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Beauty and Productivity in Academic Publishing

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Abstract

Academic publishing represents a field in which the opportunity for discrimination based on appearance should be limited since intellectual skills must play a key role. In this work, I document the beauty effect for economic scholars. Using unique data on academics who published their research papers in economic journals in 2017 and the new machine learning technique I test whether more attractive academics are more productive. I found evidence that appearance is positively and significantly associated with the success of research output as measured by the higher number of citations, the effects are robust and statistically significant.

1. Introduction

The economics of beauty is a rapidly expanding field. Since the pioneering study of the beauty premium in economics by Hamermesh and Biddle (1993), scholars have repeatedly demonstrated the presence of physical attractiveness effect on the labor market: better-looking individuals have a greater chance to be hired, achieve career success more easily, and earn 5 to 20 percent more than their less attractive colleagues. Most recent literature, however, conveys that the magnitude of beauty premium depends on occupation and a particular type of working task (Deryugina and Shurchkov (2014); Hernandez-Julian and Peters (2017); Kanazawa and Still (2017)). Several studies document a reverse, so-called ”beauty is beastly effect” (Johnson *et al.* (2010)), which reveals that beauty can be disadvantageous in the certain employment context (for example, for female applicants for traditionally masculine occupations).

After three decades of studying, there is no agreement on the magnitude of the effect and the source of labor outcome differentials between more-attractive and less-attractive workers. The most common explanation for the beauty premium is that it represents taste-based discrimination of decision-makers, and the great majority of literature focuses on a discrimination nature of a beauty premium. The evidence of discrimination was demonstrated by Mobius and Rosenblat (2006), Scholz and Sicinski (2015), Mateju and Anyzova (2017). The second possible explanation is a productivity-enhancing effect of beauty, which results from the fact that physical attractiveness is an indirect determining factor of individual productivity. This effect was indicated by Berri *et al.* (2010), Ahn and Lee (2014), Paphawasit and Fidrmuc (2017). It is not always straightforward to disentangle the effect that arises from

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differences in productivity from the one that arises from taste-based discrimination, and the efforts towards distinguishing these effects are limited in recent academic literature. The most obvious solution is to investigate the potential productivity-enhancing effect of beauty within occupations with limited face-to-face interaction. If beauty correlates with productivity for some occupations, it must be supported by the evidence of beauty premium in a case when the worker cannot be seen.

The nature of the academic profession suggests that scholars distribute their working hours between different types of activities. Previous studies mostly focus on the impact of beauty on teaching evaluations (Hamermesh and Parker (2003), Ponzo and Scoppa (2013), Wolbring and Riordan (2016).

However, it might be challenging to evaluate true teaching quality due to the potentially endogenous character of the relationship between students and teaching instructors. Students not only give better teaching scores to the more attractive instructors but also induce more beautiful teachers to improve their teaching quality to be treated more nicely by their students.

Academic publishing, in contrast, appears to be a promising area for exploring the nondiscriminative effect of physical attractiveness, since beauty is unlikely to affect the aspects of the publication process and citing directly. If employers discriminate on the grounds of beauty, attractive scholars may experience improved employment and career opportunities. If colleagues discriminate against more attractive scholars, they may be easily offered to be a part of scientific teams and find co-authorship. Nevertheless, their attractiveness could not transform directly into higher publication rates or higher citation counts since journal articles do not include authors' photos and are cited for their contribution to the scientific field. Moreover, for journals that utilize double-blind peer reviews, the identities of authors are concealed throughout the review, and reviewers, who play a crucial role in the publication process, do not even know who the authors are. Hence, the more impersonal setting of citations accumulated by each paper makes the positive inverse relationship interpretation implausible. Another crucial question is why might beauty matter for the number of citations. On the one hand, appearance is related to individual characteristics (e.g. self-confidence or charisma) that are created through a process of expectancy confirmation (Langlois *et al.* (2000)). Therefore, more attractive scholars become more confident and might be more prone to submit their articles to international conferences and research seminars, promote awareness about their papers, and consequently increase the number of citations. Also, it is more probable that the more physically attractive scholars join their more senior colleagues, particularly those of the opposite sex, which contributes to producing higher-quality papers.

In this work, I utilize a research design that uses citations as a measure of academic success, which allows to minimize the potential impact of taste-based discrimination. I investigate the effect of attractiveness on research productivity in economics, and, using a new machine-learning approach to measure facial beauty of academics, I indicate that beauty is positively and significantly associated with the citation counts obtained by the scholars who published their articles in economic journals in 2017. The results confirm the findings of earlier research by Paphawasit and Fidrmuc (2017) and Hale *et al.* (2021).

The remainder of this paper is structured as follows. In Section 2, the discussion on how scholars evaluate beauty and productivity is provided. In Section 3, I describe the empirical approach. Section 4 outlines the data collection process. In Section 5 the results of estimation are provided and discussed. In Section 6 I describe the process of robustness check. Section 7 concludes the paper, and the Appendix section provides additional important tables.

2. Measuring the Effect of Beauty on Productivity

2.1 How Scholars Evaluate Productivity

Worker productivity is typically quantified as an output (units produced), relative to input (number of hours worked or the cost of labor). However, individual labor productivity highly depends on the setting in which it is learned. Scholars usually use input measures, such as worker's wage, to assess productivity at the individual level (Frieze *et al.* 1991, Hamermesh and Biddle 1993, Biddle and Hamermesh 1995). Nevertheless, wages do not always reflect workers' productivity (Sauermann (2016)), or they might not be available. In such a case, researchers use or design performance-based measures that represent workers' productivity in specific settings. For example, Talamas *et al.* (2016), Hernandez-Julian and Peters (2017) use grade point average to measure student performance. Ponzo and Scoppa (2013), Wolbring and Riordan (2016) create composite measures of teaching quality based on course evaluation and students' ratings, while Hamermesh and Parker (2003) use students' reviews of the course to determine teachers ' productivity.

Academic employees usually distribute their working hours between research, teaching, and administration. Hence, the production process in academia has a composite nature, and productivity calculation requires adaptation to the study context. For this research, I analyze research productivity, which is a crucial element of the academic evaluation process. Research productivity has been measured in several ways in the empirical literature. Considering the "effort" aspect of the production process, the number of publications per researcher is an intuitive measure of research productivity, and numerous authors used this criterion in their research (Dilger *et al.* (2015), Hale *et al.* (2021), Haghani *et al.* (2022)). A significant drawback of using the measure is that the number of publications is associated with individual productivity, but does not consider the quality of the publications. Another commonly used bibliometrics indicator is h-index (Kpolovie (2017), Smith *et al.* (2018)). The h-index was introduced in 2005 by physicist Jorge Hirsch, and it takes into consideration both the number of publications and citation impact, however, this measure ignores the impact of publications with a number of citations below a certain level (so-called "h-level") and does not adjust for the number of co-authors and their contributions (Petersen and Succi (2013)).

Citation counts (or times cited) were first used for measuring the impact and quality of specific publications in work by Gross and Gross (1927). Later citation counts were repeatedly used to measure the individual and institutional-level performance of researchers (e.g., Tijssen *et al.* (2002), Sisk (2019)). Most recently Sen *et al.* (2010) propose assessing academic productivity by the number of publications, citations and the facts of co-authorship and grant funding. Paphawasit and Fidrmuc (2017) create a measure of average individual academic productivity that takes into account the number of citations, journal rank, and journal's impact factor to determine a researcher's academic contribution. The evidence that attractiveness matters for citation counts might appear counterintuitive, given that citations are unlikely affected by direct face-to-face contact between the cited and the citing, however, positive and significant effects of beauty on citation counts have been documented in previous studies (Paphawasit and Fidrmuc (2017), Hale *et al.* (2021)). The potential explanations of these findings are most likely indirect effects of beauty. Higher citation counts are likely associated with more successful presentation of articles in research seminars and conferences by more attractive academics. Moreover, beauty might increase a scholar's chances of being invited into scientific projects as a co-author.

Using the citation counts as a measure of the output of academic work requires consideration of several issues. One crucial issue arises from the fact that academic publishing often involves collaboration. Empirical literature shows some evidence of how collaboration influences research evaluation. Abramo *et al.* (2011) concluded that misrepresentation occurs in scientific productivity measurement when the number of co-authors or their position in the list is ignored. Abramo and D'Angelo (2014) propose to use the so-called fractional impact measure that represents the inverse of the number of authors in the academic domains where the practice is to place the authors in alphabetical order but assumes different weights in other academic fields. Another important issue concerns the randomness of the sample of collected publications. The fact is that one cannot consider all the publications of each scholar since academics may differ in their career stages, time spent on teaching, and other activities. Therefore, researchers who have been active for a longer period, usually have more publications than those who joined the academic field more recently or those who temporarily left the field for some reason. Hence, in this work, I collect only publications that appeared in the same year.

2.2 How Scholars Evaluate Beauty

Beauty is often considered an ascriptive characteristic, and it is said to be " in the eye of the beholder." However, the definition of beauty is not entirely subjective. Scholars have repeatedly revealed the existence of universal standards of beauty by demonstrating considerable agreement among independent raters about the attractiveness of individuals (Hamermesh and Biddle (1993); Biddle and Hamermesh (1995); Cipriani and Zago (2011)). The most commonly used measure of physical attractiveness in the literature is facial beauty since people form their first impressions from faces.

The empirical literature uses a wide variety of methods to create beauty scores. Occasionally scholars use self-reported ratings or interviewers' ratings of beauty. The most frequently used approach to measure physical attractiveness relies on independent photo-based ratings of beauty (Biddle and Hamermesh (1995), Cipriani and Zago (2011), Mobius and Rosenblat (2006), Scholz and Sicinski (2015), Salter *et al.* (2012), Hernandez-Julian and Peters (2017)). However, at present time, the use of a machine learning approach for face recognition is a growing practice. Sutić *et al.* (2010) proved the effectiveness of using the machine learning approach with an accuracy of 70 percent for face attractiveness recognition. Altwaijry and

Belongie (2013) first used a machine learning approach to rate the attractiveness of photos. The researchers in the field of economics of beauty, however, do not make extensive use of machine learning to obtain beauty ratings. Recently, Guo *et al.* (2023) found that less attractive head football coaches earn a salary premium relative to more attractive coaches using a neural network to generate attractiveness scores. Bi *et al.* (2020) use the web-based application that provides a facial beauty score and reports that facial attractiveness is uncorrelated with publication productivity, but it is positively linked to speaking invitation. Hrazdil *et al.* (2021) employ a machine learning-based attractiveness evaluation algorithm and verify that firms led by CFOs with a higher score of facial beauty receive more beneficial loan contracts from the bank institutions.

Since the number of scholars whose pictures have to be evaluated is substantial for this study, obtaining a sufficient number of attractiveness scores from raters could be more complicated and laborious compared to the machine learning approach. Moreover, using the photo ratings from volunteer evaluators can suffer from biases if the number of evaluators is rather small. Hence, I believe that using a machine learning-based algorithm for facial beauty evaluation contributes to the manageability of this research and can help mitigate potential biases in beauty ratings. To generate a continuous variable, that will reflect the attractiveness score of each author, I use the pre-trained neural network, which was designed in collaboration and created by my colleague from the faculty of Informatics and Robotics of Ufa State Aviation Technical University in 2021. The neural network is intended to analyze the facial characteristics of chosen photographs. In addressing such issues, the use of pre-trained convolutional neural networks (CNN) and transfer learning for the analysis of facial photos is a standard practice in machine learning.

2.3 How Scholars Study Association Between Beauty and Productivity in Academia

Previously, literature documented that facial attractiveness is associated with more beneficial judgment in a variety of occupations and settings. Nowadays several studies focus on whether and how beauty influences labor outcomes in academia. Most of the research in the subfield focuses on the relevance of academics' physical appearance for teaching-related success. Hamermesh and Parker (2003) uses students' instructional ratings of university professors and identifies that better-looking professors receive higher instructional ratings, and this effect is substantial and robust at all conditional quantiles of the distribution. Ponzo and Scoppa (2013) also takes students' evaluations to study the relationship between beauty and teaching quality and come to a similar conclusion: more attractive teaching instructors receive better evaluations. Beauty premium for teaching instructors is also supported by the results of Wolbring and Riordan (2016).

A number of studies examine the effect of beauty on academic career success. For example, Liu *et al.* (2022) analyze the impact of beauty on the career success of tenure-track accounting professors in the US and indicate that more attractive scholars get better first job placements and are granted tenure in a shorter period. The study by Hale *et al.* (2021) reveal that more attractive individuals are more likely to study at higher-ranked Ph.D. institutions and are more likely to locate at higher-ranking universities not only for their first work but also for job 15 years after their graduation. Additionally Hale *et al.* (2021) demonstrate no effect of attractiveness on the number of publications, but a significantly positive effect of authors' beauty on citation counts. Other studies concentrate on the effect of beauty on research output. Dilger *et al.* (2015) use the photos of 49 academics who participated at the conference in Bremen in 2010 to evaluate their attractiveness. To evaluate the measures of attractiveness, competence, and trustworthiness the authors conduct an online survey of students and indicate that research productivity as measured by the number of publications combined with journal weights is not influenced by beauty, but especially by perceived trustworthiness. Using the data of 2800 authors who published their works in 16 economic journals Paphawasit and Fidrmuc (2017) have found the significantly positive effect of an individual's attractiveness on research productivity in economics. In contrast, the results of Bi *et al.* (2020) suggest that facial attractiveness has no statistically significant relation to academic output. Interestingly, the authors demonstrate that in terms of internal academic activities (as measured by speaking fees and invitations), social scientists get an advantage by being more attractive.

Recent literature also discusses potential factors that could affect the relationship between facial attractiveness and individual research productivity. First, the relationship between a scholar's gender and research productivity has been investigated in a variety of countries and academic fields. The empirical evidence on the association between research performance and gender is, however, mixed in literature. Thelwall (2018) discovered that female-authored research is marginally more cited in Spain, the UK, and the US, but less cited in Turkey and India. Lower research impact affecting females was also discovered by Brooks *et al.* (2014). On the other hand, the major study of differences between citation-based impacts of female-authored and male-authored journal articles from 2011 to 2015 found that citation rates are similar overall in the 27 fields Elsevier (2017). Second, regarding ethnicity differences, the findings from prior studies also vary. Merritt (2000) explores gender and race differences in academia by examining logged citation counts for 815 professors of U.S. law schools and reports that white men obtain significantly more citations than women or ethnic minorities. Also, Ginther *et al.* (2018) identifies that African American or Black investigators have the same number of publications in comparison with their colleagues, but these publications are cited less often. Thomson *et al.* (2021) study racial-ethnic differences among academics in the fields of biology and physics and conclude that Asian academics experience distinct disadvantages in the promotion. Next, lower academic ranks are believed to correspond to lower wages, and therefore to lower scientific output compared to higher ranks. If higher academic rank relates to higher research performance then it would be necessary to distinguish academics by rank when using estimation techniques. Abramo *et al.* (2011) analyses the relationship between individual scientific performance and academic rank and identifies that for the amount of publications and research impact, full professors show the best performance, followed by associates and assistant professors. Furthermore, even though scientific collaboration is dominant in research development, not much is known about the relationships between the number of co-authors and research productivity. Zhu *et al.* (2021) detect that research productivity is positively associated with team size, while team size and research impact demonstrate an inverted-U shaped relationship. Larivière *et al.* (2014) confirm that a large team is likely to receive more citations compared to a small team, and female-authored papers tend to be less cited than male-authored papers.

Overall, the evidence of the positive effect of beauty on job-related success in academia is accumulating rapidly: more attractive teachers receive higher students' evaluations; more attractive scholars study in higher-ranked Ph.D. institutions; more attractive academics get better job placements. However, little is known about the effect of physical attractiveness on scholars' research performance, since academic output is unlikely to be affected by beauty directly. It might be important to better understanding why beauty matters, to exclude the taste-based discrimination explanation, and to measure the advantage provided by beauty in the outcomes of competitive production processes in academia such as the number of citations.

3. Empirical Approach

A great majority of studies on beauty premium use the Mincer-type human capital model to examine the association between beauty and outcomes. The model regresses individual earnings on a continuous beauty rating and a vector of individual characteristics (e.g., age, race, marital status, parenthood):

$$ln(Earnings_i) = \beta_0 + \beta_1 Beauty_i + \beta_2 X_i + \beta_3 Y_i + \varepsilon_i \tag{1}$$

For equation 1 ln ($Earnings_i$) denotes the individual level of annual or hourly counted earnings; $Beauty_i$ indicates individual attractiveness score; X_i is a vector of individual characteristics; Y_i indicates whether an occupation requires good-looking that could enhance productivity, and ε_i is the error term.

For this study, the main research question can be formulated as follows: whether and how academics' facial attractiveness is related to their research productivity in economics. Based on the results of prior studies, my initial hypothesis is that, ceteris paribus, academics with higher facial attractiveness score obtain higher citation counts. Since the empirical models are designed to capture the relationship between attractiveness and research productivity, I control for characteristics likely to be correlated with academic experience and publications. To summarize, in this work I use the following model:

$$ln(Citations_i) = \beta_0 + \beta_1 Beauty_i + \beta_2 X_i + \beta_3 Z_i + \varepsilon_i \tag{2}$$

For Equation 2 $ln(Citations_i)$ measures the individual research productivity and denotes the natural logarithm of citation counts from Google Scholar, Scopus, Web of Science; $Beauty_i$ is an individual attractiveness score; X_i represents the vector of social determinants such as gender and ethnicity; Z_i indicates the vector of occupation-specific characteristics such as number of co-authors, work experience, academic rank, etc.; ε_i is an error term.

In this model, I use the natural log of citation counts as the dependent variable to reduce skewing and to model the relationship more carefully. This measure represents the total number of citations in a given database (Google Scholar, Scopus, or Web of Science) and covers the period between 2017 and 2021 when the data collection process was finished. I collected publications that all came out in the same year so that all publications had the same amount of time to accumulate citations. In the model described by Equation 2 I control for individual and publication characteristics that may influence the research productivity. Specifically, I control for gender (male is a reference category), ethnicity (Caucasian is a reference category), having a Ph.D. degree, academic experience (number of years since obtaining Ph.D. and its squared term), academic rank (full professor is a reference category), number of co-authors (team size). To diminish autocorrelation concerns, I cluster the standard errors at the study level in the model.

4. Data

The dataset contains information on academics who published their studies in four impacted economic journals in 2017. Generally, the data sample includes 741 academics for which I could find online photographs, but the regression sample ranges according to data accessibility for each specification. For each scholar, I observe their name, gender, ethnicity, and graduation year. Collected occupational data include the institution of Ph.D. degree, academic rank, and rank of the institution granting Ph.D. Both personal and occupational data were collected from multiple sources such as personal and institutional web pages and an online search of CVs. Ethnicity was coded based on the author's photo. Gender was coded according to the photos and names of the authors. The ranking of economics departments is based on the RePEc ranking. All of the information collected, including the author's photos, is in the public domain at the time of collection. The data collection process was terminated in November 2021.

The descriptive statistics for the sample are presented in Table 1. From the initial sample of 741 individuals, 180 are women- the sample is predominantly male. 2.4 percent of the authors selected for the analysis published more than once in the journals included in the sample. Hence, I first estimate the research productivity considering all articles published in 2017 (column (1) of Table 2), and then I run the regression only for those authors who published once in 2017 and clustering standard errors at the study level. 94 percent of the authors in the sample hold a Ph.D. and their working experience ranges from 0 to 55 years, with the average author having 11 years of experience. Most of the academics in the sample are of Caucasian race (59 percent), followed by 38 percent who are Asian appearance and 2.4 percent who are African-American (ethnicity was coded based on appearance and other information available).

4.1 Publication Productivity Data

Obtaining the earnings of academics was virtually impossible. Hence, I followed the strategies proposed by Dilger et al. (2015), Paphawasit and Fidrmuc (2017) and Hale et al. (2021) and I collected citation counts to assess research productivity. The information about publications was collected from the currently publishing impacted journals in the field of economics. Publication data include the number of publications, title of article, journal volume and issue, number of co-authors, citation counts, and journal rank. To ensure a limited face-to-face interaction context at the publication stage, I collected information only from journals that operate a double anonymized review process: Quarterly Journal of Economics, Journal of Consumer Research, Economic Modelling, and Contemporary Economic Policy.

Table 1 Descriptive Statistics

Statistic	*N*	*Mean*	*St. Dev.*	*Min*	*Max*
Beauty	741	6.234	1.203	2.100	9.090
Gender					
Male	741	0.754	0.431	0	1
Female	741	0.243	0.429	0	1
Ethnicity					
Asian	741	0.382	0.486	0	1
Caucasian	741	0.594	0.491	0	1
Black	741	0.024	0.154	0	1
Occupational Characteristics					
Having PhD	735	0.940	0.237	0	1
Work Experience	719	11.460	10.149	0	55
Team Size	741	2.891	1.085	1	6
Academic Ranks					
Assistant professor	723	0.233	0.423	0	1
Associate professor	723	0.291	0.455	0	1
Full professor	723	0.296	0.457	0	1
Non-academic	736	0.107	0.310	0	1
Journal Characteristics					
JIF	741	2.920	2.198	0.960	7.863
GS citations	737	76.811	144.137	1	1,273
Scopus citations	704	22.341	36.103	1	280
WoS citations	674	23.194	34.361	1	256

Notes: The table shows summary statistics for academics' facial beauty measurement and other variables.

The journals belong to the same category of SSCI (Social Science Citation Index), that is economics, and embody both general (Quarterly Journal of Economics, Economic Modelling) and field-specific (Journal of Consumer Research, Contemporary Economic Policy) journals to be illustrative of the research outcomes of the economists; the journals are also associated with a different geographical area (US, UK, Netherlands).

I collected information on all articles published in these journals in 2017, except for special issues. The final sample includes information on 365 papers written by 741 authors. From journal records, I also collected article details: title of the article, journal volume, and issue, number of co-authors, and citation counts.

4.2 Appearance Data

Appearance data include the attractiveness ratings of academics' online photographs, as ranked by a neural network. The photos were downloaded through Google Image Search. The search of photos was conducted using the university and the name of the academic as keywords and then I selected one most precise, big, and directly facing the camera image. It is worth mentioning that the selection process can potentially introduce some bias, although I tried to use my best judgment. The beauty measure reflects evaluations of observable characteristics of each academic, based on the machine learning approach (namely, I used the neural network which was collaboratively designed with my colleague from the Faculty of Informatics and Robotics of Ufa State Aviation Technical University for obtaining beauty ratings with permission).

The machine learning approach was utilized to generate continuous variables that represent the assessed beauty scores of each academic in the interval (1,10) where 10 is the most attractive academic and 1 is the least attractive. The neural network was pre-trained based on the dataset, which includes 5500 frontal faces of Caucasian and Asian males and females aged from 15 to 60. The photos of academics were labeled with beauty scores and facial landmarks. Utilizing the labeled photos, the ResNeXt-50 CNN, which is the most commonly used type of neural network for face recognition in deep learning, was pre-trained. A batch of raw images was fed into the ResNeXt network with a batch size of 32, and the 10000 iterations.

5. Results

Natural logarithm of Google Scholar citation counts. Table 2 summarizes the results for the effect of attractiveness on research productivity expressed as the natural logarithm of citation counts from Google Scholar. In the first specification without the control variables, and the only explanatory variable being facial attractiveness score (column (1)), I indicate a strong and significant effect: more attractive scholars get more citations.

The effects remain significant but the magnitude decreases slightly when I include individual characteristics (column(2)), team size (column 3), and academic ranks (column (4)).

These results provide supporting evidence for the hypothesis, suggesting that academics' facial attractiveness is associated with higher citation rates. However, not all control variables in the regression show results similar to those reported in previous studies. Specifically, gender and belonging to the black race are not significant for all estimated specifications. Surprisingly, the number of years since the Ph.D. does not significantly influence citation counts. Intuitively, more experienced scholars tend to be more cited. However, in practice, with more years of experience in academia, scholars may spend more hours performing administrative functions at the universities, and they do not have as much time for research as their less experienced colleagues. Additionally, receiving tenure can potentially reduce the motivation to take on new research projects. The results of regression analysis confirm previous findings about the association between team size and citation counts, suggesting that large teams produce the more important and cited results, on average. I also find that working in a non-academic field is significantly and negatively associated with the number of citations, indicating that academics produce highly cited articles in comparison with authors who work outside academia.

Natural logarithm of Scopus citation counts . Table 3 reports the results for the effect of attractiveness on research productivity as measured by the natural logarithm of citation counts from the Scopus database. The results seem to be very similar to previous findings for all the specifications. In the first specification with the only explanatory variable which is facial attractiveness score (column (1)), I again find a positive and significant effect: more attractive individuals receive more citations. The effect remains significant after including individual indicators (column(2)), team size (column(3)), and academic ranks (column (4)).

Natural logarithm of Web of Science citation counts. Table 4 summarizes the results for the effect of attractiveness on research productivity expressed as the natural logarithm of citation counts from the Web of Science database. Again, the results are very similar to previous findings based on citations from Google Scholar and Scopus databases.

The results of the regression analysis for the first specification without the control variables, and the only explanatory variable being beauty score (column (1)), revealed a very strong and significant effect. The effect of beauty remains significant when the regression specifications include individual characteristics (column(2)), team size (column 3), and academic ranks (column (4)).

Relation between beauty and other characteristics. It might be possible that beauty is more important for different groups in the sample. Hence, I further perform regression analysis of the specifications that include interaction terms between the scholar’s beauty and personal and team characteristics. First, I examine how the relation varies with gender since beauty can intuitively be more important for female researchers. However, the results of the regression analysis show the insignificant coefficients of the interaction term. Similar insignificant results are obtained if I include the interaction component between beauty and ethnicity, and beauty and team size. Consistent with the previous results reported in Tables 2-4, the main effect of beauty is positive and statistically significant in all specifications.

To test the hypothesis that more attractive female scholars have a better chance to team up with experienced colleagues, which helps them produce better papers, I created the interaction component that combines three independent variables: beauty, gender, and team size. The results of the estimation show positive and statistically significant coefficients for females who work in small teams, direct effects of beauty and team size remain statistically significant. The results seem to be very similar for all three databases under consideration. That finding partially confirms the formulated hypothesis and requires further study. Columns (1-4) of Tables A3, A4, A5 show the impact of individual components of a scholar’s characteristics on beauty, whereas column (5) reports the results of the estimation of the specification with a three-dimensional interaction term.

Table 2 Effect of Attractiveness on the Number of Citations from Google Scholar

Dependent variable : natural logarithm of Google Scholar citation counts				
	(1)	**(2)**	**(3)**	**(4)**
Beauty	0.144*** (0.041)	0.169*** (0.046)	0.151*** (0.045)	0.154*** (0.045)
Gender (female=1)		−0.086 (0.118)	−0.099 (0.114)	−0.111 (0.114)
Ethnicity (asian=1)		−0.282** (0.110)	−0.368*** (0.106)	−0.371*** (0.107)
Ethnicity (black=1)		0.063 (0.378)	0.190 (0.365)	0.268 (0.364)
Work Experience		0.019 (0.013)	0.013 (0.013)	−0.007 (0.017)
Work Experience (squared)		−0.001* (0.0003)	−0.001* (0.0003)	−0.0002 (0.0004)
Team Size			0.330*** (0.046)	0.330*** (0.046)
Teaching Assistant position				−0.329 (0.269)
Assistant Professor position				−0.211 (0.189)
Associate Professor position				−0.187 (0.148)
Non -academic position				−0.654*** (0.206)
Constant	2.221*** (0.259)	2.374*** (0.338)	1.630*** (0.343)	1.969*** (0.405)
Observations	737	692	692	685
R^2	0.026	0.041	0.107	0.125

Notes: Each column of the table reports a separate ordinary least squares regression with controls for individual characteristics (gender, ethnicity (African and Asian vs. Caucasian)), professional age (and its squared term), team size, and dummies for academic ranks. Standard errors are clustered at study level in models (2), (3), and (4). Standard errors are in parentheses. * P < 0.10, ** P < 0.05, *** P < 0.01

Table 3 Effect of Attractiveness on the Number of Citations from Scopus

Dependent variable: natural logarithm of Scopus citation counts				
	(1)	**(2)**	**(3)**	**(4)**
Beauty	0.103*** (0.035)	0.127 *** (0.039)	0.115*** (0.038)	0.117*** (0.039)
Gender (female=1)		−0.036 (0.100)	−0.050 (0.097)	−0.065 (0.097)
Ethnicity (asian=1)		−0.050 (0.093)	−0.123 (0.092)	−0.130 (0.096)
Ethnicity (black=1)		−0.041 (0.313)	0.044 (0.306)	0.114 (0.305)
Work Experience		0.018 (0.011)	0.013 (0.011)	−0.0002 (0.015)
Work Experience (squared)		−0.001** (0.0003)	−0.001* (0.0004)	0.0002 (0.0003)
Team Size			0.226*** (0.039)	0.231*** (0.039)
Teaching Assistant position				−0.225 (0.229)
Assistant Professor position				−0.201 (0.160)
Associate Professor position				−0.110 (0.126)
Non-academic position				−0.602*** (0.178)
Constant	1.958*** (0.223)	1.721*** (0.289)	1.214*** (0.295)	1.498*** (0.3473)
Observations	704	659	659	687
R^2	0.012	0.026	0.073	0.110

Notes: Each column of the table reports a separate ordinary least squares regression with controls for individual characteristics (gender, ethnicity (African and Asian vs. Caucasian)), professional age (and its squared term), team size, and dummies for academic ranks. Standard errors are clustered at study level in models (2), (3), and (4). Standard errors are in parentheses. * P < 0.10, ** P < 0.05, *** P < 0.01

Table 4 Effect of Attractiveness on the Number of Citation from Web of Science

Dependent variable: natural logarithm of WoS citation counts				
	(1)	**(2)**	**(3)**	**(4)**
Beauty	0.119***	0.124***	0.116***	0.116***
	(0.035)	(0.039)	(0.038)	(0.038)
Gender (female=1)		−0.016	−0.022	−0.040
		(0.102)	(0.100)	(0.100)
Ethnicity (asian=1)		−0.008	−0.088	−0.096
		(0.094)	(0.093)	(0.093)
Ethnicity (black=1)		0.198	0.298	0.352
		(0.311)	(0.303)	(0.302)
Work Experience		0.007	0.004	−0.001
		(0.012)	(0.011)	(0.015)
Work Experience (squared)		−0.0003	−0.0003	−0.0002
		(0.0003)	(0.0003)	(0.0003)
Team Size			0.247***	0.259***
			(0.042)	(0.042)
Teaching Assistant position				0.027
				(0.233)
Assistant Professor position				0.002
				(0.163)
Associate Professor position				−0.067
				(0.129)
Non-academic position				−0.477***
				(0.178)
Constant	1.829***	1.793***	1.197***	1.281***
	(0.219)	(0.285)	(0.295)	(0.346)
Observations	674	629	629	624
R^2	0.012	0.022	0.075	0.14

Notes: Each column of the table reports a separate ordinary least squares regression with controls for individual characteristics (gender, ethnicity (African and Asian vs. Caucasian)), professional age (and its squared term), team size, and dummies for academic ranks. Standard errors are clustered at study level in models (2), (3), and (4). Standard errors are in parentheses. * P < 0.10, ** P < 0.05, *** P < 0.01

6. Robustness Check

I run several robustness tests for my findings. First, I verify that the measure of facial attractiveness produced by the neural network is a valid alternative to real human perceptions. Following the approaches proposed by Hsieh *et al.* (2020) and Hrazdil *et al.* (2021) I randomly select a set of fifteen pictures of the academics in the sample (2 images from the third to eighth quintiles and 1 image of the second and ninth quantiles of the facial beauty measure), and I survey 200 independent evaluators to provide their ratings of the facial attractiveness of the fifteen academics. The photos of the academics are displayed to raters in a random sequence without disclosing the identities of the academics. I asked the participants the following question: “How attractive is this person in the photo?” Participants were asked to assess each photo on a ten-point scale from 1 (Unattractive) to 10 (Strikingly attractive). For each photo, I averaged responses across all participants to obtain an average facial beauty rating (Beauty Score). The mean Beauty Score by raters is 6,151. Table 5 reports the descriptive statistics of raters.

Table 5 Descriptive Statistics: Raters

Statistic	*N*	*Mean*	*St. Dev.*	*Min*	*Max*
Beauty Score	200	6.151	1.203	1	10
Gender					
Male	200	0.455	0.431	0	1
Female	200	0.545	0.429	0	1
Age					
18-24	200	0.090	0.486	0	1
25-34	200	0.315	0.491	0	1
35-44	200	0.325	0.491	0	1
45-54	200	0.160	0.491	0	1
55-64	200	0.105	0.154	0	1
64-75	200	0.005	0.154	0	1
Degree					
High school degree	200	0.140	0.237	0	1
Bachelor Degree or equivalent	200	0.200	10.149	0	1
Master Degree or equivalent	200	0.635	398.037	0	1
Ph.D degree or equivalent	200	0.025	1.085	0	1

Notes: This table shows summary statistics for independent raters.

To measure the machine learning model performance I calculate the Pearson correlation coefficient between the mean facial attractiveness rating from the 200 raters and the machinegenerated beauty index. Using Pearson Correlation Coefficient which captures linear correlations, is a standard practice to investigate neural network and subjects correlation. Since the Pearson correlation coefficient works perfectly on normally distributed data, I first checked the skewness statistics of the subsample beauty ratings obtained using the machine learning technique and the human ratings. Since the considered subsample was found to be normally distributed, the Pearson correlation coefficient and the corresponding p-value are reliable. The Pearson correlation coefficient is 0.816 with a p-value of 0,0002; the correlation is significant at the 1% level. The magnitude of the correlation coefficient is similar to the correlation coefficient documented by Hsieh *et al.* (2020) and Hrazdil *et al.* (2021).

Next, I test whether assuming equal impact for scholars of distinct research teams partially drives the results. Since the literature has found that distortion occurs when measuring scientific productivity, and the number of co-authors or their position in the byline is ignored (Abramo and D’Angelo (2014)), I re-estimate the initial regression using the fractional impact measure and the weights for position proposed by Abramo and D'Angelo (2014). I indicate that the results are not affected by this change in the model (Table A2). I further estimate the model specification that takes into account the presence of the influential scholar in each research team. To identify the presence of a very well-known author in each team, I collected information about h-indexes on Google Scholar for the subsample of 350 academics from 3 journals. According to Hirsch (2005), the value of the h-index which is higher than 40 can be considered exceptional. Hence, I estimate the regression using a dummy variable that equals 1 if there is a scholar with a higher than 40 h-index in each research team. The regression results are presented in Table A6 of the Appendix section. The effect of beauty remains statistically significant, and the presence of the author with a high value of h-index positively influences the number of citations received, keeping other variables constant. However, the h-index can give just an approximation of an individual academic influence, and many other factors should be considered when evaluating an influence in academia.

7. Concluding Remarks

In this work, I explore the association between scholars' appearance and their publication success as measured by citation counts. I indicate that physical attractiveness matters for scholars who published their articles in economic journals in 2017. Specifically, more attractive academics obtain higher citation counts, and this finding supports the previous results provided by Paphawasit and Fidrmuc (2017) and Hale *et al.* (2021). The potential explanation for why the facial attractiveness of academics might be relevant for higher citation counts is the presence of indirect effects of beauty in academia. First, the findings suggest that more attractive female scholars easily become a member of small scientific teams and thus produce higher-quality research and receive higher citation counts. Second, better-looking academics potentially have better chances to be invited to the research seminars and conferences, they can successfully present their research because of higher confidence, and consequently receive more valuable comments and attention which translates into higher citation rates.

Although the results of the study show the presence of the beauty premium in academic publishing, the empirical analysis does not provide a conclusion about whether physical attractiveness must be considered an indicative factor in this scientific domain. The specific setting of the study, on the one hand, allows to minimize the potential influence of taste-based discrimination and investigate the mechanisms that can explain how beauty bias occurs in academic publishing. On the other hand, it is inherently challenging to analyze the impact of beauty, because it cannot be tracked from the very origin. Therefore, this study, like the majority of studies on the beauty premium, demonstrates the effect of beauty only at the last stage of the sequence of potentially strengthening stages, that start in childhood.

Another important limitation of the study is the sample that inherently suffers from a selection bias because it is constrained to researchers who successfully publish their articles in one of the selected economic journals. It can happen that some of the less attractive scholars never publish their research in one of these four journals. Hence, the bias alleviates the variability of the independent variable. Although this limitation suggests that the documented results in the expected direction are likely unreliable, the findings do not imply that the beauty effect is not important in academia. To further receive more convincing results I suggest that future research explore the effect of beauty in the context which implies greater variation in the treatment variable and less noise in the measurement of the output variable.

APPENDIX

Table A1 Description of Variables Used in This Study

Variable Name	***Definition and construction***
Beauty	Academic's facial beauty, constructed using a machinelearning algorithm. The variable represents the assessed facial attractiveness score of each academic based on a continuous variable in the interval (1,10) where 10 is the most attractive academic and 1 is the least attractive.
Ln(Citations)	Natural logarithm of citation counts obtained for Google Scholar, Scopus, Web of Science databases in the period since publication in 2017 to November, 2021, when the data collection process was finished
Gender	An indicator variable that equals 1 if the academic is female, and 0 otherwise.
Ethnicity	An indicator variable that equals 1 if the academic is asian, and 0 otherwise.
Work Experience	Number of years since the academic received Ph.D or equivalent degree.
Work Experience (squared)	Squared term of the number of years since the academic received Ph.D or equivalent degree.
Team size	Number of co-authors, who worked on the particular paper
Teaching Assistant position	An indicator variable that equals 1 if the scholar had a position of teaching assistant in 2017, and 0 otherwise.
Assistant Professor position	An indicator variable that equals 1 if the scholar had a position of assistant professor in 2017, and 0 otherwise.
Associate Professor position	An indicator variable that equals 1 if the scholar had a position of associate professor in 2017, and 0 otherwise.
Non-academic position	An indicator variable that equals 1 if the scholar had a non- academic position in 2017, and 0 otherwise.

Note: This table shows description of the variables used in this study

Table A2 Effect of Attractiveness on the Number of Citations from GS

Dependent variable: natural logarithm of Google Scholar citations		
	(1)	**(2)**
Beauty	0.163*** (0.046)	0.159*** (0.046)
Gender (female=1)	−0.097 (0.117)	−0.091 (0.117)
Ethnicity (asian=1)	−0.324*** (0.110)	−0.336*** (0.110)
Ethnicity (black=1)	0.178 (0.375)	0.258 (0.374)
Work Experience	0.012 (0.013)	−0.010 (0.018)
Work Experience (squared)	−0.001 (0.0003)	−0.0002 (0.0004)
Weighted Fractional Impact	−1.285*** (0.245)	−1.310*** (0.246)
Teaching Assistant position		−0.388 (0.276)
Assistant Professor position		−0.264 (0.194)
Associate Professor position		−0.234 (0.152)
Non-academic position		−0.692*** (0.210)
Constant	3.014*** (0.365)	3.462*** (0.417)
Observations	692	692
R^2	0.078	0.093

Notes: Each column of the table reports a separate ordinary least squares regression with controls for individual characteristics (gender, ethnicity (African and Asian vs. Caucasian)), professional age (and its squared term), weighted fractional impact and dummies for academic ranks. Standard errors are clustered at study level. Standard errors are in parentheses. * P < 0.10, ** P < 0.05, *** P < 0.01

Table A3 Effect of Attractiveness on the Number of Citations from Google Scholar

	Dependent variable: natural logarithm of Google Scholar citations				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Beauty	0.145*** (0.050)	0.093* (0.054)	0.122** (0.048)	0.155*** (0.044)	0.130*** (0.043)
*Beauty*Gender (Female=1)*	0.002 (0.098)				
*Beauty*Ethnicity (Asian=1)*		0.141 (0.088)			
*Beauty*Small Team*			0.033 (0.028)		
*Beauty*Large Team*				−0.033 (0.028)	
*Beauty*Female*Small Team*					0.086** (0.35)
Gender (Female=1)	−0.127 (0.628)				−0.497** (0.194)
Ethnicity (Asian=1)					
Team Size			0.392*** (0.073)	0.392*** (0.073)	0.375*** (0.050)
Constant	2.054*** (0.415)		1.854*** (0.427)	1.854*** (0.427)	2.057*** (0.358)
Controls	YES		YES	YES	YES
Observations	684	684	684	684	684
R^2	0.123	0.126	0.125	0.125	0.130

Notes: Each column of the table reports a separate ordinary least squares regression with controls for individual characteristics, professional age (and its squared term), team size, dummies for academic ranks and interactions terms between beauty and personal and team characteristics. Standard errors are clustered at study level. Standard errors are in parentheses. * P < 0.10, ** P < 0.05, *** P < 0.01

Table A4 Effect of Attractiveness on the Number of Citations from Scopus

Dependent variable: natural logarithm of Scopus citations					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Beauty	0.113*** (0.043)	0.080** (0.046)	0.108*** (0.041)	0.115*** (0.038)	0.108*** (0.039)
*Beauty*Gender (Female=1)*	0.002 (0.083)				
*Beauty*Ethnicity (Asian=1)*		0.094 (0.077)			
*Beauty*Small Team*			0.007 (0.024)		
*Beauty*Large Team*				−0.007 (0.024)	
*Beauty*Female*Small Team*					0.078*** (0.030)
Gender (Female=1)	−0.078 (0.536)				−0.419** (0.166)
Ethnicity (Asian=1)		−0.715 (0.482)			
Team Size			0.244*** (0.062)	0.244*** (0.062)	0.265*** (0.044)
Constant	1.535*** (0.355)	1.739*** (0.375)	1.493*** (0.364)	1.493*** (0.364)	1.476*** (0.351)
Controls	YES	YES	YES	YES	YES
Observations	652	652	652	652	652
R^2	0.093	0.095	0.093	0.093	0.098

Notes: Each column of the table reports a separate ordinary least squares regression with controls for individual characteristics, professional age (and its squared term), team size, and dummies for academic ranks and interactions terms between beauty and personal and team characteristics. Standard errors are clustered at study level. Standard errors are in parentheses. * P < 0.10, ** P < 0.05, *** P < 0.01

Table A5 Effect of Attractiveness on the Number of Citations from Web of Science

Dependent variable: natural logarithm of WoS citations

	(1)	(2)	(3)	(4)	(5)
Beauty	0.106** (0.042)	0.047 * (0.046)	0.114*** (0.041)	0.093** (0.038)	0.096** (0.037)
*Beauty*Gender (Female=1)*	−0.026 (0.085)				
*Beauty*Ethnicity (Asian=1)*		0.140* (0.075)			
*Beauty*Small Team*			−0.021 (0.024)		
*Beauty*Large Team*				0.021 (0.024)	
*Beauty*Female*Small Team*					0.040* (0.032)
Gender (Female=1)	0.124 (0.541)				−0.223 (0.176)
Ethnicity (Asian=1)		−0.981* (0.471)			
Team Size			0.216*** (0.064)	0.216*** (0.064)	0.281*** (0.045)
Constant	1.378*** (0.357)	1.751*** (0.384)	1.538*** (0.368)	1.538*** (0.368)	1.362*** (0.341)
Controls	YES	YES	YES	YES	YES
Observations	621	621	621	621	621
R^2	0.091	0.096	0.092	0.092	0.094

Notes: Each column of the table reports a separate ordinary least squares regression with controls for individual characteristics, professional age (and its squared term), team size, dummies for academic ranks and interactions terms between beauty and personal and team characteristics. Standard errors are clustered at study level. Standard errors are in parentheses. * P < 0.10, ** P < 0.05, *** P < 0.01

Table A6 Effect of Attractiveness on the Number of Citations from Google Scholar

	Dependent variable: natural logarithm of GS citations
Beauty	0.165** (0.078)
Gender (female=1)	−0.307* (0.167)
Ethnicity (asian=1)	−0.084 (0.179)
Ethnicity (black =1)	−0.459 (0.961)
Work Experience	−0.009 (0.027)
Work Experience (squared)	−0.0004 (0.001)
Team Size	0.121* (0.073)
Influential academic	0.677*** (0.172)
Teaching Assistant position	−0.958** (0.442)
Assistant Professor position	−0.532* (0.289)
Associate Professor position	−0.249 (0.221)
Non-Academic position	−0.620** (0.303)
Constant	2.979** (0.679)
Observations	316
R^2	0.158

Notes: Table reports an ordinary least squares regression with controls for individual characteristics, professional age (and its squared term), team size, dummy for influential author and dummies for academic ranks. Standard errors are clustered at study level. Standard errors are in parentheses. * P < 0.10, ** P < 0.05, *** P < 0.01

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