Is there a gender difference in scientific collaboration? A scientometric examination of co-authorships among industrial-organizational psychologists

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Abstract

In modern knowledge societies, scientific research is crucial, but expensive and often publicly financed. However, with regard to scientific research success, some studies have found gender differences in favor of men. To explain this, it has been argued that female researchers collaborate less than male researchers, and the current study examines this argument scientometrically. A secondary data analysis was applied to the sample of a recent scientometric publication (König et al. 2015). The sample comprised 4,234 (45% female) industrial-organizational psychologists with their 46,656 publications (published from 1948 to 2013) and all of their approx. 100,000 algorithmically genderized collaborators (i.e., co-authors). Findings confirmed that (a) the majority of researchers' publications resulted from collaborations, and (b) their engagement in collaborations was related to their scientific success, although not as clearly as expected (and partly even negatively). However, there was no evidence that a lack of female collaboration causes females' lower scientific success. In fact, female researchers engage in more scientific collaborations. Our findings have important implications for science and society because they make gender differences in scientific success much harder to rationalize.

180 words

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"A first step in establishing your research agenda is to explicitly search for collaborators."

(McCormick and Barnes 2007, p. 10)

Introduction

Collaborations among researchers are inherent to the scientific system and have been commonplace for over 400 years (Beaver and Rosen 1978). Nowadays, collaborations are the default of doing research rather than a special feature (e.g., Castelvecchi 2015; de Solla Price and Beaver 1966; Gazni and Didegah 2011; Newman 2004), and mentoring relationships between PhD candidates and their advisors are the starting point of more or less every scientific career. The high prevalence of collaborating is no coincidence, because there is a relationship between the number of collaborations and scientific success (e.g., S. Lee and Bozeman 2005). Furthermore, the number of collaborations correlates with the impact of the publications in terms of citations (e.g., Gazni and Didegah 2011). Thus, research advises researchers to collaborate (e.g., Bowden 2011; Holgate 2012; Mayrath 2007).

Given the importance of collaboration among researchers, it is crucial to understand systematic differences in collaborating. In particular, there is still a lack of research that relates gender differences to scientific collaboration (for an overview, see Abramo et al. 2013), even though gender differences in scientific success have been heavily examined (cf. König et al. 2015). Re-analyzing the data of König et al. (2015) and, more importantly, extending their analyses, we relate gender differences in scientific collaboration documented by its final products (i.e., joint publications) to gender differences in scientific success. For the first time, this is undertaken using a large sample of researchers (*N* = 4,234) from the field of industrial-organizational (I-O) psychology and by taking into account researchers' gender as well as the gender of their approx. 100k collaborators. In this study, we aim to look behind the curtain of gender differences in scientific success in terms of publication output and publication impact (e.g., König et al. 2015; Larivière et al. 2013) by examining gender differences in collaboration as one possible explanation.

Theoretical Background

Collaborations among Scientists

A main reason for collaboration is that some tasks are not feasible with one person alone. For example, no individual would have been able to sequence the human genome—it required massive manpower (e.g., Lander et al. 2001; Venter et al. 2001). Many projects from cross-cultural psychology can function as examples from social science that required many collaborators (e.g., Schmitt et al. 2007). Another reason for collaboration is the scientific specialization: When things become advanced, you need an expert to make a significant contribution. Thus, collaboration can also stem from the necessity of another researcher's special skills/knowledge (Beaver and Rosen 1978). As scientific specialization increases, so too does the potential number of professional borders which are crossed during research projects (e.g., interdisciplinary research projects; Katz and Martin 1997).

Many studies have confirmed a high and increasing prevalence of co-authored publications across many research areas (Gazni and Didegah 2011; cf. Melin 2000). For example, Glänzel and Schubert (2004) reported that from 1980 to 2000, the average number of co-authors increased from 2.64 to 4.16 across several fields, whereas the percentage of single-authored publications decreased from 25% to 11%. Furthermore, the majority of publications in this time period were co-authored, and their relative frequency increased (see also Glänzel 2002). This trend was confirmed for several other research areas, such as distance education (Zawacki-Richter and von Prummer 2010), management (Acedo et al. 2006), political science (Fisher et al. 1998), sociology (Moody 2004), and statistics (De Stefano et al. 2013). For I-O psychology, the only data so far stem from an analysis of the authors of chapters of three editions of an I-O handbook, revealing that the majority of chapters are now co-authored (22% in 1976 vs. 73% in 2011, De Meuse et al. 2014). Thus, our first, yet only preliminary aim is to replicate the previous findings from other research areas, and we therefore hypothesize that *overall, the majority of publications are co-authored (H1a) and the prevalence of co-authored publications has increased over time (H1b).*

Possible Consequences of Scientific Collaborations

There is strong reason to believe that collaborations have favorable consequences for the scientists involved: Scientific success and the number of collaborations are correlated (Hekelman et al. 1995), and researchers attribute their success strongly to their collaborating (Mayrath 2007). Generally speaking, collaboration is positively correlated with the productivity of the collaborators (i.e., publication output; Glänzel 2002). Indeed, a positive effect of collaboration on co-authors' productivity exists even after controlling for the number of co-authors of the output publications (Ductor 2015; but see S. Lee and Bozeman 2005). Scientific publications that emerged from collaborations have also been shown to have more impact (i.e., to receive more citations; Gazni and Didegah 2011). Persson et al. (2004, p. 428) concluded that with an increasing number of co-authors, the "ratio citations/author also will increase since citations grow faster than authors." This advantage in terms of citations seems to be independent of self-citations (Glänzel 2002; Raan 1998). Thus, another aim of this study is to replicate these findings for I-O psychology, and we therefore hypothesize that *collaborating researchers—in terms of prevalence of co-authored publications and mean number of collaborators per publication—have more scientific success in terms of publication output (H2a) and in terms of publication impact (H2b).*

Given that collaborating is important for scientific success, and that previous survey research revealed gender differences (e.g., more male collaborators) in scientific collaborating (S. Lee and Bozeman 2005), the question arises whether gender differences in scientific collaborating could be one reason for the often discovered and criticized gender differences in scientific success (e.g., Garg and Kumar 2013; König et al. 2015; Larivière et al. 2013; Malouff et al. 2010, 2010; Prpić 2002). In the next section, we will elaborate on why there might be gender differences in scientific collaborating.

Gender Differences in Scientific Collaborating

From the field of networking studies, several reasons can be deduced why female researchers should rather work together with others (i.e., collaborate) if gender differences are to be expected (cf. Wolff and Muck 2009). First, women have been found to be more agreeable than men (Feingold 1994; see also Costa et al. 2001), and more agreeable people show more networking (Wanberg et al. 2000; Wolff and Muck 2009; cf. McCrae and Costa 1989). Second, in ability tests of emotional intelligence, women clearly outperform men (Joseph and Newman 2010). Emotional Intelligence refers to the ability to perceive, understand, and regulate emotions, and it has been shown to be beneficial for collaborating (e.g., Moore and Mamiseishvili 2012). Although other factors have also been argued to relate to networking (cf. Wolff and Muck 2009), these factors—Conscientiousness, Extraversion, self-monitoring, interpersonal trust, proactivity, and self-esteem—do not seem to systematically vary between women and men (for

Conscientiousness and Extraversion, see Costa et al. [2001]; for self-monitoring, see Rupert and Kent [2007]; for interpersonal trust, see Bevelander and Page [2011]; for proactivity, see Finkelstein et al. [2003]; for self-esteem, see Gentile et al. [2009]).

Although the aforementioned arguments and studies suggest either that there is a female advantage in collaboration or that there is no gender difference, other research—on situational influences on scientific careers—suggests a male advantage in collaboration. First, women traditionally have more responsibility for raising children (e.g., Rhoads and Rhoads 2012), and childcare is time-consuming, restricting researchers' time for activities such as building networks (e.g., Joecks et al. 2013; Kyvik and Teigen 1996). Second, female researchers might receive less optimal mentoring than male researchers (Seagram et al. 1998). This might reduce the quality of their socialization into the world of research, which often works implicitly (Bagilhole 1993). Good mentoring might be particularly needed for female researchers because science is traditionally dominated by men (including "old boy networks"; cf. McDowell et al. 2006).

Furthermore, biologists (e.g., Fu et al. 2012) have suggested that people have a general preference to interact with similar others—a phenomenon called homophily—and sociologists likewise talk about the homophily principle ("similarity breeds connection"; McPherson et al. 2001, p. 415). If a field is dominated by male researchers (as is typically the case), female researchers have a lower probability of finding other women with whom to collaborate in their proximity, which should then lead to a lower rate of collaborations among females compared to males (cf. Boschini and Sjögren 2007).

As mentioned, there are good arguments for either a female advantage in collaboration, a male advantage, or no gender differences, and we can now turn to the empirical data on this issue. However, so far, the empirical evidence is inconclusive. While some authors found that female researchers collaborated more (Abramo et al. 2009; Kretschmer et al. 2012; Kyvik and Teigen 1996; Ozel et al. 2014), others found male researchers to have the advantage in terms of collaboration (Abramo et al. 2013; Barrios et al. 2013; Bozeman and Corley 2004), and others still were unable to find any gender differences (McDowell et al. 2006). One reason for these inconsistencies in the research findings might lie in the restricted samples of previous studies (e.g., only faculty members from four Norwegian universities in Kyvik and Teigen [1996]; only authors of publications in gender studies journals in Kretschmer et al. [2012]). It has, however, been shown that scientific disciplines can differ in their collaboration practices (e.g., Abramo et al. 2013; Gazni et al. 2012; Newman 2001).Thus, a further aim of the present study is to add a comprehensive dataset of I-O psychologists to this stream of research and to ask *whether female or male researchers collaborate more in terms of prevalence of co-authored publications and mean number of collaborators per publication (RQ1).*

Moreover, if we only examined whether one gender collaborates more than the other, this would likely generate an incomplete picture of the field, as the homophily principle (McPherson et al. 2001) suggests that female and male researchers should prefer to collaborate with their own gender. Benenson et al. (2014) attributed gender differences in homophilic cooperation across ranks to biological and developmental principles. However, previous research on this topic is inconclusive (e.g., Benenson et al. 2014; McDowell et al. 2006; Zawacki-Richter and von Prummer 2010). Thus, we ask[1] *whether there is more collaboration—in terms of prevalence of co-authored publications and mean number of collaborators per publication—among researchers of the same gender than among researchers of different genders (RQ2).*

Gender and Scientific Collaboration, Output and Impact

[1] As we explain later, our sample of researchers is approximately gender-balanced.

If there are gender differences in collaborations of researchers, it becomes important to examine the consequences of gender differences for scientific success (i.e., publication output and impact), because gender differences in collaborating (Larivière et al. 2013) could be one reason among others (e.g., Nature Editorial 2013) why female researchers publish less and are cited less often than their male colleagues (e.g., König et al. 2015). Furthermore, if female researchers are found to collaborate less than their male counterparts and if collaboration is related to scientific success (e.g., within 100k publications of Harvard faculty; Gazni and Didegah 2011), this might be one of the explanations for the disadvantage of female researchers.

Although the idea itself is not new (e.g., Kyvik and Teigen 1996), so far, only one bibliometric study (Barrios et al. 2013) has attempted to systematically study the link between gender differences in scientific collaboration and publication impact, one aspect of scientific success. However, the dataset of Barrios and colleagues was too small (an *N* of 522 articles) to clearly determine whether the gender of co-authors mattered for publication output (i.e., the crucial analysis had a *p*-value of .052, which Barrios et al. (2013) considered not significant). The low number of documents analyzed (low at least for scientometric standards) likely stems from the fact that Barrios et al. (2013) determined the gender of authors by hand, which is likely not feasible for larger datasets. However, a recently developed webpage called *genderize.io* enables people's gender to be determined by their first names based on more than 200k distinct first names from nearly 80 countries (Genderize.io 2015). Its web application programming interface (API) allows genderize.io to be used for large-scale examination of gender differences in collaboration and scientific success (i.e., publication output, citations, and impact). Thus, drawing on genderize.io, we hypothesize that *engagement in scientific collaboration—in terms of prevalence of co-authored publications and mean number of collaborators per publication—*

mediates[2] *the relationship between gender and scientific success in terms of publication output (H3a) and in terms of publication impact (H3b).*

Furthermore, our data allow us to study the outcomes of gender differences in scientific collaboration. In particular, it has been suggested that men use networking more instrumentally to achieve goals than women (van Emmerik 2006), and this has also been found with regard to scientific collaborations: Male researchers consider instrumental reasons for collaborations as more important than female researchers (Bozeman and Gaughan 2011). Thus, we hypothesize that *gender moderates*[3] *the relationship between engagement in scientific collaboration—in terms of prevalence of co-authored publications and mean number of collaborators per publication—and scientific success in terms of publication output (H4a) and in terms of publication impact (H4b).*

In addition, it is also possible that the benefit that researchers gain from collaboration depends on the gender of the collaborators. Such differential effects were shown in a study on country differences in scientific success, which found that publications co-authored by Chinese and US psychologists were cited more often than publications solely authored by Chinese researchers but less often than publications solely authored by US researchers (Smith et al. 2014). Taking an exploratory approach, we transfer this idea of differential benefit to gender differences in scientific collaboration. Thus, we ask *whether collaborators' gender is related to scientific success in terms of publication output (RQ3a) and in terms of publication impact (RQ3b), in general.* Moreover, we ask *whether female and male researchers differ in the benefits*

[2] A mediator is a variable through which one variable influences another (Hayes 2013).

[3] A moderator is a variable that influences the association between two other variables (Hayes 2013).

they gain from collaborations with researchers of the same gender (RQ4). An overview of all hypotheses and research questions is provided in Table 10.

Studying Scientific Collaboration in the Field of I-O psychology

The field of I-O psychology is particularly suited for examining gender differences in collaboration for at least three reasons. First, I-O psychology is generally described as a field in which collaboration is crucial: Only for 2% of all occupations in O*NET is collaboration more important than it is for I-O psychologists (O*NET 2015). According to the Occupational Information Network (O*NET) of the U.S. Department of Labor (O*NET 2014), “establishing and maintaining interpersonal relationships—developing constructive and cooperative working relationships with others, and maintaining them over time” is the second most important work activity of I-O psychologists, after “getting information”. Second, collaboration might be particularly common in I-O psychology because it is situated between psychology and management (e.g., Aguinis et al. 2014). For example, Costanza and Jensen (2010) believe that the interplay with neighboring fields is a chance for the survival of I-O psychology. According to Costanza and Jensen (2010, p. 281), to achieve success in this endeavor, it is necessary to “integrate theories from multiple disciplines, adopt multiple perspectives to the questions we face, and embrace the ambiguity inherent in the organizations we study”. Third, comparable to the gender distribution in the community of professional psychologists in general (cf. American Psychological Association 2013), I-O psychology is characterized by relative gender parity (König et al. 2015), which implies that both genders can find collaborators from the other or the same gender without being affected a great deal by different base rates of colleagues with a certain gender in their proximity.

In conclusion, we argue that collaboration is crucial for scientific success, and probably especially so for scientific success in I-O psychology. When examining gender differences in scientific success, such as in I-O psychology (König et al. 2015), previous research has neglected to consider gender differences in collaboration as one of the possible explanations. In this study, we will contribute to providing a deeper understanding of gender differences in science by picking up both research threads.

Method

We used R 3.1.3 and R 3.2.1 (R Core Team 2015a, 2015b) with several additional packages[4] for data analyses. Unless otherwise noted, all tests were significant at $p < .01$.

Data

In scientometric research, co-authorship is the standard operationalization of collaboration (e.g., Abbasi et al. 2012; de Solla Price and Beaver 1966; Glänzel 2002; Glänzel and Schubert 2004; Larivière et al. 2013; Melin 2000; Naldi et al. 2004; but see also Katz and Martin 1997).

Publication data and data on Journal Impact Factor (JIF) were taken from a previous scientometric study (König et al. 2015) that did not examine gender differences in scientific collaborations or their relationships with scientific success. König et al. (2015) used a name-based data retrieval approach based on all publishing SIOP members (for more information on

[4] The following packages were used: car (Fox and Weisberg 2011), coin (Hothorn et al. 2008; see also Yatani 2014), compute.es (del Re 2013), descr (Aquino 2014, 2015), genderizeR (Wais 2015a, 2015b), gsl (Hankin 2006), lattice (Sarkar 2008), lsr (Navarro 2015), pbabpply (Solymos 2014), plyr (Wickham 2011), psych (Revelle 2015), RCurl (Temple Lang 2015), robustbase (Rousseeuw et al. 2015), rockchalk (Johnson 2015), stargazer (Hlavac 2015), stringr (Wickham 2012), and XML (Temple Lang 2013).

data collection, see König et al. 2015). Publication data were collected from the database PsycINFO (American Psychological Association 2015), and data on Journal Impact Factor (JIF) were gathered from the 2012 Journal Citation Report (Science Edition and Social Sciences Edition; Thomson Reuters 2013a, 2013b). Since we repeated the data preparation of König et al. (2015), the dataset of this study is also based on 46,656 publications written by 4,234 publishing I-O psychologists from 1948 to 2013 (cf. American Psychological Association 2015; König et al. 2015).

Sample

The sample was almost gender-balanced and fairly representative for I-O psychology (König et al. 2015). It consisted of 4,234 (45% female) publishing members of the Society of Industrial and Organizational Psychology (SIOP), which is the most important professional association for I-O psychology.

Variables

Gender. (a) The gender of the SIOP researchers was provided by the researchers themselves (57%) while applying for their SIOP membership or was manually determined by König et al. (2015) as female or male (but see American Psychological Association 2011). (b) The gender of their collaborators was algorithmically inferred from their first names (cf. Naldi et al. 2004). For this *genderizing*, we used the API of genderize.io (Genderize.io 2015) through the R package genderizeR (Wais 2015a). Based on data from social networks, genderize.io currently comprises more than 200k names with their gender from 79 countries and in 89 languages. Thus, Wais' (2015) genderizeR provides, for every first name, an inferred gender, the certainty of this inferred gender, and its count. Genderize.io has been used in several non-scientometric scenarios (Genderize.io 2015): Young (2014) used it for supplementary gender inferring of witnesses in the US Congress (see also Boscardin 2013); Ingraham (2014) examined gender differences in the directors of 2,000 movies; and Abbar et al. (2015) used genderize.io to study the eating behavior of over 120k Twitter users.

In contrast to most previous studies, we ensured the validity of the genderizing before applying it to collaborators of the SIOP researchers in our sample. Since the true gender of these 4,234 SIOP researchers was already available (König et al. 2015), we validated the genderizing approach by directly applying it to our sample of SIOP researchers. The first names of 94% of the SIOP researchers were correctly genderized, 2% were incorrectly genderized, and for 4% of the SIOP members, genderizing was not possible. Overall, true gender and genderizing result were nearly perfectly correlated (r_{φ} = .95).

The preparation of the names of SIOP researchers' collaborators for genderizing was conducted in five steps. First, we extracted the 8,959 unique first names of the collaborators. Second, we prepared these unique first names in order to be able to process them using genderizeR (Wais 2015a): Non-alphanumeric characters at the end of 1% of first-name strings were removed (e.g., "Janet."). We excluded 1% of first names with not more than two letters due to their supposed ambiguity for automatic genderizing (e.g., "Zi"). Third, since genderizeR (Wais 2015a) is only able to infer gender from single names, we kept only the first parts of 1,800 double names (i.e., characters after first non-alphanumeric character were deleted). In most cases, moreover, the first part of a double name seems to be more gender-relevant (e.g., "Klaus-Maria"). Fourth, we again excluded a further 303 first names that no longer had more than two letters due to the previous steps. In the fifth step, we then used the function textPrepare in genderizeR (Wais 2015a) separately to finally prepare the 7,240 unique first names in our data (e.g., removing special characters, lowering letters) in order to allow genderizing. Thus, 7,128 unique, adequately prepared first names were passed to findGivenNames, the specific genderizing function in genderizeR (Wais 2015a).

We were able to predict the gender of 5,543 first-name strings, which equals 3,672 unique female and 3,277 unique male researcher names (i.e., single-name strings and combined-name strings). Inspection of the first-name strings that were not genderized suggested several possible reasons, such as rarity of a name or presumable misspelling—at least from our perspective as members of a Western, Educated, Industrialized, Rich, and Democratic society (Henrich et al. 2010). Finally, with a mean certainty of 97% (*SD* = 0.09), the gender of 92% of SIOP researchers' collaborators (40% female) could be inferred. We were unable to infer the gender of 7,517 (approx. 8%) collaborators of SIOP researchers; 4% had to be excluded from genderizing, and for 3%, genderizing was not possible.

Collaboration. SIOP researchers' individual collaboration behavior was operationalized as (a) prevalence of co-authored publications (cf. Ductor 2015) and (b) mean number of collaborators per publication. For example, a SIOP researcher who (co-)authored three publications (one publication alone plus two publications with two collaborators each) would have a prevalence of co-authored publications of .67 and a mean number of collaborators of 1.33. Number of co-authors equals the number of collaborators plus 1 (i.e., the SIOP researcher him/herself), which is also the denominator for calculating shares of publications, citations, and Journal Impact Factors.

Publication output. First, SIOP researchers' individual publication output was operationalized as the absolute number of publications that were (co-)authored by them (cf. König et al. 2015). Second, it was operationalized as the individual sum of publication shares. For example, the aforementioned SIOP researcher would have an absolute number of 3 publications and a sum of publication shares of 1.67. A single publication share is also called "contribution" or "publication-equivalent" and is based on the assumption that "that each person contributed the same amount" to a publication (Naldi et al., 2004, p. 306).

Publication impact. A SIOP researcher's individual publication impact was approximated by relying on citations in PsycINFO (available for 45% of the publications[5]) and the JIF of the journals in which the publications appeared (cf. König et al. 2015). It should be noted (see also König et al. 2015) that relying solely on the JIF to estimate an individual researcher's impact would be questionable due to JIF's methodological limitations (e.g., only available for some journals, articles of one journal often differ heavily in number of citations; Bordons et al. 2002a; Seglen 1997). Impact indicators were again operationalized as individual means and sums of shares. For example, let us assume that the aforementioned SIOP researcher, who (co-)authored three publications (one publication alone plus two publications with two collaborators each), received 4 citations for each publication and published the publications in journals with Journal Impact Factors of 2.00, 1.50, and 4.00, respectively. In this example, the researcher would have a mean number of citations of 4.00 (i.e., [4 + 4 + 4]/3), a sum of citation shares of 6.67 (i.e., 4 + 4/3 +4/3), a mean JIF of 2.50 (i.e., [2.00 + 1.50 +4.00]/3), and a sum of JIF shares of 3.83 (i.e., 2.00 + 1.50/3 +4.00/3).

Collaborator gender. SIOP researchers' individual tendency to collaborate with researchers of the same gender was operationalized as prevalence of collaborators of the same gender. For example, a male SIOP researcher who (co-)authored three publications (one publication alone, two publications with two collaborators each [male, male; male, female]) would have a prevalence of male collaborators of 75% (vs. 25% for female collaborators). Thus,

[5] In PsycINFO, information on citations in the database itself is still only available for relatively few publications.

his homophily indicator would be .75. For SIOP researchers' gender-specific collaboration prevalences, we used the overall number of collaborators with a valid gender. If it had not been possible to infer the gender of one of the male collaborators in the previous example, the prevalence of male collaborators would have been 67% (vs. 33% for female collaborators).

Results

Table 1 provides an overview of all variables with their descriptive statistics and intercorrelations; using Kendall's τ (e.g., Capéraà and Genest 1993; Kruskal 1958) instead of Pearson's *r* as suggested by a reviewer, we confirmed König et al.'s (2015) intercorrelations among scientific success variables (i.e., publication output, publication impact). Besides giving a glimpse into our main results, the correlation matrix reveals the importance of considering various aspects of collaborations and publication impact; publication output variables, however, are closely related ($\tau = .82$).

On average, publishing active researchers collaborated with 1.91 researchers per publication (*Max* = 89, *Mdn* = 1.67, *SD* = 2.32) and had a collaboration prevalence of 68.71% (*Max* = 100%, *Mdn* = 81.82%, *SD* = 34.97%). Using non-parametric testing as suggested by one of the reviewers, we confirmed König et al.'s (2015) findings on gender differences in scientific success for all variables except for mean JIF (Table 2): Female researchers appeared to be scientifically less successful in terms of publication output and publication impact.

H1a, in which we hypothesized that the majority of publications are co-authored, was confirmed. Of all publications ($M_{\text{collaborators}} = 2.13$, $Mdn = 2.00$, $SD_{\text{collaborators}} = 2.76$), 82% had at least one collaborator. According to a binomial test, the probability of a publication being authored by more than one author is significantly greater than it would be by chance ($CI_{95\%} = [0.82;0.82]$, $h = 1.38$). H1b, in which we hypothesized that the prevalence of co-authored publications has increased over time, was confirmed by robust linear regression (Table 3) and visual inspection (Figure 1).

H2a, in which we hypothesized that collaborating researchers produce more publication output, was partially confirmed (Table 1). Researchers' prevalence of co-authored publications was positively correlated with their number of publications ($\tau = .20$) but was not correlated with their sum of publication shares ($\tau = .01$, *ns*). A similar differentiation was found for the mean number of collaborators per publication ($\tau_{\text{No. of publications}} = .25$; $\tau_{\text{Sum of publication shares}} = .03$, $p < .05$; Table 1). This result might call into doubt the benefit that an individual researcher can gain from large research collaborations. H2b, in which we hypothesized that collaborating researchers are more often cited and manage to publish in more impactful journals, was barely confirmed at all (Table 1): Only the mean number of collaborators was significantly positively (but weakly) correlated with researchers' mean JIF ($\tau = .06$). Researchers' prevalence of co-authored publications and mean number of collaborators, however, were slightly negatively correlated with their publications' impact in terms of citations and their sums of JIF shares (Table 1). We discuss these findings later in more detail.

The answer to RQ1, in which we asked whether female or male researchers collaborate more, is that female researchers collaborate more than male researchers. There were significant gender differences in the prevalence of co-authored publications ($Mdn_{\text{female}} = 86\%$, $Mdn_{\text{male}} = 80\%$, $W = 2{,}477{,}408$, $z = 6.55$, $r = .10$) and in the mean number of collaborators ($Mdn_{\text{female}} = 1.83$, $Mdn_{\text{male}} = 1.53$, $W = 2{,}476{,}926$, $z = 6.47$, $r = .10$); the effect size r was computed as $r = z/\sqrt{N}$ (e.g., Field 2009, p. 550).

RQ2, in which we asked whether there is more collaboration among researchers of the same gender than among researchers of different genders, can be answered in the affirmative.

Across all researchers, 57% (*Mdn* = 58%) of their collaborators were of the same gender, which differs significantly from the 43% (*Mdn* = 42%) of their collaborators with the opposite gender, $Min(T_+, T_-)$ = 3,390,787, z = 14.65, and r = .25 (cf. Aho 2014; Field 2009, p. 558).

H3, in which we hypothesized that engagement in scientific collaboration mediates the relationship between gender and scientific success, was disproved by the aforementioned gender differences in scientific success and in collaborating. Female researchers collaborate more often and with more researchers than male researchers (cf. results for RQ1) but are scientifically less successful (Table 2). Thus, female researchers' lower scientific success cannot be mediated by engagement in collaboration, which is rather positively correlated with scientific success (Table 1).

H4a, in which we hypothesized that gender moderates the relationship between engagement in scientific collaboration and publication output, was partially confirmed (Table 4). In terms of the absolute number of publications (Models 1a, 1b) as well as the sum of publication shares (Model 2a), female and male researchers benefit differently from engagement in scientific collaborations. In terms of the absolute number of publications as well as of the sum of publication shares, the slopes are significantly steeper for male researchers. H4b, in which we hypothesized that gender moderates the relationship between engagement in scientific collaboration and publication impact, was confirmed with regard to the mean number of citations (Model 1a in Table 5); again, male researchers benefit more from collaborations.

The answer to RQ3, in which we asked whether collaborators' gender is related to scientific success in terms of publication output (RQ3a) and in terms of publication impact (RQ3b), is rather "no": The gender of collaborators is not meaningfully correlated with scientific success (Table 1), except perhaps for mean number of citations ($r_{\text{female, male}} = \pm.04$) and mean JIF ($r_{\text{female, male}} = \pm.07$). Although weak, relationships are in favor of male collaborators.

RQ4 asked whether female and male researchers differ in the benefit they gain from collaborations with researchers of the same gender. This was found to be partially the case for publication impact but not for publication output (Table 6). Robust regression analysis revealed statistically significant moderations for the mean number of citations (Model 1 in Table 7) and for mean JIF (Model 3 in Table 7); male researchers benefit more strongly from collaborations with researchers of the same gender than female researchers.

Additional Analyses

To test whether a *Matthew effect* of collaborations (i.e., researchers who have already gathered many collaborators will gather even more; Merton 1968; Perc 2014) can also be found in our data, we tested whether the positive relationship between the mean number of collaborators per career year and the years of researchers' publishing career was moderated by researchers' overall mean number of collaborators. Robust regression analysis (Table 8) and visual inspection (Figure 2) indicated a significant moderation effect: Researchers with a high overall mean number of collaborators show an exceptional increase in their mean number of collaborators across their career; they are also significantly younger (i.e., their first publications were more recent, $Mdn_{\text{low}} = 1996$, $Mdn_{\text{high}} = 2004$, $W = 1{,}583{,}606$, $z = -16.52$, $r = -0.25$).

Furthermore, we analyzed homophilic collaboration over time because previous research has suggested that homophilic collaboration of female researchers decreases over their publishing careers (Bozeman and Corley 2004). We tested whether prevalence of collaborations between SIOP researchers and collaborators of the same gender changed over researchers' careers and whether such development was moderated by SIOP researchers' gender. Overall, robust regression analysis (R^2_{adj} = .46; Table 9) revealed that (a) male researchers were more homophilic in their collaborations than female researchers and (b) homophily slightly increased over the career years. More interestingly, there was a significant moderation effect: Among female researchers, the prevalence of collaborations with researchers of the same gender increases more strongly than among male researchers (Figure 3).

Following the suggestions of one the reviewers, we relied on non-parametric/robust statistical approaches to ensure that our results were not biased by skewed distribution of the data. However, we also repeated our analyses with parametric approaches and found only slight differences.

Discussion

The main goal of this study was to examine the consequences of collaboration, especially for gender differences in scientific success. While collaborating seems to have a rather positive effect on scientific success in terms of publication output, gender differences in collaborating cannot explain the gender differences in scientific success (e.g., König et al. 2015). Contradicting the idea that too little collaboration causes their lower scientific success, female researchers engage even more strongly in collaboration than male researchers. In line with Hyde's (2005) conclusion that females and males are much more alike than different (see also König et al. [2015] on a lack of gender differences beyond success measures), this study deepens our understanding of scientific collaborations, scientific success, and gender differences in both. As expected, the majority of publications were authored by more than one researcher. Although this has always been the case for I-O psychologists, as eight out of ten publications are authored together with at least one collaborator, collaboration has become a ubiquitous part of the work of today’s I-O researchers. Thus, in terms of the prevalence of collaborating, I-O psychology seems quite similar to research in general (Glänzel and Schubert 2004) and to management research in particular (cf. Acedo et al. 2006).

Since collaboration was positively related to scientific success in terms of publication output, there is some reason to believe that successful researchers rightly attribute their success to their collaborating (Mayrath 2007). However, researchers seem to benefit from collaborations because they are listed in long author bylines, echoing the findings of Lee and Bozeman (2005). After controlling for the number of co-authors (i.e., publication shares), the relationship between the prevalence of collaborative publications or the mean number of collaborators and publication output dropped dramatically or even became insignificant. Thus, we were unable to replicate the finding that the increase in the number of researchers' collaborators is smaller than the increase in their publications (see also Persson et al. 2004).

Empirical relationships between indicators of collaboration and publication impact were close to zero, thus reflecting de Solla Price and Beaver's (1966, p. 1017) early view that "the conventional explanation of collaboration as the utilization of many different skills and pairs of hands to do a single job otherwise impossible to perform, is woefully inadequate and misleading." Whether or not researchers engage in collaborations seems to be of only moderate relevance for their publication impact. Moreover, a high prevalence of collaborative publications and a high mean number of collaborators were even shown to be slightly detrimental to researchers' publication impact. Thus, researchers who use collaborations as a door opener to get into highly impactful journals (e.g., by taking part in seminal, large-scale projects) should be aware that it often does not work out as they might have hoped in terms of citations or JIF.

Our interest in gender differences in scientific collaboration was mainly driven by the suggestion that gender differences in scientific success might be mediated by gender differences in collaboration (as argued by Larivière et al. 2013). However, female researchers actually engaged more often (i.e., higher prevalence of collaborative publications) and more strongly (i.e., higher mean number of collaborators) in scientific collaborations. This finding matches the results of psychological research on individual characteristics that are relevant for collaboration behavior. Gender differences in agreeableness and emotional intelligence in favor of women led us to call into question the assertion that female researchers collaborate less than their male colleagues. At least for I-O psychology, our results show that such doubts were justified. Female researchers are not less capable of collaborating than their male colleagues—even in the face of possible situational barriers. At first glance, such a finding might be considered a good thing. At second glance, however, it lends credence to suspicions that there might be additional reasons for gender differences in scientific success that are far less socially tolerable (cf. Nature Editorial 2013): Other constraints than the assumed gender differences in scientific collaborating (e.g., more responsibility for childcare; Rhoads and Rhoads 2012) may indeed cause female researchers' lower scientific success. Thus, it might be concluded that our results are disappointing for those who had hoped that encouraging female researchers to collaborate more would put an end to the waste of female human capital in science (e.g., Larivière et al. 2013; West et al. 2013).

Furthermore, we examined the interaction effect of gender and collaboration on scientific success. In line with previous research on collaborating (Bozeman and Gaughan 2011) and networking (van Emmerik 2006), gender moderated the positive effect of collaboration on scientific success: Male researchers appeared to collaborate significantly more successfully, especially in terms of publication output. So far, we can only speculate about the true reasons behind such a moderation effect. However, there has been considerable research into why identical behavior evokes different consequences for women and men. In particular, Knobloch-Westerwick et al. (2013) demonstrated the suitability of important aspects of Eagly and Karau's (2002) role congruity theory for ratings of the quality of scientific contributions and of interest in collaborating—for female as well male raters. We speculate that female researchers manage to collaborate with others, but that they are confronted with extra hindrances that keep them from turning collaborations in scientific success. In their role congruity theory, Eagly and Karau (2002, p. 576) postulated two prejudice mechanisms that can cause “more obstacles for women to overcome in becoming successful in these [leadership] roles.” Stereotypical female characteristics (e.g., being more communal than men), which are perceived as contradicting leader characteristics (Eagly and Karau 2002), could also be perceived as less suitable by collaborators or even reviewers (cf. Bornmann et al. 2007; Brown 2014; Demarest et al. 2014; but see C. J. Lee et al. 2013). Moreover, if female researchers behave as “typical” researchers (i.e., male researchers) are supposed to behave, their behavior could be perceived as negative because it is considered as violating their ascribed female role (Eagly and Karau 2002).

The prevalence of homophilic collaborations was confirmed by the fact that 57% of researchers’ collaborations were between researchers of the same gender. In fields where collaborating is crucial for scientific success, homophily threatens this success, especially for the smaller gender group, which is most often the group of females (McDowell et al. 2006). In the search for collaborators, members of the smaller group are faced with a much lower base rate of possible candidates. However, in I-O psychology, where the estimated prevalence of female researchers is 45%, such a threat seems manageable, at least for the time being. Nevertheless, as male researchers are more homophilic, and considering that prevalences of female researchers shrink with increasing career levels (e.g., Sheltzer and Smith 2014; Treviño et al. 2015), we worry that homophily might become an issue especially for female researchers at higher career levels.

Furthermore, a Matthew effect for collaboration seems to exist in I-O psychology: Those researchers with high mean numbers of collaborators (above the median) exhibit a steeper increase in their mean number of collaborators across their career than those researchers with a low mean number of collaborators. They are also significantly younger than the latter. Thus, not only do younger I-O psychologists collaborate more strongly overall, but they also increase their engagement more strongly across their careers. Such a difference in collaboration might be a further consequence of recent changes in the scientific environment. For younger I-O psychologists, the academic job market is more competitive, academic job requirements are tougher, and researchers are exposed to a higher publication pressure (Barnard-Brak et al. 2011). Younger scientists might have to optimize their careers more strongly than in years past, and our findings suggest that they took the advice on the importance of collaborating (e.g., Bowden 2011; McCormick and Barnes 2007) very seriously.

Limitations

Like all studies, our study has limitations that need to be addressed. First, algorithmic first-name-based gender predictions come with inaccuracies. For instance, there might be a Western bias (cf. Henrich et al. 2010) in the first names that are available in the name database which we used or there might be names that would have required authors' countries of origin to be taken into account to determine their gender (e.g., the name "Andrea"—female in most countries, male in Italian; see also Genderize.io 2015). However, information on authors' affiliation—the country in which an author contributed to a publication (cf. American Psychological Association 2009)—is often not available or is of little use for localization purposes because the indicated country is not necessarily their country of origin (see also Spurk et al. 2015). According to the American Psychological Association (2009), authors indicate their departmental affiliation at the time when they conducted the study, which often does not include their countries of origin (e.g., research stay abroad). Furthermore, our approach hopefully ensured that gender predictions were of the highest validity: We prepared name data manually before the first names were passed to genderizeR (Wais 2015a); all gender predictions were based on the same single, comprehensive database (Genderize.io 2015); and we empirically established the high validity of our approach for algorithmic first-name-based gender predictions. Nevertheless, more research is needed that compares the validity of different genderization approaches.

Second, although it has been suggested that collaboration is of similar importance in all areas of research (Committee on Facilitating Interdisciplinary Research et al. 2004; Committee on the Science of Team Science et al. 2015; Spurk et al. 2015; but for multidisciplinary vs. social sciences, see Gazni et al. 2012), we have to repeat the limitation mentioned by König et al. (2015) that results based on a sample of I-O psychologists of an international—but US-based—association for I-O psychology might be of limited generalizability. Limitation in generalizability is at least threefold: (a) The I-O psychological community examined in our study could differ from other I-O psychological research communities (e.g., in certain countries, Barrios et al. 2013). (b) The field of research of I-O psychology could differ from other psychological fields of research (e.g., Krampen et al. 2011). (c) Psychological research could differ from other fields in terms of how to collaborate, to do research, or to assess scientific success (e.g., Bordons et al. 2002b; Yuret 2014).

Third, we considered only two gender categories in our study, which is a simplification (cf. American Psychological Association 2011; Menking 2015). Unfortunately, more complex gender conceptions have barely been considered in psychological research (but see Society for the Psychological Study of Lesbian, Gay, Bisexual, and Transgender Issues 2014; Tate et al. 2013), and the simple, dichotomous female-male differentiation is still the absolute default.

Fourth, we relied on PsycINFO's citation data, which were limited to citations within PsycINFO itself and which were only available for 45% of the publications. To the best of our knowledge, no information was available that revealed why the information is missing for some papers and whether information omissions could have been systematic. Future research is therefore needed (cf. Harzing 2012) that explicitly examines coverage and quality of PsycINFO's citation data.

Implications

We found no evidence that the gender difference in scientific success might be caused by gender differences in collaboration: Although female researchers engage more strongly in collaboration, they are scientifically less successful. Based on the findings of our study, we believe that promoting female collaboration (cf. Larivière et al. 2013) would not level out the gender difference in scientific success.

The findings of our study highlight the role of collaborating in scientific success. In this realm, our study hopefully helps to clarify the role of multi-authored publications in scientific careers and the value of such collaboration. In the pursuit of tenure (i.e., a permanent working contract as a researcher at a university), young academics often find themselves in a dilemma: While science is becoming more collaborative, by requiring solo research, the evaluation criteria that young academics are subjected to often fail to reflect this reality (McGovern 2009).

Hopefully, this study may encourage the powers that be to adapt the evaluation criteria to the reality of those being evaluated.

Confirming what previous psychological findings suggested with regard to gender differences in scientific collaboration (no differences, or a slight difference in favor of female researchers), this study exemplifies the benefits of interdisciplinary psycho-scientometric research. In the case of our study, psychology helped us to ask questions (e.g., Why might there be gender differences in job performance?), while scientometrics helped us to find ways to answer them (e.g., How can we measure collaboration?).

While scientometric research has been criticized for often being either too superficial or detached from reality (Glänzel and Schoepflin 1994), our methodologically straightforward scientometric study addressed a real-life question. We hope that this study can serve as a blueprint for future studies in different fields, with different questions, and enhanced methods.

Future Research

This study emphasizes the need for more research examining assumed gender differences that are thought to shape different realities for women and men at work (see also Lips 2013). Such differences in realities might “result from differences in resources attributable to choices, whether free or constrained” (Ceci and Williams 2011, p. 3157). Thus, future research should examine which particular choices of females and males at work are free while others are constrained, and why this is the case. Studies could directly incorporate researchers’ own views of their work and their careers. By conducting interviews, surveys, or symposia, it would be possible to directly examine the validity of proposed explanations (cf. Jyrkinen and McKie 2012; McDonald et al. 2005; Rosenthal et al. 1996).

According to König et al. (2015), there is reason to believe that the gender differences in scientific success will decrease over time (see also Barnett and Hyde 2001). Future research should examine such hypothesized developments. In fact, longitudinal scientometric studies could be conducted by applying our and König et al.'s (2015) approach to previous and future member lists of SIOP researchers on an annual basis ("Gender Monitoring"; cf. Schui and Krampen 2015). Furthermore, such approaches could equally be extended to I-O psychological and psychological research communities other than the US-oriented SIOP, such as the European Association of Work and Organizational Psychology (EAWOP), or the German Psychological Society (Deutsche Gesellschaft für Psychologie, DGPs).

As name-based scientometric analyses such as those conducted in the present study are lacking in terms of their ability to efficiently identify unique co-authors (e.g., due to different name spellings, different authors with identical names, typos), future research could try to exploit unique author identifier variables (e.g., using ORCID.org) or to win over researchers themselves for maintaining their own publication lists (e.g., ResearchGate).

Conclusion

Countries need research to ensure social prosperity for their citizens (e.g., Holliday 2012; Malakoff 2000; Üsdiken 1996). In 2011, countries across the world spent 1,435,000,000,000.00 $ on research and development (National Science Board 2014). Thus, gender differences to the disadvantage of female researchers are an expensive waste of human capital (König et al. 2015; Larivière et al. 2013). In this scientometric study, engagement in collaboration was shown to be of some relevance for scientific success—rather in terms of publication output than impact. However, our finding that female researchers collaborate more often and, on average, with more colleagues contradicts the idea that female researchers are less successful than their male researchers due to a lack of scientific collaboration. More research is needed which examines possible reasons and remedies.

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Table 1

Overview of Variables with Means, Standard Deviations, and Intercorrelations (Kendall's τ)

Variables	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. Gender (0 = female, 1 = male)	.55	.50												
Collaboration														
2. Collaboration (%)	68.71	34.97	-.09											
3. Collaborators mean	1.91	2.32	-.08	.61										
4. Female collaborators (%)	38.41	26.70	-.19	.08	.17									
5. Male collaborators (%)	61.59	26.70	.19	-.08	-.17	-1.00								
6. Collaborators of same gender (%)	56.90	28.28	.33	-.03[ns]	-.09	-.12	.12							
7. Collaborators of opposite gender (%)	56.90	28.28	-.33	.03[ns]	.09	.12	-.12	-1.00						
Publication output														
8. No. of publications	11.02	17.78	.10	.20	.25	.03[ns]	-.03[ns]	.01[ns]	-.01[ns]					
9. Sum of publication shares	5.10	8.38	.13	.01[ns]	.03[a]	.00[ns]	.00[ns]	.03[ns]	-.03[ns]	.82				
Publication impact														
10. Mean no. of citations	19.58	35.92	.08	-.07	-.05	-.04[a]	.04[a]	.00[ns]	.00[ns]	.32	.31			
11. Sum of citation shares	71.84	170.56	.11	-.04[a]	-.07	-.02[ns]	.02[ns]	.02[ns]	-.02[ns]	.60	.58	.66		
12. Mean JIF	2.53	1.99	.03[ns]	.00[ns]	.06	-.07	.07	.00[ns]	.00[ns]	.18	.15	.33	.26	
13. Sum of JIF shares	10.81	20.47	.13	-.04	-.06	-.02[ns]	.02[ns]	.04[a]	-.04[a]	.72	.68	.37	.62	.39

Note. JIF = Journal Impact Factor (Thomson Reuters 2013a, 2013b). All correlations significant at $p < .01$ unless otherwise noted. Due to pairwise deletion, sample sizes vary between 2,761 and 4,234.

[a] $p < .05$.

Table 2

Variables of scientific success with descriptive statistics and gender differences

	M Mdn	SD $Range$	M_{female} Mdn_{female}	M_{male} Mdn_{male}	W	z	r
Publication output							
No. of publications[a]	11.02	17.78	8.14	13.41	1,918,059	-7.74	-0.12
(n_{female} = 1,920, n_{male} = 2,314)	4.00	[1; 123]	3.00	4.00			
Sum of publication shares	5.10	8.38	3.57	6.37	1,805,298	-10.52	-0.16
(n_{female} = 1,920, n_{male} = 2,314)	1.83	[0.01; 73.53]	1.50	2.17			
Publication impact							
Mean no. of citations[a]	19.58	35.92	17.59	21.23	907,000	-5.00	-0.09
(n_{female} = 1,300, n_{male} = 1,565)	10.00	[1; 1,022]	9.00	11.14			
Sum of citation shares	71.84	170.56	51.43	88.80	851,849	-7.50	-0.14
(n_{female} = 1,300, n_{male} = 1,565)	12.00	[0.02; 2,232.00]	8.25	16.94			
Mean JIF[a]	2.53	1.99	2.49	2.57	1,290,343	-2.23[b]	-0.04
(n_{female} = 1,488, n_{male} = 1,816)	2.24	[0.11; 38.60]	2.16	2.31			
Sum of JIF shares	10.81	20.47	6.98	13.95	1,096,043	-9.35	-0.16
(n_{female} = 1,488, n_{male} = 1,816)	2.85	[0.02; 307.10]	2.12	3.94			

Note. Wilcoxon-Mann-Whitney test was used for testing gender differences (unless otherwise noted, W significant at $p < .01$). The effect size r was computed as $r = z/\sqrt{N}$ (e.g., Field 2009, p. 550). JIF = Journal Impact Factor (Thomson Reuters 2013a, 2013b).

[a] For more information, see König et al. (2015).

[b] $p < .05$.

Table 3

Prevalence of publications with at least one collaborator regressed on publication year (1948-2013).

	No. of publications with collaborators (%)
Constant	50.24
Publication year (centered)[a]	0.58
$R^2_{adj.}$	.68

Note. N = 66 publication years with 2 outliers (i.e., cases with robustness weights of zero; cf. Rousseeuw et al. 2015). The robust regression was based on so-called MM-type estimators (cf. Yohai 1987; Koller and Stahel 2011). All coefficients significant at $p < .01$.

[a] Publication years were centered on 1948 (i.e., year of first publication in the sample).

Table 4

Publication output (i.e., number of publications, sum of publication shares) regressed on gender, collaboration (i.e., prevalence of co-authored publications, mean number of collaborators per publication), and their interaction (i.e., moderation).

	No. of publications		Sum of publication shares	
	Model 1a	Model 1b	Model 2a	Model 2b
Constant	1.74	3.43	1.53	1.92
Gender (0 = female, 1 = male)	0.09[ns]	0.19[ns]	0.05[ns]	0.27
Collaboration (%)	0.03		0.00	
Collaborator mean		0.34		-0.05[a]
Collaboration (%) x Gender	0.01		0.01	
Collaborator mean x Gender		0.37		0.05[ns]
$R^2_{adj.}$	.11	.04	.03	.01

Note. N = 4,234 researchers, with numbers of outliers (i.e., cases with robustness weights of zero; cf. Rousseeuw et al. 2015) varying between 262 and 321. The robust regression was based on so-called MM-type estimators (cf. Yohai 1987; Koller and Stahel 2011). All tests significant at $p < .01$ unless otherwise noted.

[a] $p < .05$.

Table 5

Publication impact (i.e., mean number of citations, sum of citation shares, mean JIF, sum of JIF shares) regressed on gender, collaboration (i.e., prevalence of co-authored publications, mean number of collaborators per publication), and their interaction (i.e., moderation).

	Mean no. of citations		Sum of citation shares		Mean JIF		Sum of JIF shares	
	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 4a	Model 4b
Constant	11.77	11.97	11.53	13.38	2.19	2.18	2.21	3.23
Gender (0 = female, 1 = male)	-2.78^{ns}	1.72	-1.97^{ns}	1.47^{ns}	-0.15^{ns}	0.10^{ns}	0.52^{ns}	0.55
Collaboration (%)	-0.01^{ns}		-0.00^{ns}		0.00^{ns}		0.01^{ns}	
Collaborator mean		-0.32^{ns}		-0.76		0.04^{ns}		-0.12^{a}
Collaboration (%) x Gender	0.06		0.06^{ns}		0.00^{ns}		0.00^{ns}	
Collaborator mean x Gender		0.13^{ns}		0.51^{ns}		0.01^{ns}		0.05^{ns}
$R^2_{adj.}$	.01	.01	.01	.01	.00	.00	.01	.01

Note. $N_{\text{Models 1a, 1b, 2a, 2b}}$ = 2,865 researchers. $N_{\text{Models 3a, 3b, 4a, 4b}}$ = 3,304 researchers, with numbers of outliers (i.e., cases with robustness weights of zero; cf. Rousseeuw et al. 2015) varying between 43 and 355. The robust regression was based on so-called MM-type estimators (cf. Yohai 1987; Koller and Stahel 2011). JIF = Journal Impact Factor (Thomson Reuters 2013a, 2013b). All tests significant at $p < .01$ unless otherwise noted.

[a] $p < .05$.

Table 6

Publication output (i.e., number of publications, sum of publication shares) regressed on gender, homophilic collaboration (i.e., prevalence of collaborators of the same gender), and their interaction (i.e., moderation).

	No. of publications	Sum of publication shares
	Model 1	Model 2
Constant	5.73	2.46
Gender (0 = female, 1 = male)	2.45	0.82
Collaborators of the same gender (%)	0.00^{ns}	-0.00^{ns}
Collaborators of the same gender (%) x Gender	-0.01^{ns}	-0.00^{ns}
$R^2_{adj.}$	.01	.02

Note. N = 3,529 researchers with 132 and 167 outliers (i.e., cases with robustness weights of zero; cf. Rousseeuw et al. 2015), respectively. The robust regression was based on so-called MM-type estimators (cf. Yohai 1987; Koller and Stahel 2011). All tests significant at $p < .01$ unless otherwise noted.

Table 7

Publication impact (i.e., mean number of citations, sum of citation shares, mean JIF, sum of JIF shares) regressed on gender, homophilic collaboration (i.e., prevalence of collaborators of the same gender), and their interaction (i.e., moderation).

	Mean no. of citations	Sum of citation shares	Mean JIF	Sum of JIF shares
	Model 1	Model 2	Model 3	Model 4
Constant	12.76	13.14	2.56	3.15
Gender (0 = female, 1 = male)	-0.08[ns]	1.52[ns]	-0.48	0.64[ns]
Collaborators of the same gender (%)	-0.03[a]	-0.03[ns]	-0.01	-0.00[ns]
Collaborators of the same gender (%) x Gender	0.04[a]	0.03[ns]	0.01	0.00[ns]
$R^2_{adj.}$	.01	.01	.01	.01

Note. $N_{\text{Models 1,2}}$ = 2,833 researchers with 43 and 343 (i.e., cases with robustness weights of zero; cf. Rousseeuw et al. 2015), respectively. $N_{\text{Models 3,4}}$ = 3,239 researchers with 12 and 267 outliers (i.e., cases with robustness weights of zero; cf. Rousseeuw et al. 2015), respectively. The robust regression was based on so-called MM-type estimators (cf. Yohai 1987; Koller and Stahel 2011). JIF = Journal Impact Factor (Thomson Reuters 2013a, 2013b). All tests significant at $p < .01$ unless otherwise noted.

[a] $p < .05$.

Table 8

Mean number of collaborators per career year regressed on the years of researchers' publishing career, researchers' overall mean number of collaborators (low vs. high), and their interaction (i.e., Matthew effect).

	Collaborators mean
Constant	1.31
Collaborators mean (0 = low, 1 = high; median split)	1.32
Publishing career	-0.00^{ns}
Publishing career x Collaborators mean	0.01
$R^2_{adj.}$	.83

Note. N = 129 female plus male career years with 3 outliers (i.e., cases with robustness weights of zero; cf. Rousseeuw et al. 2015). The robust regression was based on so-called MM-type estimators (cf. Yohai 1987; Koller and Stahel 2011). All tests significant at $p < .01$ unless otherwise noted.

Table 9

Prevalence of collaborators with the same gender regressed on gender and publishing career (i.e., years after first publication).

	No. of publications with collaborators of the same gender (%)
Constant	45.76
Gender (0 = female, 1 = male)	19.89
Publishing career	0.15[a]
Publishing career x Gender	-0.18[a]
$R^2_{adj.}$	.46

Note. N = 125 female plus male career years. The robust regression was based on so-called MM-type estimators (cf. Yohai 1987; Koller and Stahel 2011). All tests significant at $p < .01$ unless otherwise noted.

[a] $p < .05$.

Table 10

Overview of hypotheses and research questions

	Result
We hypothesize that …	
… overall, the majority of publications are co-authored (H1a) and the prevalence of co-authored publications has increased over time (H1b).	confirmed
… collaborating researchers—in terms of prevalence of co-authored publications and mean number of collaborators per publication—have more scientific success *in terms of publication output (H2a) and in terms of publication impact (H2b).*	partially confirmed
… engagement in scientific collaboration—in terms of prevalence of co-authored publications and mean number of collaborators per publication—mediates the relationship between gender and scientific success *in terms of publication output (H3a) and in terms of publication impact (H3b).*	not confirmed
… gender moderates the relationship between engagement in scientific collaboration—in terms of prevalence of co-authored publications and mean number of collaborators per publication—and scientific success *in terms of publication output (H4a) and in terms of publication impact (H4b).*	partially confirmed
We ask whether …	
… female or male researchers collaborate more in terms *of prevalence of co-authored publications and mean number of collaborators per publication (RQ1).*	females
… there is more collaboration—in terms of prevalence of co-authored publications and mean number of collaborators per *publication—among researchers of the same gender than among researchers of different genders (RQ2).*	yes
… collaborators' gender is related to scientific success in terms of publication output (RQ3a) and in terms of publication impact (RQ3b), in general.	rather no
… female and male researchers differ in the benefits they gain from collaborations with researchers of the same gender (RQ4).	yes

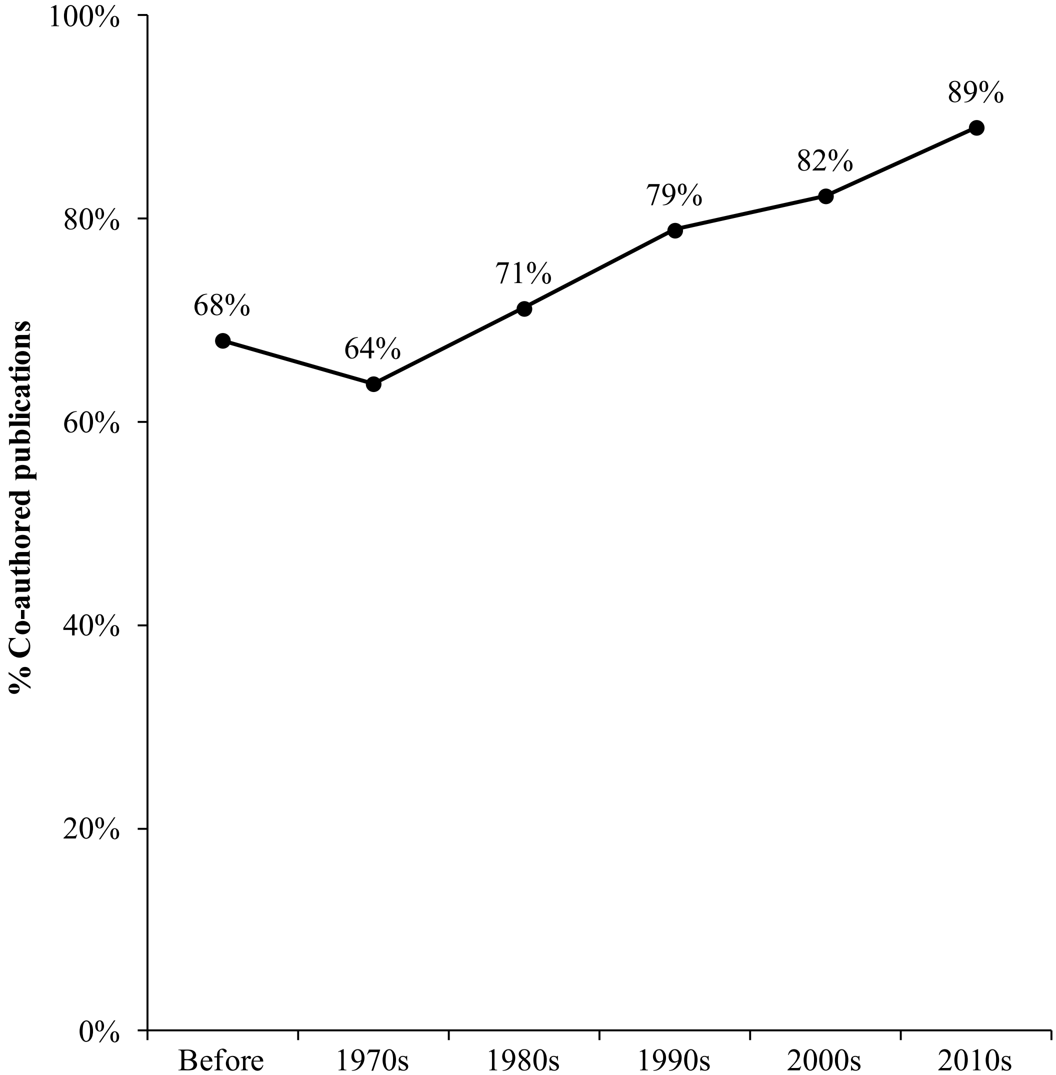

Figure 1. Prevalences of publications with at least one collaborator. Publication years 1948-1969 were collapsed (cf. "Before") to create this figure because publication numbers were too small (i.e., below 100 each).

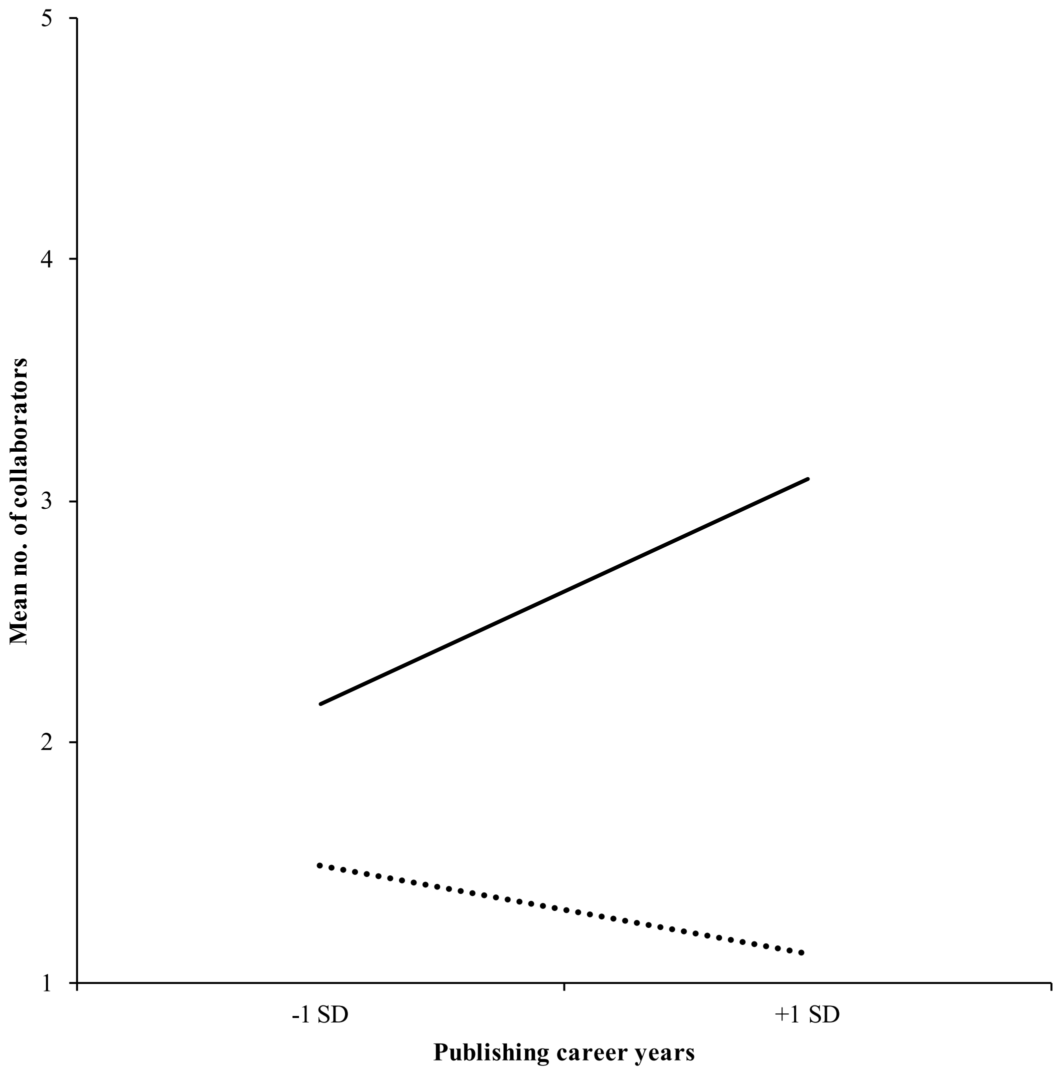

Figure 2. Illustration of the Matthew effect, i.e., the moderation (cf. Table 8) of the relationship between the mean number of collaborators per career year and the years of researchers' publishing career by researchers' overall mean number of collaborators (dashed = low, solid = high; median split).

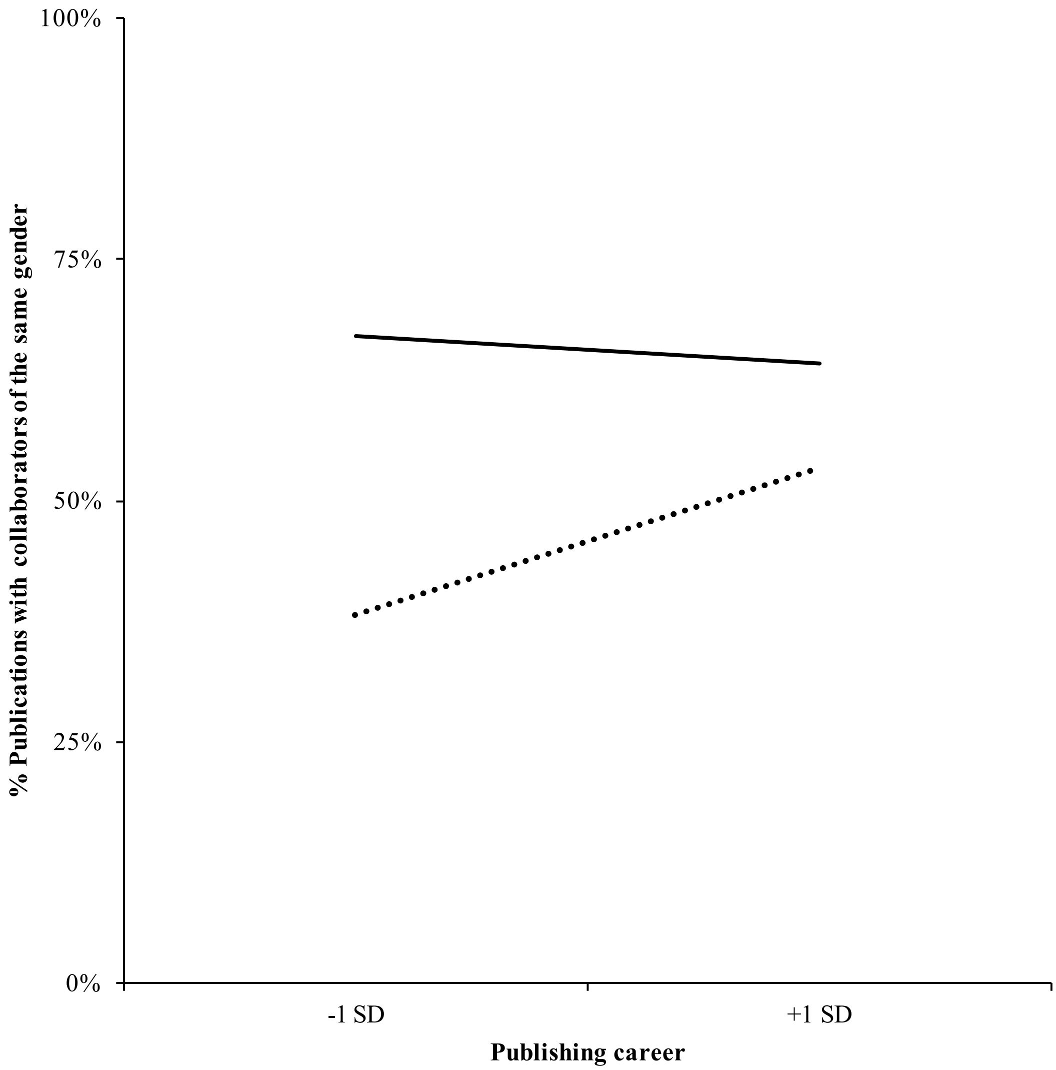

Figure 3. Illustration of the significant gender moderation (dashed = female, solid = male) of the relationship between the years of researchers' publishing career and engagement in scientific collaboration with researchers of the same gender (cf. Table 9).