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BEAUTY AND PRODUCTIVITY IN ACADEMIC PUBLISHING

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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 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. However, the effect magnitude is rather small, and it becomes even smaller when I control for the ranking of the Ph.D. granting institution.

JEL: C83, J3, J7, M51
Keywords: Beauty bias, productivity, discrimination, academic publishing

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 & Shurchkov (2014); Hernandez-Julian & Peters (2017); Kanazawa & 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 & Rosenblat (2006), Scholz & Sicinski (2015), Mateju & Anyzova (2017). The second possible explanation is a productivity-enhancing effect of beauty, which results from the fact that physical attractiveness is a determining factor of individual productivity. This effect was indicated by Berri *et al.* (2010), Ahn & Lee (2014), and Paphawasit and Fidrmuc (2017). It is not always straightforward to disentangle the effect that arises from 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.

Academic publishing appears to be a promising area for exploring the non-discriminative effect of physical attractiveness. Particularly, if employers discriminate on the grounds of beauty, attractive scholars may experience improved employment opportunities and career opportunities. If colleagues use discrimination against more attractive scholars, they may be easier offered to be a part of scientific teams and find co-authorship. Nevertheless, their attractiveness should not transform into higher publication rates or higher citation counts because editors and reviewers do not usually meet the authors during the process of publication. For journals that use double-blind 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, however this assumption may not always be valid for small scientific sub-fields, where leading experts may know each other's works quite well. Scholars' attractiveness should not translate into higher citation rates as well, because readers usually have no intention to check who the authors are.

To the best of my knowledge,there are only several studies that focus on the relationship between beauty and research productivity, and these studies have had conflicting results. Dilger *et al.* (2015) indicate that research performance is not influenced by beauty, but especially by perceived trustworthiness. In contrast, Paphawasit and Fidrmuc (2017) have found the significantly positive effect of an individual's attractiveness on research productivity in economics. The results of Bi (2020) demonstrate that facial beauty has no statistically significant relation to citation-based productivity for full-time and part-time academics, but idetify positive association between beauty and public speaking invitation and fees. Hale *et al.* (2021) document no effect on the number of publications, but significantly positive effect of authors' beauty on academic job outcomes and citations. In this work, I investigate the effect of facial attractiveness on research productivity in economics, and I indicate that physical attractiveness 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). However, the magnitude of the effect of beauty on research performance is rather small in comparison with the previous results.

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 Appendix A section provides additional important tables.

2 Measuring the effect of beauty on productivity

The purpose of this chapter is threefold: first, it intends to show how research productivity is assessed in literature; second, it aims to describe how scholars assess physical attractiveness in research settings; third, I review current literature on the association between physical attractiveness and productivity in academia.

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 learnt. 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 & 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 & Peters (2017) use grade point average to measure student performance. Ponzo & Scoppa (2013), Wolbring & Riordan (2016) create composite measures of teaching quality based on course evaluation and students' ratings, while Hamermesh & Parker (2003) use students' reviews of the course to determine teacher's productivity.

Academic employers usually distribute their working hours between research, teaching, and administration. Hence, the academics' production process has a composite nature, and productivity calculation requires adaptation to the study context. For the purpose of 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 amount 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 & Succi (2013)).

Citation counts (or times cited) were first used as a way for measuring the impact and quality of specific publications in work by Gross & 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 and 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. Using the citation counts metric 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 & 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 ”on 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 & Hamermesh 1995; Cipriani & 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 & Hamermesh 1995, Cipriani & Zago 2011, Mobius & Rosenblat 2006, Scholz & Sicinski 2015, Salter *et al.* 2012, Hernandez-Julian & 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 & 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 the machine learning to obtain beauty ratings. Recently, Guo *et al.* (2023) find that less attractive head football coaches earn a salary premium relative to more attractive coaches using a neural network to generate attractiveness score. Bi (2020) use the web-based application that provides a facial beauty score and report 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, then obtaining a sufficient number of attractiveness scores from raters could possibly 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 to mitigate potential biases in beauty ratings. To generate a continuous variable, which 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 there are several studies that 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 & 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 & 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 & 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 career success of tenure-track accounting professors in US, and indicate that more attractive scholars get better first job placements and are granted tenure in a shorter period of time. In their study Hale *et al.* (2021) reveal that more attractive individuals are more likely to study at higher-ranked Ph.D. universities and are more likely to locate at higher-ranking institutions not only for their first job, but also for employment in 15 years after their graduation. Additionally Hale *et al.* (2021) demonstrate no effect of attractiveness on the number of publications, but 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 on-line 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 (2020)) suggest that facial attractiveness has no statistically significant relation to productivity growth for academics. Interestingly, the authors demonstrate that in terms of internal academic activities (as measured by speaking fees and invitation), social scientists gain an advantage from being more attractive. Hence, 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.

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):

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

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:

Hypothesis: Ceteris paribus, academics with higher facial attractiveness score obtain higher citation counts.

Several factors could affect the relationship between facial attractiveness and individual research productivity. 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). 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 ethnical minorities. Also, Donna K. Ginther (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. Jr. *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 assistants 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. Nibing Zhu (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.

To summarize, in this work I use the following model:

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

For Equation 2 $ln(Citations_i)$ measures the individual research productivity and denotes the natural logarithm of citation counts from Google Scholar and Scopus; $Beauty_i$ 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. Another crucial question is what database to choose for counting the citations since it is known that scientific databases vary in coverage according to the scientific fields. Several studies attempt to identify whether one scientific database is better than another (Bar-Ilan *et al.* (2007), Mongeon & Paul-Hus (2016),). The three standard databases are Web of Science, Scopus, and Google Scholar. Web of Science and Scopus databases cover a vast number of studies although the scientific domains intersect only partially: Web of Science covers engineering and natural sciences widely, whereas Scopus covers social science articles more extensively. Google Scholar has a tendency to show a slightly higher number of citations since it indexes some amount of non-scholarly information, and sometimes Google Scholar includes duplicate records, giving an exaggerated number of citations. However researchers continue to use citation counts from Google Scholar in their studies on research impact(Dilger *et al.* (2015), Bi (2020), Hale *et al.* (2021)). In this work I use citation counts from Scopus (since, on average, it tends to include a slightly broader range of publications in economics) and Google Scholar (since it allows me to compare my findings to the results of prior studies).

In the model described by Equation 2 I control for individual and publications' 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 it's squared term), academic rank (full professor is a reference category), economic department rank (a set of dummies that indicates belonging to the particular decile of distribution of universities ranks), number of co-authoes (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. Gender and ethnicity were coded based on the author's photo. 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 A1 of Appendix Section. 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 (coloumn (1) of Table 1), 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 white (59 percent), followed by 38 percent who are asian appearance and 2.4 percent who are black (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 limited face-to face interaction context I collected information about publication only from for journals which operates a double anonymized review process: Quarterly Journal of Economics, Journal of Consumer Research, Economic Modelling, Contemporary Economic Policy. The journals belong to the same category of SSCI(Social Sciencies Citation Index), that is economics. I collected information on all articles published in these journals in 2017, with the exception of special or conference issues. The final sample includes information on 365 papers written by 741 authors. From journal records I also collected article details: title of article, journal volume and issue, number of co-authors, citation counts and journal impact factor.

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 name and name of the academic as key words and then I select one most precise, big, and directly facing the camera image. It is worth mentioning that selecting process can potentially introduce some bias, although I tried to use my best judgement.

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 allows to generate continuous variables. These variables represent the assessed beauty scores 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. The additional benefit of using the machine learning approach is that the beauty measure does not depend on facial expression, because this type of pre-trained deep learning model as used for this research has pretty high face recognition accuracy.

5 Results

I begin by testing whether publication impact as measured by natural logarithm of citation counts is associated with facial attractiveness.

Natural logarithm of Google Scholar citation counts . Table 1 summarizes the results for the effect of attractiveness on research productivity expressed as the natural log 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. The evidence that attractiveness matter for citation counts might appear counterintuitive, given that the publication process in economics usually does not involve authors' photos, however, positive and significant effects of beauty on citation counts have been documented in previous studies (Paphawasit and Fidrmuc (2017), Hale *et al.* (2021)). Recent literature discusses several potential mechanisms explaining the effect of physical attractiveness on individual research impact. First, appearance has been found to be 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 people become more confident and might be more prone to submit their articles to international conferences and thus receive greater exposure. Also, they might be more prone to request constructive comments at the conferences, and,as a consequence, may produce higher quality articles that receive more citations.

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. On the other hand, the results 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-academical field is significantly and negatively associated with the number of citations, indicating that academics produce higher cited articles in comparison with authors who work outside academia.

Natural logarithm of Scopus citation counts . Table 2 reports the results for the effect of attractiveness on research productivity as measured by the natural log 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 decreases in magnitude, but remains significant after including individual indicators (column(2)), team size (column(3)), and academic ranks (column (4)). I further examine whether and how including the ranks of the Ph.D. granting institution(i.e. economic department's ranks taken from the RePEc database) influences research performance. Ranks were taken for the year 2017, and a rank of 1 indicates the most highly ranked economic department in RePEc database. Since I observe many values of departments' ranks, I compute deciles in their distributions. To perform the regression I split up the univariate university rank variable into 10 different dummy variables representing inclusion or exclusion from a particular decile, with the reference category of belonging to the tenth decile, hence, in regression I omit this decile ranks to avoid the "dummy variable trap". In Table 3, I again use the natural logarithm of citations from Google Scholar (column (1)) and Scopus (column (2)) and retest the initial hypothesis with significant regressors only. The results indicate that being a student of higher-standard economics institutions is associated with higher citation rates, as I expected. More interestingly, the positive effect of facial attractiveness becomes considerably smaller and less significant when I include indicators for a rank of the Ph.D. granting institution. This finding partially supports the results of Hale *et al.* (2021) who report that university rank is positively and significantly associated with citation counts. The result indicates that the difference in citation counts between more-attractive and less-attractive academics is linked to the differences in prior education, and also to the prestige of the economic department at which the scholar studied. Hence, reducing in these educational differences lowers the differences in citation counts.

Table 1: Effect of attractiveness on the number of citations from Google Scholar

	Dependent variable:			
	natural logarithm of citation counts			
	(1)	(2)	(3)	(4)
Attractiveness Score	0.144***	0.169***	0.151***	0.154***
	(0.041)	(0.046)	(0.045)	(0.045)
Gender (female=1)		−0.086	−0.099	−0.111
		(0.118)	(0.114)	(0.114)
Ethnicity (asian=1)		−0.282**	−0.368***	−0.371***
		(0.110)	(0.106)	(0.107)
Ethnicity (black=1)		0.063	0.190	0.268
		(0.378)	(0.365)	(0.364)
Work Experience		0.019	0.013	−0.007
		(0.013)	(0.013)	(0.017)
Work Experience (squared)		−0.001*	−0.001 *	−0.0002
		(0.0003)	(0.0003)	(0.0004)
Team Size			0.330***	0.330***
			(0.046)	(0.046)
Teaching Assistant position				−0.329
				(0.269)
Assistant Professor positio				−0.211
				(0.189)
Associate Professor position				−0.187
				(0.148)
Non-academic position				−0.654***
				(0.206)
Constant	2.221***	2.374***	1.630***	1.969***
	(0.259)	(0.338)	(0.343)	(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 2: Effect of attractiveness on the number of citations from Scopus

	Dependent variable:			
	natural logarithm of citation counts			
	(1)	(2)	(3)	(4)
Attractiveness Score	0.103***	0.127 ***	0.115***	0.117***
	(0.035)	(0.039)	(0.038)	(0.039)
Gender (female=1)		−0.036	−0.050	−0.065
		(0.100)	(0.097)	(0.097)
Ethnicity (asian=1)		−0.050	−0.123	−0.130
		(0.093)	(0.092)	(0.096)
Ethnicity (black=1)		−0.041	0.044	0.114
		(0.313)	(0.306)	(0.305)
Work Experience		0.018	0.013	−0.0002
		(0.011)	(0.011)	(0.015)
Work Experience (squared)		−0.001**	−0.001*	0.0002
		(0.0003)	(0.0004)	(0.0003)
Team Size			0.226***	0.231***
			(0.039)	(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***	1.721***	1.214***	1.498***
	(0.223)	(0.289)	(0.295)	(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 3: Effect of attractiveness on the number of citations with Ph.D universities ranks

	Dependent variable:	
	natural logarithm of citations	
	(1)	(2)
Attractiveness Score	0.080**	0.069**
	(0.037)	(0.033)
Ethnicity (asian=1)	−0.221**	−0.033
	(0.092)	(0.081)
Team Size	0.253***	0.176***
	(0.041)	(0.036)
Non-academic position	−0.178	−0.224*
	(0.140)	(0.126)
Decile 1	1.653***	1.146***
	(0.129)	(0.113)
Decile 2	0.275*	0.174
	(0.165)	(0.142)
Decile 3	0.589**	0.593***
	(0.235)	(0.208)
Decile 4	1.098 ***	0.900***
	(0.292)	(0.253)
Decile 5	0.028	0.019
	(0.204)	(0.182)
Decile 6	−0.101	−0.047
	(0.255)	(0.232)
Decile 7	0.027	0.078
	(0.273)	(0.33)
Decile 8	−0.454	−0.367
	(0.277)	(0.252)
Decile 9	0.793***	0.547**
	(0.261)	(0.227)
Constant	1.996***	1.412***
	(0.266)	(0.236)
Observations	708	677
R^2	0.295	0.224

Notes: Each column of the table reports a separate ordinary least squares regression with controls for Ph.D. granting institution . Standard errors are clustered at the study level. 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. In this section, I provide a brief discussion of the results of the robustness check. All the corresponding tables can be found in the Appendix Section.

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 eight 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 ask 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 average responses across all participants to obtain an average facial beauty rating (Attractiveness Score). The mean Attractiveness Score by raters is 6,151. Table A2 in the Appendix section reports the descriptive statistics of raters. I calculate the Pearson correlation coefficient between the mean facial attractiveness rating from the 200 raters and the machine-generated beauty index. The correlation coefficient is 0.815 and 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 the results are driven by the specific scientific database choice. I re-estimated the key regressions using citation counts from the Web of Science database. I find that the positive and significant association between beauty and citation counts from the Web of Science is robust to this change (Tables A3 and A4 in Appendix Section). I also 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 & D'Angelo (2014)), I re-estimate the initial regression using the fractional impact measure and the weights for position proposed by Abramo & D'Angelo (2014). I indicate that the results are not affected by this change in the model (Table A5).

7 Concluding Remarks

In this work, I explore the association between scholars' appearance and their publication success as measured by citation counts, and 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, more attractive scholars easily become a member of the scientific teams and thus produce higher-quality research and receive higher citation counts. Second, better-looking academics can successfully present their research at the conferences and consequently receive more valuable comments and attention which translates into higher citation rates.

My findings demonstrate that the effect of beauty on research impact of economic scholars is rather small in magnitude, and it becomes even smaller and less significant when taking into account the ranks of Ph.D. granting institutions. This result indicates that the difference in citation counts between more-attractive and less-attractive academics is linked to the differences in prior educational background (i.e. the reputation of the economic department at which the economic scholar studied), and might be linked to other unmeasured factors that positively affect citation counts.

Although the results of the study show the presence of the beauty premium in academic publishing in economics, the magnitude of this effect is almost negligible, and hence this work fails to provide the conclusion about whether physical attractiveness must be considered an indicative factor in this scientific domain. I beleive that the results of this study, however, might contribute to understanding of differences in respect to academics' research performance.

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Appendix A

Table A1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Attractiveness	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: This table shows summary statistics for academics' facial beauty measurements and other variables.

Table A2: Descriptive Statistics: Raters

Statistic	N	Mean	St. Dev.	Min	Max
Attractiveness	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	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.

Table A3

	(1)	(2)	(3)	(4)
Attractiveness Score	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
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table A4

	Dependent variable:
	natural logarithm of WoS citations
Attractiveness Score	0.070**
	(0.033)
Ethnicity (asian=1)	−0.016
	(0.082)
Team Size	0.215***
	(0.038)
Non-academic position	−0.258**
	(0.124)
Decile 1	1.169***
	(0.121)
Decile 2	0.164
	(0.152)
Decile 3	0.560***
	(0.215)
Decile 4	0.817***
	(0.258)
Decile 5	−0.046
	(0.178)
Decile 6	0.107
	(0.236)
Decile 7	0.045
	(0.236)
Decile 8	−0.372
	(0.243)
Decile 9	0.683**
	(0.236)
Constant	1.339***
	(0.239)
Observations	644
R^2	0.223
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A5

	Dependent variable:	
	natural logarithm of GS citations	
	(1)	(2)
Attractiveness Score	0.163***	0.159***
	(0.046)	(0.046)
Gender (female=1)	−0.097	−0.091
	(0.117)	(0.117)
Ethnicity (asian=1)	−0.324***	−0.336***
	(0.110)	(0.110)
Ethnicity (black=1)	0.178	0.258
	(0.375)	(0.374)
Work Experience	0.012	−0.010
	(0.013)	(0.018)
Work Experience (squared)	−0.001	−0.0002
	(0.0003)	(0.0004)
Weighted Fractional Impact	−1.285***	−1.310***
	(0.245)	(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***	3.462***
	(0.365)	(0.417)
Observations	692	692
R^2	0.078	0.093
Note:	*p<0.1; **p<0.05; ***p<0.01	

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