (1.6451)	0.510 (1.1235)	0.608 (0.8162)	0.806 (0.7286)	0.681 (0.7325)	0.0834 (0.9146)	0.581 (1.1076)
East Asian	-0.0139 (0.8267)	-0.695 (0.5942)	-0.939 (0.6074)	-1.178* (0.5780)	-1.318* (0.5236)	-1.725** (0.5457)	-1.274 (0.7189)	-0.982* (0.4940)	-1.845** (0.7066)
MENA	12.27* (5.1528)	7.895 (5.1890)	-0.877 (5.5655)	-1.242 (4.4095)	-0.876 (4.6557)	-2.092 (4.1990)	-1.471 (4.6402)	-0.310 (6.0843)	-0.447 (7.6442)
Low income country	-0.679 (0.9187)	-0.740 (0.6959)	-0.607 (0.6276)	-0.355 (0.5455)	-0.317 (0.3376)	-0.422 (0.3135)	-0.330 (0.3119)	-0.191 (0.3269)	-0.0988 (0.3890)
Lower middle income country	0.541 (0.2961)	0.232 (0.2310)	0.0141 (0.2011)	-0.159 (0.1950)	-0.275 (0.1818)	-0.188 (0.1670)	-0.243 (0.1589)	-0.131 (0.2508)	0.0145 (0.3695)
Upper middle income country	-0.715 (0.5229)	-0.00875 (0.2138)	-0.200 (0.1216)	-0.349* (0.1481)	-0.440** (0.1678)	-0.335* (0.1679)	-0.232 (0.1939)	-0.230 (0.2311)	-0.147 (0.1699)
Assistant professor	-0.680* (0.2865)	-0.754** (0.2327)	-0.523*** (0.1559)	-0.483* (0.2053)	-0.183 (0.1887)	-0.143 (0.1905)	-0.0355 (0.1770)	0.0793 (0.1842)	0.329 (0.2510)
Associate professor	-0.111 (0.3028)	-0.174 (0.2184)	-0.0207 (0.1205)	-0.116 (0.1820)	-0.0529 (0.1551)	-0.131 (0.1714)	-0.0477 (0.1531)	-0.183 (0.1694)	-0.124 (0.2219)
Other occupations	-0.534 (0.3679)	-0.715** (0.2234)	-0.382* (0.1793)	-0.398* (0.1987)	-0.276 (0.2229)	-0.225 (0.2015)	-0.164 (0.1661)	-0.0300 (0.1539)	-0.00159 (0.2455)
Teamsize	0.414*** (0.0949)	0.323*** (0.0587)	0.293*** (0.0488)	0.365*** (0.0534)	0.344*** (0.0419)	0.344*** (0.0537)	0.324*** (0.0594)	0.340*** (0.0662)	0.257** (0.0802)
Work experience	-0.0629 (0.0430)	-0.0554 (0.0291)	-0.0362 (0.0233)	-0.0269 (0.0245)	0.00426 (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)	0.00138 (0.1069)	-0.0855 (0.1640)	-0.104 (0.1690)
Black*Average beauty score	-0.889 (3.2542)	-1.824 (1.7904)	-1.811 (1.7484)	-1.198 (1.2487)	-0.180 (1.0582)	-0.0687 (0.8613)	-0.418 (0.6901)	-0.451 (0.7342)	0.404 (0.7863)
South Asian* Aver beauty score	0.311 (0.7793)	0.0386 (0.6173)	0.120 (0.4153)	-0.0274 (0.2791)	-0.0548 (0.2095)	-0.133 (0.1924)	-0.0756 (0.2033)	0.0505 (0.2528)	-0.117 (0.2966)
East Asian* Average beauty score	-0.0874 (0.2040)	0.0613 (0.1582)	0.134 (0.1670)	0.219 (0.1532)	0.244 (0.1382)	0.301* (0.1301)	0.234 (0.1671)	0.171 (0.1380)	0.374* (0.1782)
MENA*Average beauty score	-3.456* (1.6817)	-2.495 (1.7075)	0.328 (1.8150)	0.373 (1.4496)	0.199 (1.4854)	0.624 (1.3003)	0.449 (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

Appendix J Three most attractive authors by gender

Three most attractive female authors

(1) Name and picture withheld because no consent was received from the author (7.55, American Economic Review)

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

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

Three most attractive male authors

Andrea Salvatori, Economist (7.55, Labour Economics)

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

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