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BEAUTY AND PRODUCTIVITY: A META-ANALYSIS

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Beauty and Productivity: A Meta-Analysis

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Abstract:

The economics of beauty is now a burgeoning field of research. Not only the magnitude but also the direction of the beauty effect on labor outcomes is a matter of discussion. In this work, I conduct a quantitative synthesis of 418 estimates of the effect of beauty on worker's productivity, as reported in 37 studies. The estimates are tested for publication selection using informal testing of the funnel plot as well as formal testing methods. The results provide substantial evidence of selective reporting: positive estimates of the beauty effect are preferred in literature. The set of 21 explanatory variables was collected to determine the sources of heterogeneity in the reported estimates. To account for the model uncertainty, I employ the Bayesian and Frequentist model averaging. The results indicate that differences in the reported estimates appear to be driven by choice of study design and sources of real heterogeneity, such as geographical regions and individual characteristics of respondents. The type of occupation and gender of respondents have no impact on the estimates of beauty effect concerning productivity. The average beauty effect is probably much lower than commonly believed based on the available empirical literature.

JEL: C83, J3, J7, M51

Keywords: Beauty bias, productivity, discrimination, meta-analysis, publication bias

1 Introduction

The beauty bias phenomenon has been discussed among sociologists and economists for the last 50 years. It describes the situation in which physically attractive individuals are treated more positively than those who are seemingly less attractive as it is assumed that "what is beautiful is good."

Since the first study of the beauty effect in economics by (Hamermesh and Biddle, 1993), economists have repeatedly found an impact of physical attractiveness on the labor market: good-looking individuals have a greater chance to be employed, work more productively and earn 5 to 20 percent more than their less good- looking colleagues. Most recent studies, however, suggest that the magnitude of beauty premium depends to a large extent on a particular type of job tasks (Hernandez-Julian & Peters 2017; Kanazawa & Kovar 2004). Many studies reported the positive effect for occupations, which require good looks, such as salespersons (Sachsida *et al.* 2003) or restaurant servers (Parrett 2015). However, several studies found evidence of beauty bias for occupations that do not even require face-to-face interaction. For example, the authors found significantly positive effect of beauty in academic writing (Paphawasit and Fidrmuc 2017) and sports (Berri *et al.* 2010; Ahn & Lee 2013).

The size of beauty premium depending on gender generate very divisive discussions among researchers. Several studies show that there is no relationship between gender and size of beauty effect on productivity ((Fletcher, 2009)). Most of studies, however, report that beauty premium is larger for men (Hamermesh and Biddle 1993; Biddle & Hamermesh 1995). In contrast, French (2002) has found a beauty premium for women, though not for men. If physical attractiveness may result in different labor market opportunities for men and women, the variation of beauty effect across genders may affect individual labor market responses.

After decades of studying, there is no agreement on the source of labor outcome differentials between attractive and less attractive individuals. One explanation for the beauty premium is that it reflects taste-based discrimination by decision-makers, and the vast majority of studies focus on a discrimination channel of a beauty premium. The evidence of discrimination was found and reported by Mobius & Rosenblat (2006), Scholz & Sicinski (2015), Mateju & Anyzova (2017). The second source is a productivity-enhancing effect of beauty, which may arise when physical attractiveness is a direct determinant of a worker's productivity. This effect was found by Berri *et al.* (2010), Ahn & Lee (2013) and Paphawasit and Fidrmuc (2017). An important issue of the economics of beauty is the real difficulty in disentangling the effect that arises from productivity differences from the one that arises from discrimination. Despite decades of research, consensus on the magnitude of the effect of beauty has not been reached, and neither is there an agreement on mechanisms through which beauty affects labor outcomes.

This research aims to review the empirical literature quantitatively, focusing on the following questions: (1) Does the publication bias affect the estimated beauty effect on productivity in literature? (2) Which factors govern the differences in the results of beauty effect estimates? (3) Is the beauty effect consistent across different types of occupations? To the best of my knowledge, an extensive meta-analysis of the relation between beauty and productivity has not yet been conducted.

In order to address these questions, modern meta-analysis techniques have been applied. The presence of publication selection was tested both visually (using funnel plot) and formally (using funnel tests and alternative approaches). Focusing on the aspects related to data specifications, characteristics, and methodologies, a set of 21 explanatory variables was collected. To account for inherent model uncertainty, the Bayesian model averaging technique was employed followed by a frequentist check of the variables with the highest posterior inclusion probability. Furthermore, the robustness check is conducted using the Frequentist model averaging methodology.

The remainder of the paper is structured as follows. In Section 2, the discussion on how researchers measure beauty and productivity is provided. Section 3 outlines the data collection process. Section 4 describes the methodology of a mean effect estimation. In Section 5, the presence of publication bias in the literature is tested. Section 6 and Section 7 focuse on explaining the heterogeneity between the beauty effect estimates. Section 8 concludes the paper, and the Appendix Appendix A section provides the list of the studies included in the dataset and additional important tables.

2 Measuring the effect of beauty on productivity

In this section, a brief description of how primary studies estimate the effect of an individual's physical attractiveness on productivity is given. The researchers examine whether the physical attractiveness proxies for unobserved productivity. It means that a productivity-enhancing effect may arise when physical attractiveness is a direct determinant of a worker's productivity. Still, in labor economics, there is no direct evidence of the impact of physical attractiveness on productivity. It is not evident that the individual's productivity produces economic benefits as well.

It is known from the literature that there are no universal metrics for beauty and productivity. Worker productivity typically depends on the setting in which it is collected. It can be measured as an output (units or sales produced), relative to an input (number of hours worked or the cost of labor). Worker productivity may also be derived from aggregate measures at the firm's level as a value-added per worker (Pfann *et al.* 2000). Most commonly, researchers 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). When investigating the productivity-enhancing effect of beauty, wages have their shortcomings. Sauermann (2016) claims that such factors as age and tenure can determine salaries, at least partially. Moreover, most of the corporative data do not contain information on hourly wages, but rather on monthly wages. Hence, wages do not always directly reflect worker's productivity, or it may not be available.

Researchers thus exploit or create performance-based measures that capture worker's productivity in specific settings. For example,French (2002), Talamas *et al.* (2016), Hernandez-Julian & Peters (2017) use grade point average to gauge student performance. Ponzo & Scoppa (2013), Wolbring & Riordan (2016) create composite indicators of teaching quality based on course evaluation and students' grades, while Hamermesh & Parker (2003) use students' assessment of the course to evaluate teacher's productivity.Sen *et al.* (2010) suggest assessing academic productivity by the number of publications and facts of co-authorship, citations, 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. Sometimes productivity is only observable at the team level, and it isn't easy to estimate the individual contributions to team productivity. For example, it is the case of team sports, where all performances of different players strongly depend on the performances of their teammates.

While measuring worker productivity is not always straightforward, beauty is often perceived as an ascriptive characteristic, and it is ”on the eye of the beholder.” In reality, it is not correct to assume that the definition of beauty is entirely subjective. Researchers repeatedly confirm the existence of universal standards of beauty by finding substantial agreement among independent raters about the physical attractiveness of individuals (Hamermesh and Biddle 1993; Biddle & Hamermesh 1995; Cipriani & Zago 2011).

The optimal measure of beauty would probably account for all personal characteristics, which can form a visual impact on an observer. However, facial beauty is the most commonly used measure of physical attractiveness in the literature. It seems to be a reliable proxy because people form their first impressions from faces. 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)).

A vast majority of studies included in the meta-analysis use the Mincer type human capital model to examine the relation between beauty and labor outcomes. The model regresses individual earnings on a continuous beauty rating and a vector of individual characteristics (e.g., race, marital status, parenthood):

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

where $ln(Earnings_i)$ 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.

The dataset is not restricted to the studies that employ the earnings model since the considered relationship between beauty and productivity can be estimated using different strategies. The researchers use adaptations of the conceptual productivity model formulated by Hershauer & Ruch (1978), which represents productivity as a function of different factors: task capacity, individual capacity, individual effort, and uncontrollable interferences.

The model is often represented in the following form:

$$Productivity_i = \beta_0 + \beta_1 Beauty_i + \beta_2 X_i + \beta_2 Z_i + \epsilon_i \tag{2}$$

For Equation 2 $Productivity_i$ denotes the individual productivity in measures of occupation under consideration; $Beauty_i$ is an individual average beauty score; X_i represents the vector of social determinants such as gender, country, age, etc.; Z_i indicates the vector of occupation-specific characteristics such as team size, tenure, etc.; ϵ_i is an error term.

3 Data

According to the approach proposed by Stanley (2013) in the "Meta-Analysis of Economics Research Reporting Guidelines", the research had started with searching and collecting of the relevant empirical literature on beauty's effect on productivity. The studies were identified by searching in Google Scholar, RePEc and Scopus databases for any reference to "beauty", and "physical attractiveness", combined with such keywords as "productivity", "performance evaluation" and "discrimination". The abstracts of these works were considered, and only those that contain the empirical estimates have been collected for further investigation. Additionally, the references of the most-cited studies were checked to expand the list of literature. The overall number of studies at the first stage was 76. The search was conducted using English keywords and terminated on March 1, 2019.

Only the literature, which reports any measure of precision, such as standard errors, t-statistics, or p-values, was considered for further analysis in order to use the modern meta-analysis techniques and control for the publication bias. All the studies were revised at the second stage to see whether they include beauty or physical attractiveness rating as an explanatory variable and a proxy of productivity (earnings or performance ratings) as a dependent variable.

Most of the selected studies report multiple estimates of the relationship between beauty and productivity. According to the recent meta-analytic practices, all estimates given in individual studies were collected, the resulting dataset contains 418 estimates from 37 studies. 32 of these studies are published in the refereed journals, 2 are working papers, 3 papers are the parts of dissertations. The list of studies included in the meta-analysis is presented in Appendix Appendix A section.

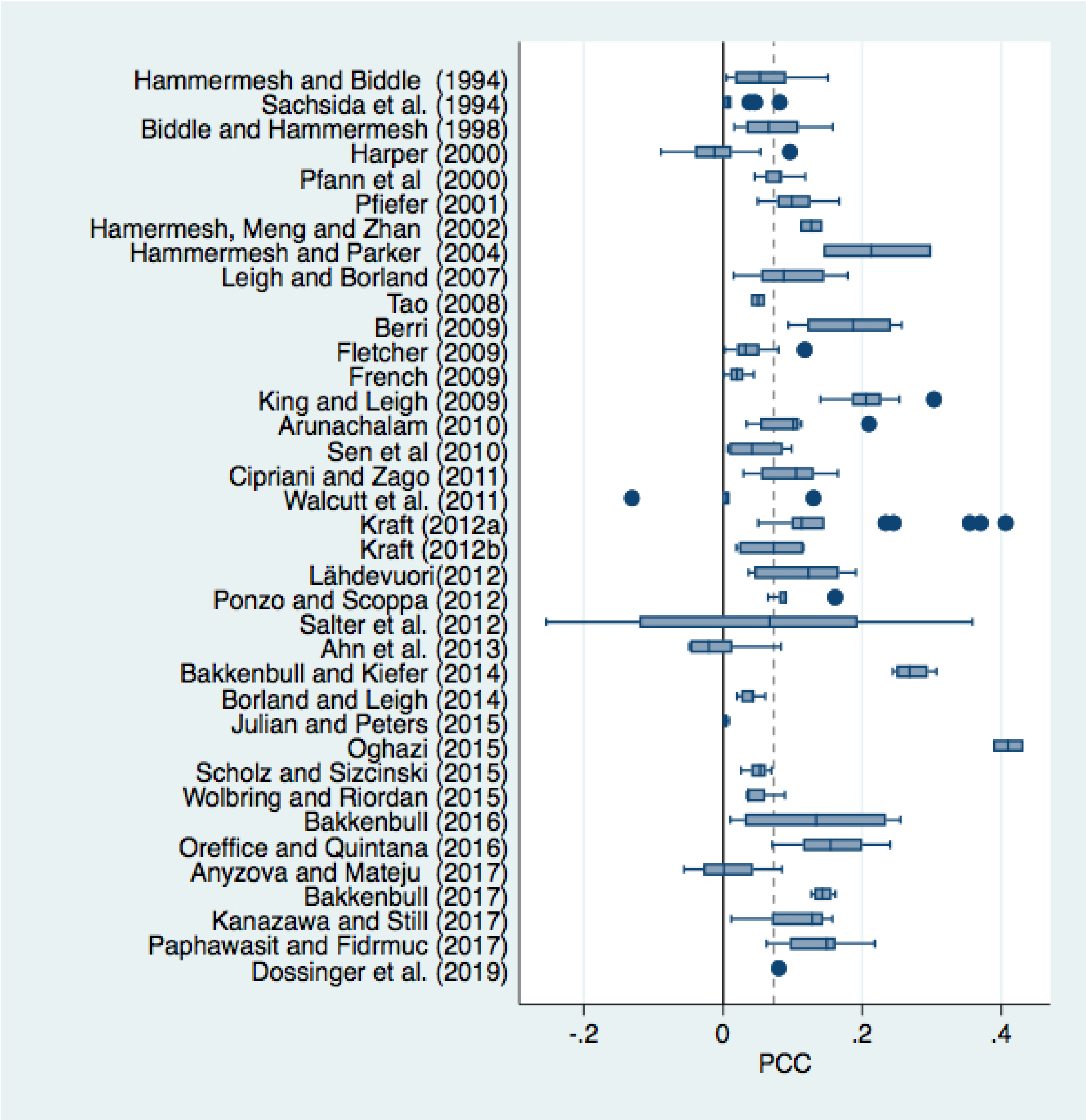
The earliest study included in the meta-analysis has been published in 1993 (Hamermesh and Biddle), and the latest one has been published in 2019 (Dossinger *et al.*). Based on the Google Scholar citation numbers, the most cited papers are Hamermesh and Biddle (1993) - 1653, Biddle & Hamermesh (1995) -510 and Hamermesh & Parker (2003) -440.

The authors include approximately a similar set of control variables in their estimations, which mainly consists of variables of individual characteristics of respondents. Most of the studies control for the age of a respondent (14 from 37), experience (18 from 37), and education (15 from 37). Several studies control for a race, gender, cognitive skills of respondents as well. The highest number of studies examines beauty bias for the Europeans, Americans, and Canadians. Several studies use datasets with mixed nationalities of respondents.

The dataset demonstrates substantial heterogeneity in terms of the methodology employed, geographical region, and time period covered, it also differs by gender. To assign a pattern to these differences, I compiled a set of 21 explanatory variables describing various characteristics of data, methodologies, and publication qualities for each collected estimate of beauty effect. The sources of heterogeneity are analyzed in Section 6.

Table A2 presents the summary statistics for the partial correlation coefficients for different subsets of data. The forest plot in Figure 1 shows that the partial correlation coefficients of estimates of beauty effects are not homogeneous and differ across and within studies. Of the 418 estimates of the beauty effect on productivity, 186 coefficient estimates are positive and statistically significant,129 are positive but insignificant, 10 are negative and significant, and 89 are negative but insignificant. The mean reported estimate of the beauty effect is 0,073, the mean value weighted by the inverse number of estimates per study is 0,097. However, the beauty effect size is much smaller against the results of the meta-analysis of experimental studies (Hosoda *et al.* 2003) even before the checking for publication selection. Doucouliagos (2011) provided the guidelines under which the partial correlation coefficient in the range between 0.07 and 0.17 in absolute value is considered "small". Hence the partial correlation coefficient of 0,073 represents a small effect of beauty on worker's productivity.

Figure 1: Forest plot



Notes: The figure shows a forest plot of the estimates of beauty effect reported in empirical literature. The boxes on the graph represent the interquartile range ($P_{25} - P_{75}$), the median is marked. Whiskers show the interval from ($P_{25} - 1.5 * interquartilerange$) to ($P_{75} + 1.5 * interquartilerange$) if such estimates exist. Dots show the outliers reported in each study.

4 Estimating the mean effect

Regression coefficients that describe the size and direction of the relationship between physical attractiveness and productivity are of key interest to further analysis. The problem arises from the fact that different studies use different units to measure both variables. Estimates from the selected studies, therefore, are not explicitly comparable. Standardized estimates of the effect size, which allow comparing results of different studies directly, are needed. The modern meta-analyses use partial correlation coefficients to solve this problem (Doucouliagos & Stanley 2009; Efendic *et al.* 2011; Valickova *et al.* 2015). A partial correlation coefficient is represented by the following equation:

$$PCC_{ij} = \frac{t_{ij}}{\sqrt{t_{ij}^2 + df_{ij}}} \tag{3}$$

In Equation 3, PCC_{ij} refers to partial correlation coefficient from i^{th} regression's estimate of the j^{th} study; t_{ij} denotes t-statistics of i^{th} regression estimate of the j^{th} study ; df represents corresponding number of degrees of freedom.

To employ the modern meta-analysis techniques, a corresponding standard error for each estimate of the partial correlation coefficient must be calculated. The standard error can be obtained from the previously described estimates, employing the following equation by Fisher (1954):

$$SEPCC_{ij} = \frac{PCC_{ij}}{t_{ij}} \tag{4}$$

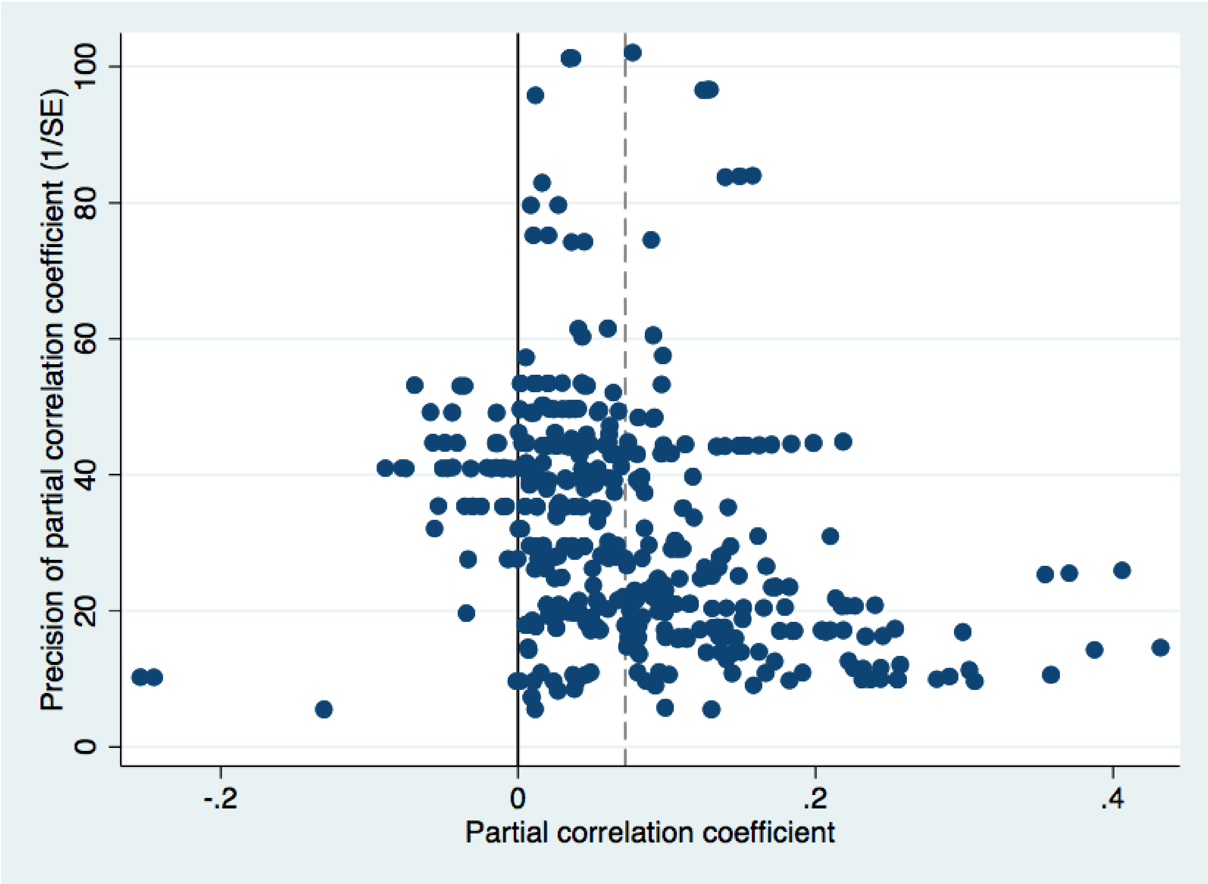
In Equation 4 $SEPCC_{ij}$ is conventional measure of precision, which denotes standard error of the partial correlation coefficient PCC_{ij} ; t_{ij} denotes t-statistics from i^{th} regression estimate of the j^{th} study.

5 Publication Bias

The identification of possible publication bias is the most crucial task of meta-analysis. The meta-analytic approach is found to be robust against publication selection problem, and hence it allows us to draw precise conclusions. The most commonly used technique to detect publication bias is a graphical analysis, which implies a visual examination of a funnel plot. The funnel plot depicts the inverse value of standard errors on a vertical axis against the effect sizes on a horizontal axis. Estimates should range randomly around a true effect if studies are not affected by publication selection.

The funnel plot for 37 studies is depicted in Figure 2. In order to improve the representativeness of results, the estimates with extreme precision values (higher than 120) were excluded from the plot; all estimates will be included in the meta-regression onward.

Figure 2: Funnel plot



Notes: The horizontal axis shows the beauty effect represented by the PCC. The vertical axis shows the precision represented by the inverted value of SE. The dashed vertical line demonstrates a zero PCC of the beauty effect; the solid vertical line demonstrates the mean PCC. The estimates should be symmetrically distributed around the mean effect in the absence of publication bias..

The funnel plot suggests a small positive true effect, but it does not resemble a funnel and shows an imbalance in the reported beauty effects, as a right-hand tail of the funnel appears to be heavier. There is a significantly lower number of estimates on the left half of the plot. Hence, the positive estimates are preferably selected for publication. This finding supports a prevailing theoretical view of the positive relationship between beauty and productivity. Visualization of the estimates helped to obtain a general picture of the bias, which might be present in the literature. However, the visual method is quite subjective when testing for the publication bias and underlying value of the beauty effect.

Table 1 and Table 2 summarize results of the following regression:

$$PCC_{ij} = PCC_0 + \beta_1 * SEPCC_{ij} + \mu_{ij} \tag{5}$$

where PCC_{ij} denotes i_{th} partial correlation coefficient of the beauty effect estimated in the j_{th} study and $SEPCC_{ij}$ denotes the corresponding SE. The PCC_0 represents the underlying genuine effect absent publication bias. The coefficient of SE (β_1) identifies the direction and magnitude of the publication bias; μ_{ij} is an error term. If the null hypothesis of $\beta_1 = 0$ is rejected, there is the evidence for funnel asymmetry. The direction of bias is determined by a sign of the β_1 estimate. A statistically significant estimate of the intercept PCC_0 indicates that, on average, there is the true effect of beauty on productivity.

Four specifications, which allow mitigating the problem of potential heteroscedasticity of μ_{ij}, have been applied for testing. The first column of Table 1 reports the OLS estimates clustered at the study level. We assume μ_{ij} are uncorrelated across studies, while the errors belonging to the same study may be correlated. The second column reports the estimates, which use the inverse value of the number of observations for the standard error as an instrument. Some estimation techniques might affect estimates and their standard errors in the same direction; therefore, we need to use an instrument that correlates with the standard error but not with estimation techniques. The third column shows the fixed effect model's estimates with the standard errors clustered at the study level. This specification helps control for unobserved study-specific characteristics by decomposing μ_{ij} into two components: one captures study-level fixed effects, and another refers to estimate-level disturbances. The fourth column reports the estimates of the between effects model, which assumes that the true effect could vary from study to study. The estimates in Table 2 were weighted by the inverse value of the standard errors (the columns (1) and (2)). Using the precision weights has enabled to assign greater importance to more precise estimates. The estimates were also weighted by the inverse number of observations per study (columns (3) and (4) of Table 2) in order to treat the large and small researches equally.

According to the Funnel Asymmetry Tests (FAT), the publication bias is statistically significant for the unweighted estimates of the beauty effect (Table 1). Three of the four estimated models indicated the presence of positive publication bias. Precision Effect Tests (PET) indi-

Table 1: Tests of publication bias and true effect

	(1) OLS	(2) IV	(3) FE	(4) BE
PCCSE (publication bias)	0.820**	0.886*	-0.123	0.684*
	(0.46)	(0.48)	(0.23)	(0.45)
Constant (effect absent bias)	0.041*	0.038	0.082**	0.065**
	(0.02)	(0.03)	(0.01)	(0.03)
N (number of estimates)	399	399	399	399

Notes: The table reports the results of testing for publication bias. The estimates with precision >120 excluded. OLS = ordinary least squares. IV = the inverse value of the number of observations is used as an instrument for the standard error. FE = study-level fixed effects. BE = between effects. Standard errors in parentheses are robust and clustered at the study level. * P < 0.10, ** P < 0.05, *** P < 0.01

Table 2: Tests of publication bias and true effect (weighted sample)

	Precision		Study	
	(1) WLS	(2) IV	(3) OLS	(4) IV
PCCSE (publication bias)	1.172**	1.163**	0.541	0.665
	(0.45)	(0 .49)	(0.46)	(0.49)
Constant (effect absent bias)	0.026	0.026	0.073***	0.067***
	(0.02)	(0.02)	(0.02)	(0.02)
N (number of estimates)	399	399	399	399

Notes: The table reports the results of estimates, weighted by the precision or study. The estimates with precision >120 excluded. Study = the model is weighted by the inverse of the number of estimates per study. Precision = the model is weighted by the inverse of the standard error of an estimate. WLS = weighted least squares. Standard errors in parentheses are robust and clustered at the study level. * P < 0.10, ** P < 0.05, *** P < 0.01.

cated the significant underlying effect of beauty on three of the four models. The FAT results for the weighted sample show that models weighted by the inverse value of the standard errors (WLS and IV) indicated strong positive publication bias for the estimates of the beauty effect. The coefficients of true effect are statistically significant for the OLS and IV models, weighted by the number of estimates.

The alternative methods of correcting the publication bias were also employed to check the robustness of the previous results. First, the "Top10" method, introduced by Stanley *et al.* (2010), was used. This method suggests that using 10 percent of the most precise estimates for calculations gives more efficient results than summary statistics. The average beauty effect of the most precise estimates is 0.035, which implies that the publication bias's magnitude is commensurate with previous meta-regression tests. Second, a novel non-parametric stem-based method by Furukawa (2019) was employed to correct the publication bias. The method generalizes the "Top10" technique and relates to the stem of the funnel plot. The result for the beauty effect estimates is 0.02, which is lower than the results of the "Top10" estimation.

6 Heterogeneity

The meta-regression equation was augmented by a vector of the collected variables which potentially influence the reported beauty effect estimates to investigate systematic patterns in the heterogeneity of the beauty effect:

$$PCC_{ij} = PCC_0 + \beta_j * \sum_j X_{ij} + u_{ij} \tag{6}$$

where PCC_i is the partial correlation coefficient of the beauty effect estimate; PCC_0 represents the constant; β_j identifies a vector of the coefficients and X_{ij} represents the set of explanatory variables which capture data, estimation and publication characteristics, including the standard error (publication bias); u_i is an error term. The publication bias, if present, varies randomly across studies and only a systematic variation of the true effect modeled.

According to the literature reviewed, the effects of beauty on productivity differ across genders, occupations, cultures, and geographical regions. Considering the fact that some of these differences may determine the magnitude of the beauty effect and hence, may produce heterogeneity of the reported results, the set of 21 characteristics reflecting the data, methods, specifications, and publication status from each primary study was collected.

6.1 Variables

The explanatory variables that are collected to explain heterogeneity were grouped into the following blocks: 1) Data specifications and characteristics, 2) Variable definitions, 3) Estimation characteristics, 4) Publication characteristics. Tables Table A3and Table A4 in Appendix A describe the 21 explanatory variables with their statistical characteristics.

Data Specification and Characteristics. Most of the studies under review rely on independently pooled cross-sectional data. Several studies, however, have used longitudinal data to examine the relationship between beauty and productivity over time. Hence, a dummy variable for the studies that rely on panel data (*Panel*) is included in the list of explanatory variables; the reference category represents the studies, which used the cross-sectional data.

Cultural differences in the evaluation of beauty may cause some variation of the beauty effect across geographical regions and countries. Beauty ratings of the respondents from fifteen countries examined in the literature. Approximately one-third of all reported estimates obtained for the US respondents; another third obtained for the European respondents. Therefore, the dataset divided by five regions, and the regional dummy variables *Europe* and *North America* included in the analysis instead of the underlying characteristics of the countries.

Differences in the magnitude of beauty effects for males and females have been widely discussed in the literature. Hosoda *et al.* (2003) examined the relevance of gender differentials in the beauty effect and considered that the variation of beauty effect across genders explained by the "lack of fit" theory introduced by Heilman (1979). The same theory predicts that physical attractiveness would interact with a "dressy" occupation. The dummy variables *Male* and *Female* introduced to the meta-regression model. The reference category represents the studies, which use a combined group of respondents. When controlling for the "dressy" type of occupation, it proceeded from the assumption that beauty might be more important for jobs with more frequent face-to-face interactions. Hence, the list of explanatory variables includes the dummy variable *Dressy*. The occupations divided into dressy and non-dressy categories based on the set of occupations presented by Hamermesh and Biddle (1993).

Researchers in the field of labor economics often control the models for such individual characteristics as age, education, and job experience of the respondents. Following their experience, I include dummies *Age*, *Experience* and *Education* to the meta-regression model. Education and experience suppose to have a positive effect on an individual's productivity: more educated and experienced employees should be more productive. The effect of controlling for age is not straightforward. On the one side, an employee becomes more experienced with age and hence more productive. On the other side, some real possibilities become lower with age, which might be an important factor for some occupations.

The increasing number of research shows that other individual characteristics, such as communication skills, leadership, and confidence, can correlate with beauty scores and enhance labor productivity. Controlling for these characteristics have confirmed their importance in the most cases (Langlois *et al.* (2000); French 2002; Fletcher 2009). Therefore, the dummy variable *Cognitive Skills* is included in the list of potentially influencing factors for the beauty effect.

Variables Definition. Despite transforming the estimates into the partial correlation coefficients, some systematic deviations might remain untreated because of using different productivity and beauty measuring approaches in the literature. As already discussed in the previous sections, there are two common ways to assess worker productivity in the literature. Mean reported estimates of the beauty effect obtained by using the earning-based model differ from the estimates obtained by using the performance-based model (Table A2). The dummy variable *Performance-based* is introduced to determine whether the difference between using an earning-based model and the estimates obtained by using the performance-based model holds after controlling for other aspects of data. The reference category represents earnings-based estimations.

Reported estimates may also differ depending on the type of beauty's rating used for research. A large number of studies use standardized beauty ratings obtained from multi-raters evaluations. The other studies use beauty ratings obtained from the self-evaluations of the respondents. The ratings obtained from multi-raters evaluations tend to skew to the right, while the ratings obtained from self-evaluations of the respondents are generally lower. Beauty estimates are classified by measuring technique, and *Multiple Raters* and *Self-Evaluation* dummies are included in the list of explanatory variables. The reference category represents the studies, which used beauty ratings obtained from one interviewer.

Controlling for the data homogeneity might be an important issue for the estimations. To identify potential sources of the beauty effect, a substantial number of studies use the data of employees from a relatively homogeneous group (the same occupation). The dummy *Homogenous*, therefore, was included in the list of controls for the meta-regression model. The inclusion of the *Log* dummy aims to control for log transformations of the dependent variable.

Estimation Characteristics. Researchers use various techniques to estimate the relationship between beauty and individual productivity. Most studies estimate the beauty effect by using linear regression and OLS, although some of the studies assume heteroscedasticity and employ TSLS (Kraft, P. 2012) and the quantile regression (Paphawasit and Fidrmuc 2017). Overall, the eight estimation techniques may potentially drive differences in results. However, most of the techniques have been used only once, for particular research. The dummy variable *OLS* introduced to the meta-regression model.

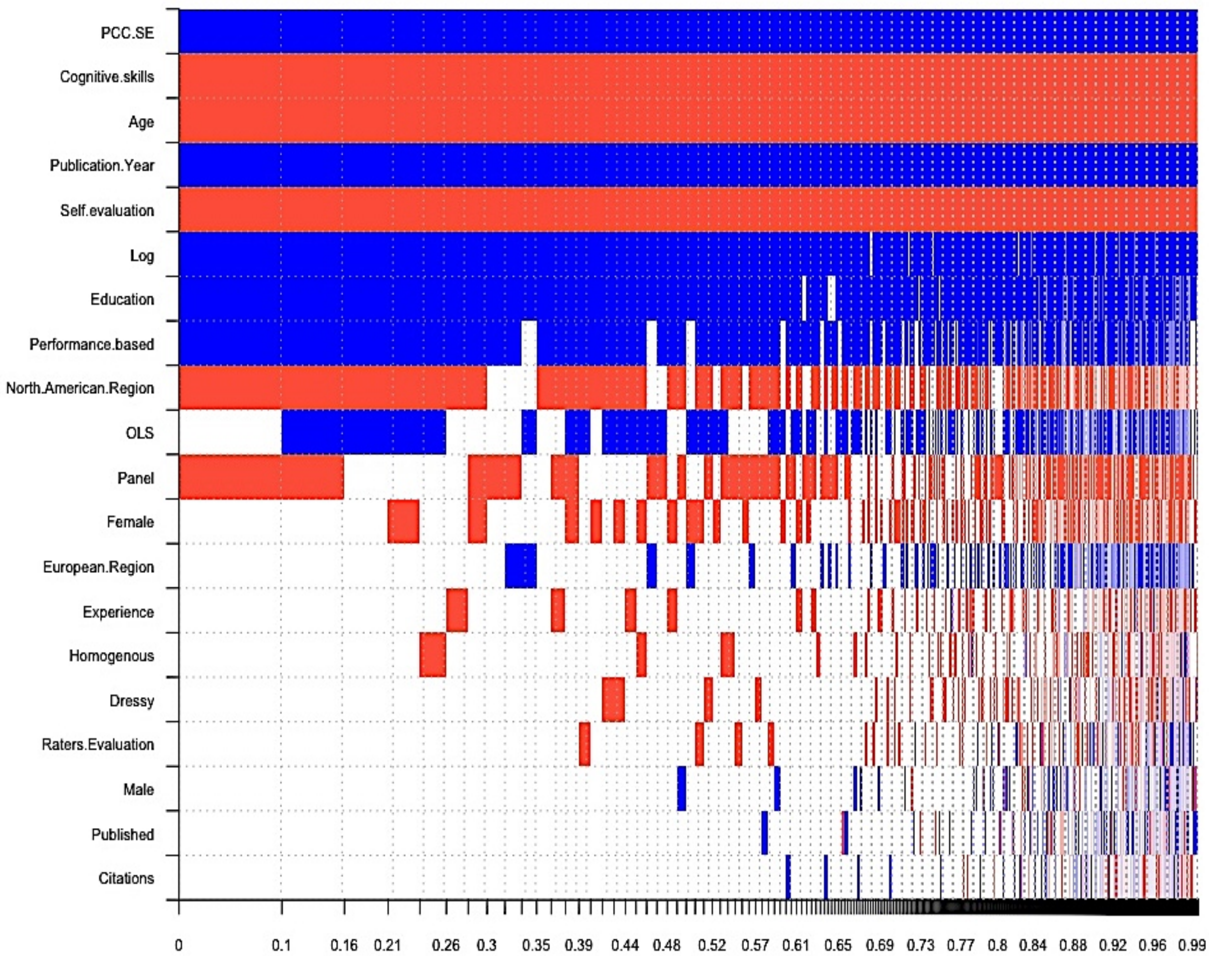
Publication Characteristics. To account for the methodological innovations, the number of modern meta-analyses (Valickova *et al.* 2015; Havranek *et al.* 2018) include the year of publication in meta-regression model since the advanced methodological and estimation techniques are more likely to cover the unobserved data characteristics, which can affect the reported results. Hence, the *Publication Year* is included in the list of explanatory variables to control whether the role of the beauty impact on productivity has changed over time.To consider the quality of research, we use another two publication characteristics.The variable which counts the number of per-year citations in Google Scholar (*Citations*) is introduced to assess how often the research used as a reference in the literature. The variable *Published* indicates that the study published in academic journals.

6.2 Estimation

The effective methodological tool is needed to analyze the sources of heterogeneity with a relatively high number of explanatory variables collected from the empirical literature. With 21 explanatory variables, 2^{21} different models could be estimated, but we need to determine the most relevant set of explanatory variables to avoid redundancy. Following the most recent meta-analyses (Havranek & Irsova 2017; Havranek *et al.* 2018), the BMA technique is implemented in this research.

Before applying the BMA, all estimates have been weighted by the number of observations per study. Since the results of previous research have shown the well predictive performance of the combination of UIP and the unit information g-prior, this combination was used. The BMA procedure was performed using the BMS package in the R software environment. The results of the BMA estimation are visualized in Figure 3. The numerical representation of the BMA results is represented in the left-hand panel of Table 3 .

Figure 3: BMA visualisation



Notes: The figure represents the results of the BMA. The vertical axis depicts the explanatory variables ranked according to their PIP in descending order. The horizontal axis depicts the values of the cumulative posterior model probability. The blue color of the cells shows the estimated parameter of a relative variable is positive. The red color of the cells shows the estimated parameter of a relative variable is negative. A cell without color shows the related variable not included in the model.

Table 3: Explaining heterogeneity in the estimates of beauty and productivity relationship

Response Variable:		*BMA*			*FC*	
est of beauty effect	*PIP*	*PM*	*PSD*	*Coef*	*SD*	*p-val*
Constant	1	-59.944	NA	-53.893	16.586	0.001
Standard Error	1	0.935	0.141	0.897	0.240	0.001
Variables Design						
Performance-based	0.875	0.234	0.122	0.246	0.077	0.003
Raters Evaluation	0.103	-0.007	0.049			
Self Evaluation	0.999	-0.559	0.120	-0.590	0.145	0,000
Log	0.983	0.345	0,106	0.341	0.09	0.001
Data Characteristics						
Dressy	0.108	-0.012	0.053			
Panel	0.530	-0.128	0.140	-0.22	0.145	0.132
Age	0.999	-0.453	0.083	-0.474	0.141	0.002
Experience	0.145	-0.018	0.056			
Education	0.964	0.289	0.102	0.276	0.112	0.019
Male	0.069	0.003	0.027			
Female	0.281	-0.039	0.073			
North America	0.989	-0.249	0.066	-0.054	0.004	0.000
Europe	0.193	0.028	0.068			
Estimation Characteristics						
OLS	0.555	0.101	0.106	0.146	0.086	0.099
Publication Characteristics						
Publication Year	0.999	7.886	1.086	7.6747	2.180	0.001
Citations	0.0523	0	0			
Published	0.061	0.001	0.021			

Notes: BMA= Bayesian Model Averaging, FC= Frequentist Check, PIP= Posterior Inclusion Probabilty, PM= Posterior Mean, PSD= Posterior Standard Deviation, Coef= OLS coefficient, SD= Standard Deviation, *p*-val= P-value. In the frequentist check we include only variables with PIP higher than 0.5

The columns in Figure 3 represent the processed models, which are arranged from left to right in descending order. The models are sorted according to their inclusion probability. The rows display explanatory variables, which are arranged from top to bottom in descending order. The variables have been sorted according to their posterior inclusion probability (PIP). In this way, each cell in Figure 3 displays a specific variable in a specific model. Each blue-colored cell shows that the variable was included in the model and that the sign of the estimated coefficient is positive. Each red-colored cell indicates that the variable was included in the model and that the sign is negative, respectively. The blank cells reveal that the variables were not included in the model.

The estimation report of BMA (Table 3) includes the values of three underlying statistical measures. First, the Posterior Inclusion Probability (PIP) shows the posterior probability of inclusion of a particular variable in a model. A higher value of PIP is attributed to the higher importance of particular variables when explaining the heterogeneity. Second, the Weighted Posterior Mean (WPM) represents an analog of the model average parameter estimate. The third measure is the Weighted Posterior Variance, which represents the analog of standard deviation.

The principles of interpretation of posterior inclusion probability were formulated by Jeffreys (1961). The author considers the PIP values between 0.5 and 0.75 as weak, values between 0.75 and 0.95 as positive, values between 0.95 and 0.99 as strong, and values above 0.99 as decisive evidence for an effect. The results show decisive evidence of an effect in the cases of *Standard Error*, *Publication Year*, *Self Evaluation*, *Age* and *Cognitive Skills*; strong evidence of an effect in the cases of *Log* and *Education* variables; positive evidence of an effect for *Performance Based Productivity* variable; and weak evidence of an effect in the cases of the *OLS*, *Panel*, *American Region* variables.

The following approach to assess the remaining heterogeneity is based on a frequentist check. The frequentist check includes the variables from BMA with PIP higher than 0.5. This specification estimated by OLS with robust SE clustered at the study level. The results of the frequentist check estimation can be found in the right-hand panel of Table 3. The results show that all variables, except the *OLS* and *Panel*, are statistically significant at 5 percent level.

7 Results

We applied the FMA methodology as a robustness check for the results of BMA and OLS models previously estimated.The FMA specification includes all collected explanatory variables. Before applying the FMA, all estimates were weighted by the inverse of the number of estimates per study.The results of the FMA can be found in Table 4 , and it shows that the results are predominantly in line with the BMA exercise except for the case of *OLS* explanatory variable.

Table 4: Explaining heterogeneity in the estimates of beauty and productivity relationship. Frequentest Model Averaging

Response Variable: estimates of beauty effect	*Coefficient*	*StDev*	*p-value*
Constant	-60.284	16.974	0
Standard Error	1.006	0.151	0
Variables Design			
Performance-based	0.449	0.135	0.001
Raters Evaluation	-0.136	0.122	0.263
Self Evaluation	-0.587	0.125	0
Log	0.314	0.093	0.001
Data Characteristics			
Dressy	-0.112	0.119	0.347
Panel	-0.141	0.107	0.188
Age	-0.462	0.085	0
Experience	0.109	0.158	0.488
Education	0.312	0.105	0.003
Male	-0.021	0.099	0.832
Female	-0.151	0.089	0.093
North America	-0.220	0.093	0.018
Europe	0.03	0.095	0.749
Estimation Characteristics			
OLS	0.218	0.092	0.019
Publication Characteristics			
Publication Year	7.931	2.241	0
Citations	0	0.004	0.978
Published	0.077	0.093	0.408

Notes: The table shows the results of the FMA. Mallow's criterion is used to select the optimal weights for modeling. The number of models reduced using orthogonalization of the covariate space.

Resulting from all specifications and estimation methodologies, the evidence for the publication bias remains after the inclusion of explanatory variables. The coefficient on the *Standard Error* is robustly significant when we control for 20 additional factors related to studies and estimates.

Results for Design of Variables. The evidence for the positive effect of inclusion of the variable *Performance-based productivity* is significant for both model averaging approaches and the frequentist check. This result suggests that the choice of proxy for productivity measuring is relevant for beauty effect investigation. Researchers who use performance-based measures of productivity, and therefore more homogeneous data from specific occupations, obtain higher estimates. The definition and design of *Beauty* is also relevant in determining the sources of heterogeneity of beauty effect estimates. All estimated specifications confirm the importance of inclusion of the *Self-Evaluation* explanatory variable. The sign of the coefficient is negative: the respondents usually understate self beauty ratings. Hence, the studies which use self-evaluated beauty ratings tend to report significantly lower estimates of beauty effect.

Results for data characteristics. According to the results, a coefficient of *Dressy* variable is insignificant. This finding implies that a type of occupation does not systematically affect the reported beauty effect estimates. Hence, the estimates of beauty effect for occupations that require good looking produce commensurate beauty effect compared to other occupations. This conclusion supports the findings of Kraft, P. (2012), Arunachalam & Shah (2012), Paphawasit and Fidrmuc (2017).

The use of panel data for estimations does not prove decisive in the FMA and frequentist check specifications. The BMA reported weak evidence for the panel data effect on beauty estimates. The low availability of longitudinal data on physical attractiveness supplemented with economic characteristics might be a reason for a considerably smaller number of studies that use panel datasets. However, it seems to be essential to study a beauty effect over time.

Other important factors that produce the heterogeneity of reported estimates are the individual characteristics of respondents, namely, *Age*, *Education* and *Cognitive skills*. The strong negative effect on the magnitude of the beauty effect is attributed to the *Age*. In contrast, the inclusion of the *Education* variable leads to the increase of the beauty effect. Controlling for

Cognitive skills substantially reduces the magnitude of the beauty effect. This finding is in line with previous results of Salter *et al.* (2012), Scholz & Sicinski (2015). The authors concluded that the magnitude of the beauty effect is decreasing after the inclusion of cognitive characteristics such as IQ tests, communication skills, measures for confidence and personality; however, the beauty effect does not vanish.

According to the results of the BMA and FMA exercises, there is no evidence of significant differences in the beauty effect estimates attributed to gender. This finding suggests that it does not matter whether the authors use male sample, female sample or mixed samples of respondents. The result contradicts previous findings in the field of labor economics. The effect is shown to be different for men and women by Biddle & Hamermesh (1995), French (2002), Sen *et al.* (2010) and others. However, the beauty premium gap across genders is expected to decrease due to the raised participation of women in the labor market.

The estimation results regarding the regional differences in the beauty effect are mixed. The estimates of the beauty effect for respondents from European countries do not differ significantly, while the estimates for respondents from the North American region seem to be lower than those for other countries. This finding suggests that the respondents from the US and Canada experience a smaller beauty effect. The possible explanation is that the US and Canada have modern economies, where social orientation plays an important role. Information on the series of protection measures for employees in the US supports this statement (the city of San Francisco in 2001 and the District of Columbia in 2008).

Results for estimation characteristics. The analysis suggests that researchers who prefer to use the OLS estimator obtain higher values of beauty effect in comparison with the authors who use other estimation techniques. However, the evidence on the importance of OLS using is weak and non-consistent across different model averaging approaches. It seems logical that more advanced estimation techniques would provide more accurate estimates of the beauty effect.

Results for publication characteristics. The additional results related to publication characteristics are important for the research. The first result is the high posterior inclusion probability of *Publication Year* in the BMA and FMA models. A time period when the study was published matters for the magnitude of the beauty effect. According to the results, the coefficient of the variable *Publication Year* is significant and positive. It means that the most recent studies report systematically higher results. The use of publication year may reflect the changes in the estimation approaches and methodologies applied. However, this finding does not meet the expectations and require further study in the longer term. The aspects of research quality that are captured by the other two proxies (*Publication Status* and *Citations*) do not systematically affect the estimates of the beauty effect.

8 Concluding Remarks

In this work, I conducted a quantitative synthesis of 418 estimates of the effect of beauty on productivity, as reported in 37 studies. This is the first meta-analysis on the relation between beauty and productivity to the best of my knowledge. In order to avoid misleading interpretations of the beauty effect on productivity from potentially biased results from empirical literature, the beauty effect was carefully tested for publication selection using informal testing of the funnel plot as well as formal testing methods. The results suggest that the estimates of beauty effects are influenced by publication bias arising from selective reporting: positive estimates are preferred in literature. The magnitude of publication bias is sizeable. Hence, the average beauty effect is probably much lower than commonly believed based on the available empirical literature. Taking into account the presence of publication bias, the results do not support previous findings provided by Hosoda *et al.* (2003) in the meta-analysis of the beauty effect on job-related outcomes in experimental studies, which imply that beauty is always an asset for individuals.

To determine the key factors that influence the magnitude of the beauty effect and produce heterogeneity of reported results apart from publication bias, the Bayesian model averaging technique and OLS-based frequentist check were used. To check the robustness of the findings, I applied the Frequentist Model Averaging and found that the results are predominantly in line with BMA.

The differences in the reported estimates appear to be driven by sources of real heterogeneity, such as individual characteristics of respondents and geographical regions. Controlling for individual characteristics such as age, education, and cognitive skills strongly impacts the resulting estimates.

The results also suggest that the study design has an impact on the reported beauty effect concerning productivity. Researchers who prefer to use beauty ratings based on the self-evaluation of respondents obtain substantially smaller estimates than researchers who use beauty ratings based on the raters' evaluation. The authors who choose performance-based measures of productivity, and therefore homogenous data from specific occupations obtain higher estimates than those who use earnings as a proxy for measuring productivity. This finding partially explains the large magnitude of beauty effect estimates over the last decade: the most recent studies predominantly examine the effect of beauty on productivity within occupations.

Another critical finding implies that the estimates in the sample do not seem to be significantly different when the occupation requires good looks. This result contradicts the reported evidence on the higher beauty effect for "dressy" occupations. However, it confirms the findings of Hamermesh and Biddle (1993), who argue that the impact of beauty remains proportional across different types of occupations.

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Appendix A

Table A1: List of studies included in meta-analysis

Author(s)	Year	Author(s)	Year
Ahn and Lee	2014	King and Leigh	2009
Anyzova and Mateju	2018	Kraft	2012(a)
Arunachalam and Shah	2012	Kraft	2012(b)
Bakkenbüll and Kiefer	2015	Leigh and Borland	2007
Bakkenbüll	2016	Oghazi	2016
Bakkenbüll	2017	Oreffice and Quintana-Domeque	2016
Berri et al.	2011	Paphawasit and Fidrmuc	2017
Biddle and Hamermesh	2008	Pfann	2000
Borland and Leigh	2015	Pfiefer	2012
Cipriani and Zago	2011	Ponzo and Scoppa	2012
Dossinger et al.	2019	Sachsida et al.	1994
Fletcher	2009	Salter et al.	2012
French et al.	2009	Scholz and Sicinski	2015
Hamermeshand Biddle	1993	Sen et al.	2016
Hamermesh and Parker	2005	Tao	2008
Hamermesh et al.	2002	Walcutt	2011
Harper	2000	Wolbring and Riordan	2016
Julian and Peters	2017		
Kanazawa and Still	2017		

Table A2: PCC of beauty effects for different subsets of data

	N	Mean	St.dev	Min	Max
Productivity type					
Earnings-based	283	0.067	0.078	-0.089	0.406
Performance-based	135	0.084	0.101	-0.254	0.432
Gender of respondents					
Males only	151	0.057	0.070	-0.089	0.299
Females only	149	0.056	0.074	-0.130	0.307
Both genders	118	0.114	0.105	-0.254	0.432
Beauty assessment					
Self-rated	19	0.034	0.066	-0.13	0.179
Interviewer-rated	203	0.047	0.065	-0.089	0.257
Multiple raters	196	0.103	0.097	-0.254	0.432
Geographical region					
Europe	123	0.057	0.087	-0.089	0.432
North-America	169	0.055	0.068	-0.254	0.358
Others	126	0.112	0.096	-0.130	0.406
Mixed nationalities	44	0.115	0.096	-0.049	0.307
Occupation type					
Dressy occupations	138	0.082	0.096	-0.25	0.432
Other occupations	82	0.085	0.088	-0.049	0.307
Estimation type					
OLS	329	0.069	0.089	-0.25	0.432
Other estimators	89	0.087	0.075	-0.049	0.307
Decades of publication					
1990	77	0.057	0.044	0.005	0.158
2000	155	0.054	0.081	-0.089	0.303
2010	186	0.095	0.098	-0.254	0.432
Publication status					
Published studies	323	0.064	0.085	-0.25	0.432
Unpublished studies	95	0.101	0.085	-0.130	0.406
All estimates	418	0.073	0.087	-0.254	0.432

Notes: The table reports mean values of the partial correlation coefficients for different subsets of data. OLS = ordinary least squares. St.dev= Standard Deviation

Table A3: Description and summary statistics of explanatory variables

Variable	*Description*	*Mean*	*SD*	*WM*
Beauty PCC	Partial correlation coefficient derived from the estimate of beauty effect	0.073	0.086	0.097
Standard Error	The estimated standard error of the beauty effect estimate	0.041	0.029	0.05
Data Characteristics				
Panel	=1 if panel dataset is used	0.07	0.255	0.125
Male	=1 if the estimates of the study are for male respondents only	0.361	0.481	0.273
Female	=1 if the estimates of the study are for female respondents only	0.356	0.480	0.339
Age	=1 if the estimation controls for age of the respondent	0.282	0.451	0.323
Experience	=1 if the estimation controls for job experience of the respondent	0.567	0.496	0.455
Education	=1 if the estimation controls for education of the respondent	0.447	0.498	0.364
Cognitive	=1 if the estimation controls for cognitive skills of the respondent	0.447	0.498	0.364
Dressy	=1 if the concerned occupation requires good looks or or based on social interactions	0.330	0.471	0.405
North America	=1 if the beauty effect estimated for US/Canada	0.404	0.491	0.324
Europe	=1 if the beauty effect estimated for EU countries	0.294	0.456	0.297

Notes: SD = standard deviation, SE = standard error, WM = mean value weighted by the inverse of the number of estimates per study

Table A4: Description and summary statistics of explanatory variables

Variable	*Description*	*Mean*	*SD*	*WM*
Variables Design				
Performance-based	=1 if the dependent variable is performance-based	0.323	0.468	0.419
Log	=1 if logarithmic transformation is applied in model	0.722	0.448	0.670
Homogenous	=1 if the study use homogenous group of respondentst	0.871	0.336	0.801
Raters Evaluation	=1 if the beauty is assessed by group of raters	0.469	0.500	0.568
Self-Evaluation	=1 if the beauty is assessed by respondent	0.469	0.500	0.568
Estimation Characteristics				
OLS	=1 if OLS estimator is used to examine the beauty effect	0.871	0.336	0.801
Publication Characteristics				
Publication Year	Logarithm of the publication year	7.604	0.004	7.605
Citations	Logarithm of the number of Google Scholar citations (on Dec,2018)	3.566	2.336	2.659
Published	= 1 if the study is published in a journal	0.773	0.420	0.730

Notes: SD = standard deviation, SE = standard error, WM = mean value weighted by the inverse of the number of estimates per study

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