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Climbing to the top: How female and male coinventors shape the rise of star innovators

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ABSTRACT

The persistent underrepresentation of women in innovation systems may entail the loss of high-potential inventors, that is, the future "stars" of technological advancement. As innovation increasingly arises from team-based efforts within and across organizations, understanding how gender shapes collaborations and the emergence of top innovators is critical. In this article, we investigate the time it takes an inventor to become a star in their field and the relationship with the gender and star status of their coinventors. Tracking 100,000 inventors who filed their first patent in 2000 over a 20-year period, we find that female inventors and those that collaborate with female coinventors take significantly longer to reach stardom in their innovative output. Conversely, a higher share of star coinventors, regardless of their gender, is associated with a faster transition. Notably, female inventors experience an additional acceleration in becoming stars when they patent together with male star coinventors, but not necessarily with female stars. These findings underscore the importance of gendered team dynamics and peer effects in shaping careers centered on technological and scientific breakthroughs, and they point to the importance of organizational and managerial levers in addressing gender-based disparities in innovation outcomes.

Introduction

Innovation is increasingly being recognized as a collective and interactive process. As technological complexity rises and knowledge becomes more specialized, scientific breakthroughs are relying more and more on the recombination of diverse expertise within teams (Adams, 2012; Agrawal et al., 2016; Jones, 2009). Knowledge networks and collaborations form the backbone of modern innovation systems, since they facilitate the transfer of ideas and competencies, as well as the access to resources (Guan & Liu, 2016; Singh & Fleming, 2010; Wuchty et al., 2007). The growing interdependence among innovators underscores the importance of understanding how collaborative structures influence both individual trajectories and broader patterns of knowledge production (Grigoriou & Rothaermel, 2014).

Within these collaborations, a small number of highly productive individuals, who are often referred to as “star” scientists, play a disproportionate role in driving innovation. These highly productive and influential inventors not only contribute directly through their own work but also enhance the performance of their collaborators, and they serve as central nodes in organizations and knowledge networks (Azoulay et al., 2010; Khanna, 2021, 2023; Oettl, 2012). Stars influence other inventors through both their capabilities and their status, which can act as a powerful signal of quality and legitimacy (Higgins et al., 2011; Kehoe et al., 2018) and can attract new talent and resources (Agrawal et al., 2017; Bol et al., 2018; Waldinger, 2016). Therefore, stars shape the dynamics and composition of innovation teams, and their access to opportunity.

Despite the increasing interest in the role of stars within scientific groups and the long-standing literature on collaborations and the management of inventor teams, the role diversity plays in the scientific interaction with stars has not yet been addressed thoroughly. In particular, there is a limited understanding of the role of stars in relation to one of the most well-documented sources of inequality in innovation systems: the gender gap (Groysberg & Lee, 2009; Haseltine & Chodos, 2017; Hunt et al., 2013; Lax Martinez et al., 2016; Oldroyd & Morris, 2012). Women continue to represent only a small percentage of all innovators (USPTO, 2019; J. Wang & Maynard, 2025) and an even smaller percentage of stars (Caviggioli et al., 2022). However, despite the clear evidence on the gender gap and the scarcity of top female scientists, the consequences of this gap in coinventor teams are not fully understood.

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Specifically, the existing literature says little about how women's and men's career trajectories differ when they collaborate with stars. Since most stars in patenting are men, this raises two distinct but related questions: does collaboration with stars matter equally for the transition of women and men to stardom? And, are female and male stars linked with different spillovers in their relationship with coinventors?

Understanding the role of gender in the spillovers from star inventors to their colleagues is crucial for innovation management purposes. Organizations and policymakers interested in leveraging on the capabilities of star scientists could in fact design the team composition requirements to promote a greater inclusion and support of the potentially "lost Marie Curies" within innovation systems. However, from a theoretical perspective, it remains unclear how matches between star inventors and coinventors of either gender can be structured to maximize innovative outputs. On the one hand, top female scientists may create a more flexible work environment for their collaborators that accounts for gender-specific constraints (e.g., childcare and work-life balance), and they may ease communication with and trust in other female inventors on the basis of shared experiences and identity validation (Holman et al., 2018; Kegen, 2013; Szell & Thurner, 2013). On the other hand, since female scientists often have to face constraints in their access to funding, visibility, networks, and reputational capital, due to their gender (Rua-Gomez et al., 2023), collaborating with top male inventors who have greater access to these resources may be advantageous, as it could open more doors for women in the progression of their careers. Thus, it is essential to empirically analyze these gendered interactions to determine which ones are the most fruitful.

This article contributes to this debate by examining the role of gender and top scientists in coinventor teams, focusing on the time it takes inventors to eventually become stars. In particular, we ask whether female inventors face a slower transition to stardom, whether the gender composition of coinventor teams is associated with this transition, and whether the presence and gender of star coinventors is linked with different trajectories for women and men.[1] To this end, we considered all the inventors who filed for their first patent in the United States in the year 2000 - 100,000 individuals - and followed them and their coinventors over 20 years. "Star" individuals are identified in our baseline sample as those inventors who are both extremely prolific and highly cited, namely those who are in the top percentiles of the distribution of patents and citations in their technological field.

We find that female inventors on average require a longer time to become star innovators, a result that is in line with the existing literature on the gender gap and female disadvantages in patenting. Then, we examine the role of coinventors, their gender and the presence of stars within the coinventor groups. We observe a greater delay in becoming a star for any female inventor in a team with a large share of female coinventors, compared to male inventors. Conversely, we find a higher share of star coinventors corresponds to a significant acceleration in the time to stardom for any given inventor, and this result is more pronounced for female inventors, who experience a greater acceleration than their male counterparts. When we distinguish the star coinventors by gender, we observe that this greater acceleration for female inventors is linked more to the presence of male star coinventors, rather than of female stars. These findings contribute to the literature by showing that the gender composition of inventor teams and the presence of star collaborators are jointly associated with the emergence of future stars, and that these associations differ systematically according to gender.

The rest of the article is organized as follows. Section 2 positions our research questions within the existing literature, and it develops our theoretical expectations and hypotheses regarding gender and collaborations with star inventors. Section 3 illustrates the data. Section 4 presents the empirical methodology, while the results are presented in Section 5. Finally, Section 6 discusses the interpretation of our main findings, and Section 7 concludes the paper.

Theoretical background and hypotheses

Although the evidence on the gender gap in innovative organizations in the fields of science and technology has expanded significantly in recent decades, there is still a limited understanding of how gender and star status jointly shape inventor teams. In particular, the existing studies do not clearly distinguish between collaborations without stars, where gender composition is the relevant dimension, and collaborations with stars, where status-based spillovers interact with gender. Moreover, to date, there are very few models that characterize the role of male and female stars in the career path of inventors. To address this gap, we draw on existing theories and evidence about inventors' collaborations and women's careers in scientific organizations to develop our theoretical reasoning and formulate our hypotheses.

Gender in scientific collaborations and teams of inventors

The majority of scientists in the STEM (science, technology, engineering and mathematics) fields, especially in patent-intensive sectors, are men, and gender differences persist both in productivity and career progression (EPO, 2026; Huang et al., 2020). Female inventors remain significantly underrepresented throughout the world, despite a recent trend of increasing participation in patenting activities (Heikkilä, 2019; Sugimoto et al., 2015; USPTO, 2019; Wang & Maynard, 2025). For instance, the share of female inventors at both the European Patent Office (EPO) and the US Patent and Trademark Office (USPTO) is around 13–15% (Tahmooresnejad & Turkina, 2022; USPTO, 2020).

There are numerous causes of the underrepresentation of women in patenting, which can be traced back to the multiple determinants of the gender gap, especially in scientific careers (Avolio et al., 2020; Huang et al., 2020; Tomassini, 2021). The professional choices of female scientists are shaped by a combination of individual preferences, psychological traits, educational backgrounds, skill sets, and family responsibilities (Ceci & Williams, 2011; Fox et al., 2017). Moreover, at a systemic level, women in innovation systems may experience social norms, stereotypes, and explicit or implicit biases. These challenges can then translate into everyday obstacles to productivity, different decisions and outcomes, and long-term glass ceilings[2] in the advancement of careers (Charlesworth & Banaji, 2019; Van Den Besselaar & Sandström, 2016). These hindrances may arise because of the limited number of women in laboratories, in firms engaged in R&D and innovation, and in scientific institutions, which leads to a lack of tailored services,[3] but also because of unwelcoming workplaces, discrimination, and even sexual harassment in these organizations (Jagsi et al., 2016; National Academies of Sciences, Engineering & Medicine, 2018).

Moreover, women in science may experience specific disadvantages in accessing tangible and intangible productive assets. First, in terms of financial resources, the evidence on research grants shows that women frequently have access to less funding (Bedi et al., 2012; Oliveira et al., 2019; Pohlhaus et al., 2011; Witteman et al., 2019). Second, they may experience lower visibility, as evidenced by such metrics as citations and

[1] We are well aware of the fact that gender is a more complex social construct than the male/female and men/women binary dichotomies. Unfortunately, for the purposes of our analysis, the available data only allowed us to distinguish these two categories, which we have used throughout the paper.

[2] The term "glass ceiling" refers to an invisible barrier within a hierarchical organization that prevents certain groups, such as women and minorities, from advancing to higher-level positions, despite their qualifications and achievements (Morrison et al., 1994).

[3] For example, specific facilities, such as child breastfeeding/lactation rooms, which contribute to the productivity of women who have recently had children (Tang et al., 2021), are not present in all research organizations or institutions (Powell, 2019).

first author's position (Holman et al., 2018; Maddi & Gingras, 2021; Ni et al., 2021; Roper, 2019). Third, they may have access to smaller, less prestigious international networks of co-authors and coinventors than their male counterparts, and they may occupy less favorable positions in a network (Caviggioli et al., 2026; Jadidi et al., 2018; Kwiek & Roszka, 2021; She et al., 2025). Most of the research on these mechanisms in scientific professions has focused on publications and bibliometric evidence (Halevi, 2019; Larivière et al., 2013). However, there is a growing body of studies that has confirmed the existence of these challenges in accessing financial resources, networks, and visibility for patenting specifically (Bell et al., 2019; Hunt et al., 2013; Mayer & Rathmann, 2018; Sugimoto et al., 2015; Tahmooresnejad & Turkina, 2022; Wang et al., 2020; Whittington, 2018).

Moreover, patenting is increasingly the outcome of collaborative efforts (Kerr & Kerr, 2018; Wuchty et al., 2007), and the disadvantages experienced by individual female scientists should therefore be contextualized within coinventor teams. From a theoretical standpoint, the literature indicates that the presence of female scientists can expose a whole team to the prejudices and challenges experienced by women in accessing resources, in reaching networks, and in gaining visibility in a male-dominated environment. Some evidence suggests that collaborations with female inventors also involve those gendered disadvantages that can reduce productivity and progression to the top of the field (Avin et al., 2015; Karimi et al., 2018; Lerchenmueller et al., 2019; Meng, 2016).

However, when referring specifically to women who work with other female scientists, two opposite forces have been identified in the literature. On the one hand, collaborations among women may amplify the disadvantages experienced by individual female inventors, thereby reducing the success of the whole team, due to the compounding effects of these constraints (Reardon, 2022). On the other hand, a female scientist who works in a team with a large share of women may experience the advantages of gender *homophily*, namely the preference of and ease in associating with similar individuals (Lawrence & Shah, 2020).[4] There is some suggestive evidence that gender homophily may introduce professional benefits from working with like-minded people, such as simpler communication, enhanced predictability of behavior, and greater trust and reciprocity (Hein et al., 2025; Holman et al., 2018; Kegen, 2013; Szell & Thurner, 2013). For example, since women on average display lower risk-taking attitudes and competitiveness orientation than men, they could experience less stress and interpersonal conflict when they work in female-dominated teams (Flory et al., 2015; Niederle & Vesterlund, 2007).

Thus, from these literature findings, we can argue that the time required by an inventor to become a star in their field is influenced by both the inventor's gender and the gender of the coinventors. First, we expect that the large set of female disadvantages in sciences will slow down the career progression of individual female inventors, who should, on average, take longer than their male counterparts in their trajectory to become stars. These disadvantages, which are rooted in societal norms and prejudices against women in STEM, create both subtle and overt barriers that can hinder the career progression of female inventors as such barriers accumulate over time. For many women, this results in unwelcoming workplaces, discrimination, and glass ceilings, which limit their access to crucial resources, such as funding, networks, and visibility, and ultimately make their professional journey to the top more challenging - and hence, on average, slower - than that of their male colleagues. Thus, our first hypothesis is:

Hypothesis 1. *Female inventors, on average, are slower in their transition to the status of star than male inventors.*

The disadvantages female inventors have to face are also expected to influence coinventor teams. However, when a female scientist collaborates with other women, two opposing forces come into play: on the one hand, working with female coinventors entails the compounding of female disadvantages, and she is likely to experience more limitations in her team's access to both tangible and intangible resources; on the other hand, however, she might benefit from a more supportive, welcoming, and flexible environment, as well as a reduced risk of sexual harassment, as posited by theories of homophily. The net effect of these factors, in the context of patenting, is theoretically ambiguous.

As such, we expect that, if the disadvantages for women in accessing resources outweigh the benefits of homophily, they could hinder the patenting output of female scientists working with other women, thereby slowing their progression to star status. Conversely, if the relational advantages of homophily prevail, a higher share of female coinventors should be linked with a faster career path to stardom for a woman inventor. Therefore, we formulate the following dual hypothesis:

Hypothesis 2a. *The higher the share of female coinventors, the slower the transition of female inventors to the status of star, with respect to male inventors.*

Hypothesis 2b. *The higher the share of female coinventors, the faster the transition of female inventors to the status of star, with respect to male inventors.*

Hypothesis 2a emphasizes the predominance of female disadvantages as the main underlying mechanism, while Hypothesis 2b makes the opposite prediction, that is, it asserts that homophily is the key driving force.

Star coinventors and career trajectories

The literature that has focused on outstanding scientists, namely stars, suggests that these individuals can have a substantial effect on the productivity of their coinventors (Azoulay et al., 2010; Khanna, 2021, 2023; Oettl, 2012). The presence of stars is associated with direct and indirect benefits for the whole team. Stars have increased access to resources and funding (Bol et al., 2018), as well as to more prestigious networks (Azoulay et al., 2010) and more visibility (Oldroyd & Morris, 2012), which can benefit their coinventors (Khanna, 2021). The reputation of stars signals high-quality outputs (Higgins et al., 2011; Kehoe et al., 2018; Simcoe & Waguespack, 2011) and can be a significant factor in attracting new talent (Agrawal et al., 2017; Waldinger, 2016). In some cases, the interaction with star scientists might not be constructive, since it can be difficult to challenge their intellectual leadership and develop new research ideas (Azoulay et al., 2019; Li et al., 2026). However, most of the literature on stars has identified positive spillovers for the individuals who collaborate with them (Mindruta et al., 2024). In our framework, these star-related spillovers are conceptually distinct from the mechanisms discussed for non-star collaborations, because they derive from the combination of exceptional status and gendered access to opportunities.

Regarding women more specifically, the literature that studies professional interactions among scientists has demonstrated that connecting with stars introduces distinct opportunities, and it suggests that female scientists can take advantage of interactions with high-status colleagues more than their male peers, since they provide access to missing resources, funding, lab equipment, informal networks, and increased recognition (Lerchenmueller et al., 2019; Rua-Gomez et al., 2023). Thus, we conceptualize that star spillovers operate through four main channels: (i) resource acquisition, as stars facilitate access to funding, equipment, and to other productive assets; (ii) reputation endorsement, as association with a star enhances visibility, and it also signals quality and legitimacy to evaluators and peers; (iii) knowledge

[4] Homophilic behavior has been documented extensively, not only on the basis of gender, but also for certain socially salient characteristics, such as ethnicity, religion, and social class, and, in many contexts, it can lead to social segregation (Ravetti et al., 2019; Reme et al., 2022).

and skill transfer, as collaboration with highly accomplished inventors may provide learning opportunities, mentoring, and capability development; and (iv) network expansion, as stars connect coinventors with broader and more prestigious professional circles. These channels are not mutually exclusive, and they may reinforce one another over time. Although these spillovers should benefit all inventors, they may be especially consequential for women, who often have to face more stringent constraints in their access to resources, recognition, and influential networks in male-dominated innovation systems.

Building on the points mentioned above, we theorize that the presence of star coinventors should accelerate a woman inventor's path to stardom more than it would for a male inventor. Indeed, stars, by removing the systemic obstacles experienced repeatedly by women during their patenting career, can smooth the progression of female scientists over time and increase the speed of their professional advancement toward the top of their field. Overall, although having star coinventors is likely to benefit all inventors, we expect it to have a greater impact on the pace of advancement of female scientists. Thus, we derive the following hypothesis:

Hypothesis 3. *The higher the share of star coinventors, the faster the transition of any inventor to the status of star. When collaborating with stars, female inventors experience an extra acceleration, with respect to male inventors.*

Gender and stars: mentorship and role models

Finally, we consider the role of the gender of the stars themselves in inventor teams, that is, we move from a general star-spillover argument to the question of whether such spillovers differ according to the gender match between the focal inventor and the star collaborator. Previous studies highlighted that gender gaps also exist among stars, with an even greater predominance of men than among non-star individuals (Bell et al., 2019; Caviggioli et al., 2022). Among all the inventors who filed at least one patent in the US between 2008 and 2010, 14% were female, but they represented <8% of the stars (Caviggioli et al., 2022). This underrepresentation is consistent with a 'leaky pipeline' model: women are more likely to opt out of education programs and professional advancements, especially in STEM areas, and this leads to a smaller and smaller presence during the different career phases (Legewie & DiPrete, 2014; Schmuck, 2017). Accordingly, experienced female inventors with well-developed and successful careers are rare in patenting. However, the few female inventors who have become outstanding performers in their field are indistinguishable, in terms of productivity, from men (Caviggioli et al., 2022). The difficult selection process that female scientists have to undergo to achieve the status of stars most likely leads to the most motivated, resourceful, and talented innovators being selected who, once they have broken this glass ceiling, no longer present any difference from men in the number of patents or obtained citations. This evidence does not rule out that female star inventors may still be subject to biases or discrimination, and disadvantaged access to funding, networks or visibility, compared to male stars, but the evidence shows that they are able to overcome these gender-specific challenges as far as their individual output is concerned (Caviggioli et al., 2022).

Few studies have directly assessed gender and star relationships in teams of inventors: to date, there is some evidence that women have more difficulties in entering teams with stars, irrespective of the star's gender (Rua-Gomez et al., 2023). Furthermore, it has also been found that exposure to role models who work on innovation affects the probability of women pursuing a career in innovation (Bell et al., 2019). However, there is no clear theoretical or empirical framework to show how gender plays a role in teams of inventors where stars are present. Thus, we consider the broader literature on gender pertaining to mentorship relations and role models to inform the development of our hypothesis. There is ample evidence that the gender of mentors and role models in educational or labor contexts plays a significant role in the performance of their mentees, especially female ones (Carrell et al., 2010; Kofoed & mcGovney, 2019; Lim & Meer, 2017). Two different mechanisms have been highlighted in the mentor-mentee literature: a *mirror effect*, in the case of homophilic/concordant mentoring, with mentors and mentees sharing similar traits, such as gender or ethnicity, and a *window effect*, in the case of discordant mentoring (Morales et al., 2023).

Working with mentors who share a common identity has been shown to support career progression by reducing imposter syndrome or feelings of inadequacy and disconnection, while encouraging confidence and self-identification with positions of excellence (Blake-Beard et al., 2011; Hinton et al., 2020). These positive effects are often referred to as the "mirror effect". In addition, there is evidence that women in particular benefit more than men from gender concordance in mentoring relationships (Carrell et al., 2010; Morales et al., 2018). For instance, female mentees with female mentors have reported stronger psychosocial support (Allen et al., 2005; Goldstein, 1979; Kofoed & mcGovney, 2019). Moreover, the exposure to female STEM role models has been found to enhance the aspirations of female students to pursue science careers (Bettinger & Long, 2005; Breda et al., 2020; Porter & Serra, 2020). This evidence on concordant mentorship and role models has also been confirmed in professional contexts, where top female leaders are associated with higher shares of women entering such male-dominated fields as software development, or with being promoted to managerial roles (Del Carpio & Guadalupe, 2022; Kurtulus & Tomaskovic-Devey, 2012). However, whether these mirror effects also exist and translate into faster advancement in highly competitive innovation systems remains less clear, since the evidence from educational and professional settings cannot fully account for factors that are specific to inventive careers.

Conversely, the "window" effect occurs when mentors from the most powerful majority group can open new doors for their mentees, as they utilize their privileged access to resources and social capital (Morales et al., 2021; Ohlott et al., 1994; Sosik & Godshalk, 2005). For example, evidence from higher education has shown that female MBA or doctoral students with male mentors have experienced more rapid advancement in their studies, faster promotions, and higher pay than students with female mentors (Dreher & Cox, 1996; Neumark & Gardecki, 1998). High-status male mentors may create exceptional opportunities for female students, while safeguarding them from negative experiences (Eby et al., 2013; Morales et al., 2023). Overall, the window and mirror effects are not mutually exclusive, as indicated by the empirical evidence that has found both effects in mentoring relationships (Mullen & Klimaitis, 2021).[5]

Thus, we build our theoretical expectations regarding female and male star coinventors, on the basis of the theory of mirror and window effects. We argue that, in patenting, star coinventors can play a similar role to that of mentors, and they can thus facilitate the career of non-star innovators, through different mechanisms, depending on the gender of the star.

First, in the case of female star coinventors, we expect that their presence accelerates the path to stardom of any other inventor, as female stars have overcome the gender-specific disadvantages that non-star female inventors often have to face. Furthermore, collaborations between female stars and other women can lead to additional advantages, thereby offering relational benefits, associated with homophily and

[5] Moreover, some studies have found no significant influence on mentees' performance related to the presence of gender similarities or differences (DuBois et al., 2011; Smith et al., 2000). In this case, researchers suggest that gender is less important than other connections, such as shared interests, values, and goals, and that concordant or discordant relationships do not differ significantly, in terms of increased self-efficacy or outcomes (Blake-Beard et al., 2011).

concordant mentorship (the 'mirror effect'), as well as with fostering a supportive and more inclusive workplace environment. Such partnerships can enhance the motivation and aspirations of non-star women, and they can also deliver a more tailored guidance that addresses the unique challenges women encounter in the advancement of their careers. We therefore propose the following hypothesis:

Hypothesis 4. *The higher the share of female star coinventors, the faster the transition of any inventor to the status of star. When collaborating with female stars, female inventors experience an extra acceleration, with respect to male inventors.*

Second, in the case of male star coinventors, we again expect their presence to accelerate the path to stardom of any other inventor, thanks to the benefits that are connected to their outstanding status. As in our previous hypothesis regarding collaborations with female stars, we anticipate that the positive relationship should be greater for women, as they can benefit from the support of male stars to overcome some of their gender-related disadvantages. Teaming up with male stars may expedite the path to stardom of female inventors through the 'window effect,' that is, it offers visibility and endorsement that help mitigate barriers linked with gender. Therefore, our fifth hypothesis is:

Hypothesis 5. *The higher the share of male star coinventors, the faster the transition of any inventor to the status of star. When collaborating with male stars, female inventors experience an extra acceleration, with respect to male inventors.*

Fig. 1 summarizes the different theoretical channels that contribute to our hypotheses, distinguishing between non-star collaborations, where female disadvantages and homophily are the main forces at play, and star collaborations, where general star spillovers are further combined with mirror and window effects, depending on the gender of the star collaborator.

Taken together, these perspectives provide a framework to help understand how different collaboration settings can shape the transition to stardom. Female disadvantages define the broad structural condition that shapes the innovative careers of women. This condition interacts with homophily in collaborations without stars, so that female–female ties may either reinforce existing constraints or generate relational benefits through greater trust, communication, and support. In collaborations with stars, the star status introduces positive spillovers, through access to resources, reputation, and networks, which can be further qualified according to the gender of the star: female stars may activate a mirror effect through identity concordance and role-modeling, whereas male stars may activate a window effect through privileged access to legitimacy, influential networks, and external opportunities.

Data

Data sources and sample selection

In order to examine our hypotheses on the relationship between gender and star inventors in scientific collaborations, we collected data from PatentsView, a repository that contains information on granted patents from the United States Patent and Trademark Office (USPTO). The names of the inventors in this database are classified by gender through the application of a specific algorithm, which leads to the disambiguation of 93% of the patents. The debut year is defined as the earliest application year in the portfolio of granted patents belonging to each inventor.[6]

In order to consider scientists with comparable careers, we consider all the inventors who started patenting in the year 2000: this results in a total of 104,102 individuals, that is, about 2% of the whole population in PatentsView. The debut year was defined as the earliest application year in the portfolio of granted patents belonging to each inventor. Although this definition is not an exact measure of the actual start of the career of an inventor, it can be considered a reliable proxy (Costas et al., 2015; Duffy et al., 2011; König et al., 2015). We collect data for each inventor up to the year 2019, so that 20 years of career are available for the analysis. However, the algorithm employed in PatentsView is not able to associate any gender to 5% of the selected sample. Our investigation excludes those inventors whose gender has not been identified: we thus consider 98,940 subjects, of which 14.4% are female.

For each patent in the selected inventors' portfolios, we trace and analyze all their coinventors: we classify their gender and the year they debuted in patenting, and we calculate whether they are star inventors in their field or not. The issue of missing gender also affects coinventors. In our baseline analysis, we do not discard any coinventors whose gender is unknown, in order to maintain the correct size of the inventor teams. The presence of coinventors with missing information on their gender, in combination with the fact that there are also patents with no coinventors, implies that the average share of male coinventors is not exactly complementary with the share of female coinventors for each scientist in our database. As an additional robustness check, we reproduce all the results but exclude those inventors who have one or more coinventors with no identified gender. The results of this check are presented in Appendix A.3.

Operationalization of star inventors

The identification of star inventors can rely on different criteria to distinguish outstanding from average performers. An individual's patent output can be measured quantitatively and/or qualitatively (Caviggioli et al., 2022; Caviggioli & Forthmann, 2022; Khanna, 2023). In this study, we qualify "stars" as those inventors who are among the most productive inventors, in terms of the number of granted patents, in a given sector and year, and at the same time also among those whose patents have received the highest number of citations. Forward citations are considered a proxy of the technical merit of an invention (van Zeebroeck, 2011) and, in our case, their number is derived from the PATSTAT database.[7] We rank the examined inventors, with respect to their peers, along the two dimensions of quantity and quality of their output, namely, the cumulative number of inventions and the number of citations received. These measures of patent production are not limited to the inventors in our sample who debuted in the year 2000, as we also calculate them for the whole population of inventors from PatentsView.

Since the propensity of inventors to patent is different across the various technological sectors, we rank the inventors by the number of patents (and similarly by the number of forward citations) within each of the 35 technological fields available from the World Intellectual

[6] USPTO (2019) provides further details on the algorithm we applied to identify the gender of the inventors. The algorithm combines different sources of name-gender linked data, such as the Global Name Recognition system, an IBM name-search technology, and the WIPO worldwide gender-name dictionary. Each inventor is examined and assigned a score according to whether the name is masculine or feminine, considering the country of origin (or of residence) and the linguistic group.

[7] The data from PatentsView are matched with the records in PATSTAT via the crosslink table that is available at: https://rawpatentdata.blogspot.com/2019/07/patstat-patentsview-concordance-update.html (last accessed in August 2023). The count of forward citations retrieved from PATSTAT is for the DOCDB family, a collection of patent documents that covers a single invention and shares the same priorities.

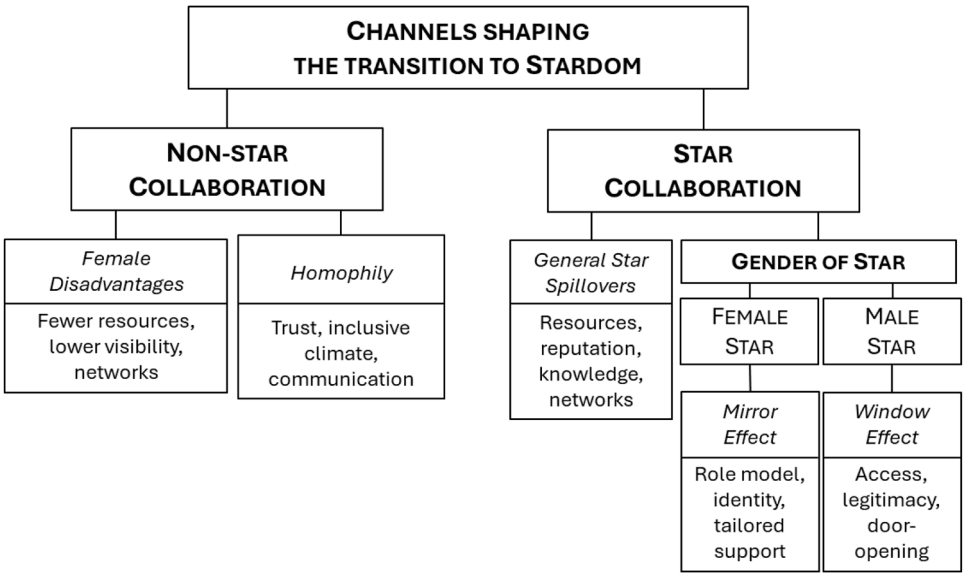


Fig. 1. Integrated theoretical framework of gender and inventive spillovers from non-star and star collaborations.

Property Organization (WIPO) concordance table.[8] This table associates the International Patent Classification (IPC) codes with the corresponding technological fields. We identify a prolific (or highly cited) inventor as one who is ranked above the 95th percentile of the distribution in their field, from the year 1868 up to the considered year, in terms of the number of patents (or citations received). We then operationalize the star variable as a dummy that is equal to one if an inventor is both prolific and highly cited in at least one technological field in a given year.

Overall, 10,820 individuals have been identified as stars (10.9% of the examined inventors). Their share in the inventors' population is higher than the 5% threshold of the definitions, due to an increasing trend in patenting and because we base our ranking on the whole population of inventors (older inventors, who might no longer be active, are kept in the ranking). A total of 10.3% of the stars are female inventors. The shares of inventors that never reach the status of star in the examined 20-year period are equal to 84% and 89% for male and female inventors, respectively. Fig. 2 shows the Kaplan-Meier curve that estimates the share of male and female inventors who debuted in the year 2000 and went on to become stars in the considered time frame. Fig. 2 includes confidence intervals that suggest the presence of statistically significant differences between groups.

It can be seen, by focusing on the speed of the career of these stars, that 11% reach this status in their debut year. Overall, 57% of the men and 60.6% of the women become stars by year five (Fig. 3). Thus, the male inventors are slightly slower and become stars with an average delay of 0.43 years, compared to the female inventors. Although the difference is quantitatively small (less than half a year on average), it is statistically significant (two-sided *t*-test, $p = 0.001$), thus indicating that the observed gender gap in the time to stardom is unlikely to be driven by a random variation. These preliminary statistics suggest that women initially have to face additional hurdles to become stars, but those who can overcome these difficulties reach the status of star faster than men.

Fig. 3 also supports our choice of a sample that covers a time window of twenty years after the first filing of a patent by any inventor. As a result of choosing this time window, if an inventor had become a star after the analyzed period, they would not be identified. However, the data distribution suggests that the considered inventors are much more likely to reach stardom in the first part of their careers: no significant number of stars can be identified in the right tail of Fig. 3. Hence, we believe that the number of inventors who become stars after the last year we consider is marginal. Thus, our truncation after twenty years should not bias the identification of stars in the sample to any great extent.

As suggested in the literature on gender studies and technological fields (Mayer & Rathmann, 2018; Puuska, 2010; Wullum Nielsen & Börjeson, 2019), differences exist across different areas of innovation. Our data confirm the presence of heterogeneity across technological fields in multiple dimensions (Table A1 in the Appendix). The fields where the presence of females is the highest are "Pharmaceuticals", "Biotechnology" and "Organic fine chemistry"; the lowest shares are observed in "Mechanical elements", "Engines, pumps, turbines" and "Civil engineering". There is a high correlation (0.94) between the share of female inventors and the share of female stars. However, in terms of time to become stars, female scientists are particularly fast in "Thermal processes and apparatus" and "Machine tools" (both male-dominated), as well as in "Other consumer goods", while male scientists are faster in "Environmental technology", "Mechanical elements" and "Handling". The correlation analysis at the field level between the presence of female star inventors and the average delay in becoming a star shows a value of 0.31. Thus, it is fundamental to control for the field of activity of any inventor, but we are not able to predict how fast the career trajectory of male and female scientists would be in a given area just from the gender shares of that sector.

Characteristics of the coinventors

A key contribution of our study is the fact that we move beyond the individual characteristics (gender and star status) of a single inventor and look at the relationship between these characteristics with other members of their patenting team. We look at the past patenting activities of each inventor in each year and calculate the cumulative number of coinventors, the share of coinventors by gender,[9] and whether some of them are stars of either gender. We compute the share of male and female coinventors and that of stars as their fractions over the total number of coinventors up to the examined year. Table 1 reports some of the descriptive statistics of the main variables of interest. The definitions of the variables (Table A2), the correlation matrix (Table A3), and

[8] Further information and data are available at https://www.wipo.int/en/web/ip-statistics, (last accessed in June 2024).

[9] If a coinventor "Jane Smith" appears in two patents, she is counted twice.

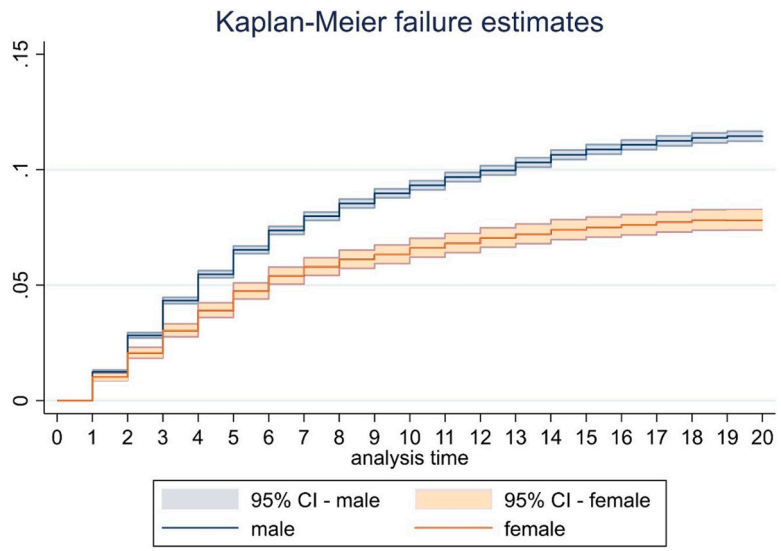


Fig. 2. Kaplan-Meier estimates: share of inventors of each gender expected to reach the status of star in the examined 20 years (year 1 on the x-axis is the debut year, 2000). 95% Confidence Intervals (CI) are reported.

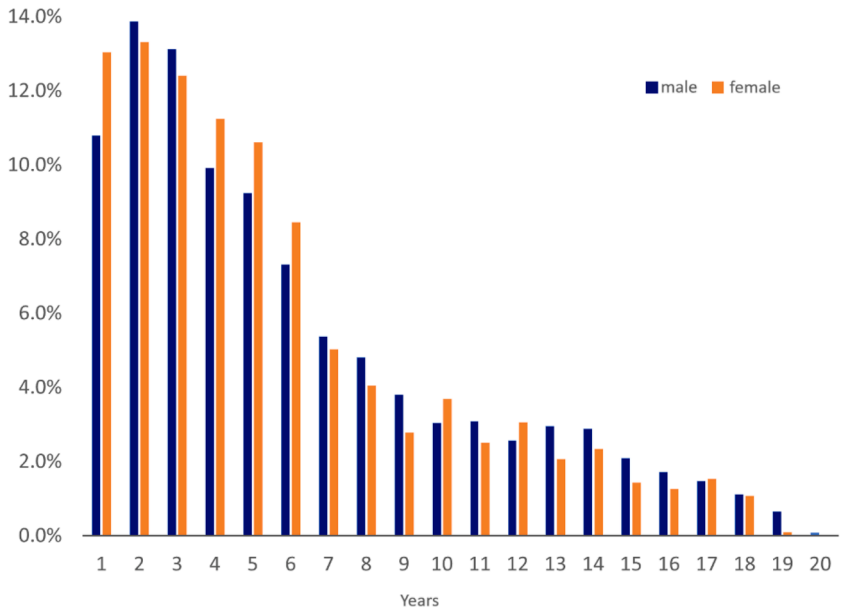


Fig. 3. Share of star inventors who reach the status of star for the first time (left y-axis) per number of years from their debut in patenting (x-axis) broken down by gender. The graph only refers to the scientists in our sample who eventually become stars.

additional summary statistics are reported in the Appendix for only the sub-samples of male and female inventors (Table A4).

Empirical model

We employ a survival analysis to investigate the correlations between the time to become a star for the first time and the gender of an inventor, as well as the characteristics of their coinventors. This approach includes observations for those individuals who become stars in their debut year. Our single "failure" model (i.e., the first time an inventor becomes a star)[10] drops 150,781 observations of inventors after their first event of becoming a star. More precisely, 1828,019 observations represent the total analysis of the time at "risk" of becoming a star for 98,940 subjects with 10,820 transitions to stardom. In our context, a longer survival is equivalent to a slower career progression and productivity growth toward the status of star.

[10] The terminology of survival analysis typically defines a change of status as a "failure", since these statistical techniques are largely used in medical literature to capture the months/years of survival after treatment for a given patient population. In our context, inventors "survive" as normal scientists after their debut in patenting until their innovative output surpasses the threshold of becoming a star: thus, a single failure is actually a successful transition to stardom.

Table 1
Panel-level summary statistics that consider observations up to the first transition to stardom (N = 1828,019).

Variable	Mean	S.D.	Min	25th Perc.	Median	75th Perc.	Max
Female dummy	0.147	0.354	0	0	0	0	1
N. of coinventors	6.617	10.677	0	1	3	8	655
Share of female coinventors	0.094	0.193	0	0	0	0.111	1
Share of male coinventors	0.74	0.365	0	0.6	1	1	1
Share of prolific star coinventors	0.195	0.284	0	0	0	0.333	1
Share of female star coinventors	0.013	0.068	0	0	0	0	1
Share of male star coinventors	0.178	0.27	0	0	0	0.333	1

We apply a parametric survival model of accelerated time to transition to stardom with a loglogistic distribution, selected according to the results of the AIC – BIC tests. This distribution is indicated for data that exhibit nonmonotonic hazard rates, specifically those with initially increasing and then decreasing rates, as seems to be the case for the probability of becoming a star, which is highest in the first few years from the debut of the patent. Thus, the model we use is.

$$\ln(T_j) = X_j\beta + z_j \quad (1)$$

where T is the survival time[11] for scientist j, X is the matrix of explanatory variables that includes the characteristics of the coinventors, and their interaction with a female dummy that captures the gender of inventor j. Thus, β *is* the vector of the coefficients to be estimated, and z is the error term with logistic density that allows for intragroup correlation (clustering on each inventor).[12]

The baseline model defines the dependent variable as the individual time necessary to reach the status of star. An inventor is described through the *Female dummy* (equal to one for women) and a set of control dummies that identify the main technological field(s)[13] of activity up to the examined year. The remaining independent variables describe the group of coinventors of each inventor up to the examined year, that is, the share of female (male) coinventors and the share of star coinventors of either gender. The models always control for the number of coinventors. Considering our data structure and variable operationalization (i.e., the presence of inventors with only solo patents; the fact that no collaborators also means zero shares of male/female coinventors; the presence of coinventors of unknown gender), we examine the share of male and female coinventors in separate models, also because of the high correlation between these two variables (see Table A3 in the Appendix), while we test the share of star coinventors, either male or female, in one specification. Since our empirical strategy identifies statistical associations rather than causal effects, the estimated relationships should be interpreted as correlations between collaboration characteristics and the timing of the transition to stardom.

Results

The main results of the survival models are shown in Table 2 and, to enhance interpretability, we complement the coefficient estimates with quantitative interpretations and marginal effects based on predicted values (see Table 3). The findings show that being a female inventor is generally correlated with a longer time to become a star inventor: this result is robust across all the models and confirms our first hypothesis. For example, the result of model 5 in Table 2 indicates that the average time to become a star inventor is 3.35 times longer for a woman than for a man, considering all the variables in that specification.

The first part of the analysis of coinventors reveals that a higher share of female coinventors is correlated with an increase in the time to become a star for any inventor, and even more so for female inventors. Thus, despite the potential theoretical benefits of homophily, the female disadvantages seem to unambiguously dominate. Therefore, Hypothesis 2a is confirmed. In other words, any inventor on average experiences various "female disadvantages" when collaborating with several female coinventors (model 2 in Table 2), and these disadvantages are particularly pronounced when the examined inventor is also a woman.

As a further check, we also consider the share of male coinventors, which is associated with a shorter time to become a star (model 3 in Table 2). It can be observed that, once again, this relationship is even greater for women, so that collaboration with a large share of men is linked with a greater acceleration in the trajectory to stardom for women than for men. In short, considering the overall pool of coinventors, these results point to a significant overarching disadvantage of having female coinventors, in particular for female scientists.

However, a more nuanced picture emerges when looking at the star coinventors. Having stars among the coinventors is always related to a significantly shorter time to become a star (model 4), as predicted in our third hypothesis, and this is also confirmed when the star coinventors are separated by gender (model 5). Indeed, collaborating with stars is always linked with a faster transition to stardom, in the case of both male and female star individuals. In other words, when an individual reaches the status of star, gender is no longer a hindering factor: having female coinventors who have reached the status of stars appears to be a bonus, notwithstanding the limited total number of female star inventors. The disadvantage we observe for female coinventors in model 2 is in fact reversed for female star coinventors in model 5. This result could derive from the support that stars (of any gender) can offer their coinventors, in terms of access to resources, networks, and visibility, and/or to the selection mechanism that makes the most motivated scientists more prone to pushing for collaborations with stars.

It is interesting to note that female inventors who pair up with a large share of female star coinventors do not obtain any significant extra premium from such an interaction (even though the coefficient of the interaction term indicates an acceleration, it is not statistically significant). Instead, when they have a high share of male star coinventors, they experience an extra acceleration in their transition to star. Therefore, the first part of both Hypotheses 4 and 5 is confirmed, namely that a higher share of both female and male star coinventors is correlated with a faster transition of any inventor to the status of star. However, for female inventors, although the "window effect" of Hypothesis 5 is confirmed, the "mirror effect" of Hypothesis 4 is not. This result is further examined in the robustness checks in Section 5.1.

In order to assess the magnitude and economic significance of our results on star coinventors, we compute marginal effects, in terms of predicted time to stardom, on the basis of model 4 in Table 2. Since our key explanatory variable is expressed as a share, a one-unit increase is not directly interpretable in practice. Therefore, we consider a more meaningful variation that corresponds to the addition of one star coinventor to an average-sized team. In our sample, this translates into an increase of approximately 0.15 in the share of star coinventors (i.e., one

[11] T indicates the number of years that an innovator takes to eventually become a star, with cumulative distribution function F of duration time T as follows: $F(t) = P(T \leq t)$. This specification indicates the probability that duration T is less than or equal to a given year, t. In other words, this function represents the probability of a scientist exiting the population of non-star scientists and becoming a top innovator before t years after their debut in 2000. The survival function is defined as $S(t)=1- F(t) = P(T > t)$.

[12] Practically, we estimate the model with a loglogistic accelerated failure time (AFT) regression using the *streg* command in Stata 17.

[13] Note that the technology field variables are not mutually exclusive, as an inventor can be active in more than one sector.

Table 2
Maximum likelihood estimation for the parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)	(3)	(4)	(5)
Female dummy	0.816***	0.550***	1.411***	1.231***	1.210***
	(0.100)	(0.120)	(0.387)	(0.162)	(0.159)
Share of female coinventors		0.743***			
		(0.222)			
Female dummy x Share of female coinventors		1.715**			
		(0.674)			
Share of male coinventors			−0.642***		
			(0.122)		
Female dummy x Share of male coinventors			−0.801*		
			(0.453)		
Share of star coinventors				−4.062***	
				(0.072)	
Female dummy x Share of star coinventors				−0.940***	
				(0.239)	
Share of female star coinventors					−4.712***
					(0.218)
Female dummy x Share of female star coinventors					−0.500
					(0.613)
Share of male star coinventors					−3.975***
					(0.075)
Female dummy x Share of male star coinventors					−0.961***
					(0.246)
N. of coinventors	−0.322***	−0.324***	−0.318***	−0.240***	−0.242***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Technology field dummies	Yes	Yes	Yes	Yes	Yes
Constant	11.224***	11.177***	11.697***	11.297***	11.290***
	(0.121)	(0.121)	(0.150)	(0.113)	(0.114)
lngamma	0.553***	0.553***	0.552***	0.417***	0.422***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Obs.	1828,019	1828,019	1828,019	1828,019	1828,019
Log lik.	−33,373.102	−33,351.511	−33,347.279	−31,641.332	−31,711.953
chi-squared	2807.506	2793.422	2916.601	4922.361	4845.128

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

Table 3
Predicted mean time to stardom (in years) after the debut when considering different levels of the share of star coinventors (0, 0.15, and 0.30).

Gender of the inventor	Share of star coinventors 0	0.15	0.3	% change 0 to 0.15	% change 0 to 0.3
Male	213.1	178.3	148.6	−16%	−30%
Female	305.0	246.7	198.7	−19%	−35%

Note: the values in years are statistical constructs that are calculated as predictive margins on the examined sample, and they have such high values because they also consider those inventors that never become stars in the considered timeframe, that is, the majority of inventors. All the other variables of the model are at their mean value.

star added to a team of six collaborators; see Table 2). Table 3 reports the predicted time to stardom for different values of this share (0, 0.15, and 0.30). When no star coinventor is present, and all the other variables are kept at their mean value, female inventors are predicted to take 1.43 times longer than male inventors to reach stardom. Increasing the share of star coinventors by 0.15, which corresponds to adding one star to the team, reduces the predicted time to stardom by approximately 16% for male inventors and by 19% for female inventors. A further increase to 0.30 (i.e., two star coinventors) leads to an even stronger reduction, thereby effectively closing the gender gap: the predicted time to stardom for a female inventor with two star collaborators becomes comparable with that of a male inventor with no star coinventors. Overall, these marginal effects indicate that the presence of outstanding collaborators substantially accelerates the transition to stardom and can largely offset the disadvantages associated with gender, particularly for female inventors.

Robustness checks

In this section, we examine the robustness of the previous results in light of some relevant time, sectoral, and data considerations that can help shed light on the underlying mechanisms.

First, we relax our baseline definition of star inventors, which requires individuals to be simultaneously in the top 5% of both productivity and citations. Specifically, we consider two alternative definitions: one based solely on prolific inventors (top 5% by number of patents) and another based solely on highly cited inventors (top 5% by forward citations). The results of these alternative specifications are reported in Table B1 in the Appendix. Overall, our main findings remain qualitatively unchanged, thereby confirming that they are not driven by the stringency of the baseline definition of star inventors. The only difference is that the interaction between female inventors and female star coinventors (namely, the "mirror effect") now becomes statistically significant for these broader definitions. This pattern may have different interpretations. On the one hand, the baseline definition identifies only a very small number of female stars, thus making any additional same-gender effect difficult to estimate precisely. On the other hand, broader definitions may capture a wider set of relevant high-performing female collaborators, for whom concordant mentoring and role-model effects may be more likely to emerge. Overall, these results suggest that mirror effects cannot categorically be considered absent, but they do not appear as fully robust features across the specifications either.

Second, we consider the time dimension, since the data indicate that the chances of becoming a star decrease as time elapses from the debut year (as previously shown in Fig. 2). Hence, we perform additional tests on subsamples that consider the first 5 and 10 years of career for an inventor from their patenting debut: Table 4 reports the results for stars, which can be compared with the results of the previous baseline model that considers 20 years of career (Table 2, models 4 and 5). We can

Table 4
Subsamples of different career lengths. Maximum likelihood estimation of the parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)	(3)	(4)
Subsample of considered years	From 2000 up to 2004 (first 5 years of career)		From 2000 up to 2009 (first 10 years of career)	
Female dummy	0.434***	0.420***	0.746***	0.731***
	(0.079)	(0.077)	(0.110)	(0.108)
Share of star coinventors	−1.735***		−2.679***	
	(0.037)		(0.051)	
Female dummy x Share of star coinventors	−0.345***		−0.569***	
	(0.114)		(0.164)	
Share of female star coinventors		−2.016***		−3.129***
		(0.099)		(0.150)
Female dummy x Share of female star coinventors		−0.205		−0.270
		(0.255)		(0.405)
Share of male star coinventors		−1.690***		−2.615***
		(0.038)		(0.053)
Female dummy x Share of male star coinventors		−0.337***		−0.581***
		(0.118)		(0.170)
N. of coinventors	−0.095***	−0.096***	−0.160***	−0.162***
	(0.003)	(0.003)	(0.004)	(0.004)
Technology field dummies	Yes	Yes	Yes	Yes
Constant	5.363***	5.353***	8.005***	7.996***
	(0.058)	(0.058)	(0.079)	(0.079)
lngamma	−0.430***	−0.426***	0.021**	0.026***
	(0.011)	(0.012)	(0.010)	(0.010)
Obs.	481,531	481,531	938,830	938,830
Log lik.	−16,712.845	−16,778.614	−24,504.844	−24,573.455
chi-squared	3461.314	3427.794	4451.688	4387.898

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

observe that all our previous results are robust, and the magnitude of the coefficients of the variables of interest increases when longer time intervals are considered. The share of star coinventors of any gender, male or female, as well as the interaction of female inventors with male stars have a larger negative magnitude when the time frame is extended. These findings suggest that the presence of stars may become more relevant in the later part of the career of an inventor, when becoming a star is in general harder and less likely.

We consider these results along the career timeline as suggestive evidence that is compatible with long-term learning effects: for inventors who are highly talented on their own, becoming a star is less closely correlated with having star coinventors, while for all the other inventors, the advantages of working with stars may manifest more after a long-term accumulation of human capital. Table B2 in the Appendix provides the results of further robustness tests on career steps: the results are consistent with the baseline model, when the initial and the growth career stages (first five years, and from years six to ten) are considered. The results suggest that star collaboration remains beneficial in the more mature career stage (from years eleven to twenty), but its gender-differentiated effect weakens.

We also report the results of the sub-sample of only those inventors who eventually become stars in the time frame of our analysis (20 years). This further analysis on only stars is limited to a different pool of inventors, since the majority of scientists (and especially female scientists) never become stars. The results of this sub-sample show that the general disadvantage of being a woman as the main inventor is no longer present (Table B3 in the Appendix). Being a woman is no longer associated with a slower time to star status, and women even appear to be faster than men in one specification (model 2 in Table B3). Collaborations with stars are always linked with faster career trajectories, but without a gender differential: all female interactions are insignificant. These results suggest that the findings from the full sample might be driven by those individuals who never become stars, thereby enhancing the gender gap for female inventors.

Next, we examine the results of the sub-samples of specific technology fields with a relatively high or low prevalence of women innovators. Tables B4 and B5 in the Appendix show that, although our core results remain valid in these specific sectors, the female interactions with stars are no longer significant when the overall share of women in a sector is high. More precisely, the collaboration with star coinventors is still linked with a significant acceleration in the time needed for an inventor to become a star in both high and low female prevalence sectors. However, in areas where women represent more than one fifth of the inventors (Biology, Chemistry, Pharmaceuticals, and related fields), the coefficient of female interactions with stars becomes statistically insignificant. Conversely, in sectors where women are heavily underrepresented, that is, where they account for fewer than one scientist out of ten, such as in Mechanical, Civil and Transport Engineering, the interaction term is significant. This result suggests that the presence of stars plays a more significant role for female inventors in the fields where women are substantially underrepresented.

In order to further explore field-level heterogeneity and its potential moderating role on collaboration with star inventors, we introduce a dummy variable that captures technological complexity by identifying high-tech fields. The results reported in the Appendix (Table B6) are fully coherent with those of the baseline model, and they confirm the robustness of our main findings. Overall, the introduction of field-level technological complexity does not alter the core empirical patterns. As far as the role of technological complexity is concerned, inventors in high-tech fields take longer, on average, to become star inventors, but collaboration with star inventors is particularly effective in these technologically complex environments, as it further reduces the time to stardom. This stronger beneficial effect holds for both female and male star collaborators. At the same time, the interaction between the female dummy and the high-tech indicator is not statistically significant, and neither are the triple interaction terms, thus indicating that although technological complexity reinforces the overall value of star collaboration, it does not significantly alter the gender-specific patterns identified in the baseline model.

The next issue we examine is our definition of stars and its overlap with seniority. It is possible that experience in the patenting process cumulates over time and, only after several years of "playing the game" of intellectual property rights protection, does a scientist become truly helpful for their colleagues. The role of seniority is particularly important, given that female participation in patenting has only been growing recently, and the number of senior female scientists is therefore still relatively limited. In our setting, coinventors are considered "senior" when they have more than ten years of experience, measured from their patenting debut. The overlap between seniority and star status is only partial: many inventors become stars early on in their career (as shown in Fig. 3). The correlation of the two variables is around 0.4, both globally and within the same gender. Table 5 presents the results of the survival models that control for collaborations with senior coinventors of either gender, instead of stars.

Despite the limited overlap between seniority and star status, the statistical analysis in Table 5 shows that experienced coinventors are also associated with a faster transition to stardom for any given inventor.

Table 5
Focus on seniority. Maximum likelihood estimation of the parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)
Female dummy	0.860***	0.859***
	(0.133)	(0.133)
Share of coinventors with >10yrs experience	−0.419***	
	(0.117)	
Female dummy x Share of coinventors >10y experience	−0.246	
	(0.409)	
Share of female coinventors with >10yrs experience		−0.268
		(0.648)
Female dummy x Share of female coinventors >10y experience		−0.045
		(1.686)
Share of male coinventors with >10yrs experience		−0.425***
		(0.118)
Female dummy x Share of male coinventors >10y experience		−0.261
		(0.417)
N. of coinventors	−0.322***	−0.322***
	(0.007)	(0.007)
Technology field dummies	Yes	Yes
Constant	11.309***	11.309***
	(0.123)	(0.123)
lngamma	0.555***	0.555***
	(0.009)	(0.009)
Obs.	1828,019	1828,019
Log lik.	−33,364.639	−33,364.566
chi-squared	2826.674	2827.593

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

However, some differences emerge from the results on stars. First, the result seems to be driven only by older male coinventors (model 2). Second, there is no significant "premium" from these collaborations for female inventors. This could indicate that experienced coinventors differ from stars, in that they cannot be as effective at sharing resources, reputation, visibility, and connections to help female inventors overcome the disadvantage of being female.

Finally, following the considerations regarding our data structure and the definition of gender in our sample, we perform different robustness checks in which we exclude scientists with coinventors with missing data on gender and those with portfolios that include single-inventor patents. The results of these checks, which confirm our previous findings on stars, are discussed in the final section of the Appendix and reported in Tables C2 and C3.

Discussion

Our findings point to a clear overall pattern in the relationship between gender, collaboration, and the transition to stardom. Female inventors take longer than men to reach star status, and this disadvantage becomes more pronounced when women collaborate in teams with a higher share of female coinventors. These results suggest that the barriers women have to face in innovation systems are not confined to individual careers and instead extend to the collaborative settings in which inventive careers develop.

Against this background, the role of star coinventors becomes particularly relevant. Collaboration with stars is associated with a faster transition to stardom for all inventors, and this acceleration is more marked for women. This pattern is consistent with the idea that star collaborators may help alleviate some of the structural constraints female inventors have to face in innovation systems, particularly with respect to resource acquisition, reputation, knowledge transfer, and network expansion. At the same time, our data do not allow us to isolate the specific channels at play, so these mechanisms should be interpreted with caution.

Furthermore, the observation that both male and female stars are associated with faster career trajectories for their coinventors echoes other evidence that shows that the productivity levels at the top of the scientific pyramid are almost indistinguishable by gender (Caviggioli et al., 2022). In this respect, we further contribute to this literature by showing that female star coinventors are in fact associated with transition patterns for their coinventors that are comparable with those linked with male stars.

One important nuance that emerges from our baseline results concerns the lack of a robust additional advantage for female inventors who collaborate with female star coinventors. Although, overall, female stars are positively associated with the transition to stardom, women do not appear to benefit systematically more from working with female stars than from working with stars in general. Thus, our baseline findings do not support a significant mirror effect. At the same time, this should not be interpreted as evidence that such an effect is completely absent, since, in our robustness checks, it emerges under broader definitions of star inventors. Overall, these results suggest that no mirror effect is uniformly present, and such an effect may depend on how "exceptional status" is defined, rather than constituting a stable feature of collaborations with female stars.

Taken together, our findings suggest that, in this context, homophily is not the main force that shapes the transition to stardom. Indeed, it does not appear to offset the disadvantage of women working in teams with higher female compositions, nor does it generate an additional advantage when female inventors collaborate with female stars. This result differs from the limited prior evidence that documented benefits from homophilic collaborations among women in science (Whittington, 2018). However, that evidence originated from a narrower setting (only Biotech) and focused on patent counts rather than the transition to star status, which may help explain the divergence.

Conclusion

In this study, we examine the role of gender and stars in teams of patenting inventors. We find that female inventors and women with higher shares of female coinventors take longer to become stars, while high shares of star coinventors, regardless of gender, are associated with a faster transition to stardom for any inventor. At the same time, the positive association between star collaboration and the transition to stardom is stronger for women, thus suggesting that star collaborators may be particularly important in helping female inventors advance within innovation systems. Finally, collaborations with male stars are robustly associated with an additional acceleration for female inventors ("window effect"), whereas no stable mirror effect is observed for female stars that collaborate with female scientists. This result is robust to splitting the sample over the different career phases of a scientist and becomes even stronger when a longer time frame is considered. Interestingly, when we adopt less stringent definitions of star inventors, the interaction between female inventors and female star coinventors becomes significant, thus suggesting that a "mirror effect" may exist when a broader set of high-performing female role models is considered.

These findings suggest several practical implications for organizations and innovation policymakers. First, efforts to promote gender equity in innovation should not focus only on increasing the number of women in inventive teams, but also on improving the quality of the opportunities available to them, including access to high-value collaborations. Second, firms, R&D units, and public research organizations could introduce formal sponsorship or mentoring schemes that connect early-career female inventors with established high-performing collaborators, without assuming that effective support should come exclusively from female stars. Third, since teams with a higher share of female inventors may experience broader structural disadvantages, rather than homophily-based benefits, policies should also address the upstream conditions that shape inventive careers, such as access to funding,

technical resources, training, and promotion opportunities, in order to foster more equitable conditions for advancement.

Overall, our results indicate that established star scientists can play a pivotal role in accelerating the emergence of new stars, particularly among underrepresented groups, that is, the "lost Marie Curies." Collaboration with star scientists is particularly valuable for female inventors and, as some of these women attain star status themselves, the benefits of their patenting collaborations are likely to extend to a broader group of colleagues, both men and women. In this sense, organizations can move beyond generic diversity commitments and adopt more targeted collaboration policies aimed at widening access to influential inventive networks and high-status partners, in order to create systemic support to help achieve greater gender equality.

Our study is not without limitations, which future research could address. First, patent data provide a valuable longitudinal view of inventive careers, but they also only capture a selective subset of innovative activities, since not all innovations are patented and some are protected through other appropriability strategies. As a result, our analysis is not able to observe inventive contributions that do not result in patent applications, nor can it assess whether gender differences also shape the likelihood of an innovation being patented in the first place. In addition, our gender measure from patents is necessarily limited to a binary classification based on name inference, which does not capture non-binary identities and may introduce measurement error. Moreover, patent records do not capture the internal organization of teams, informal mentoring, and sponsorship processes, the division of tasks, and credit within collaborations, or broader organizational conditions that may shape the inventive trajectories of women.

Second, although our models control for a rich set of inventor, team, and field characteristics, other unobserved factors (such as individual ability, organizational resources, workplace climate, or differences in how collaborators are matched) may also affect both the collaboration patterns and the transition to stardom. Third, our results do not establish an unambiguous direction of causality and should therefore be interpreted as associations rather than causal effects. In particular, in addition to concerns about omitted-variables, selection into collaboration may affect the estimated relationships: high-potential inventors may be more likely to gain access to stars, while stars and organizations may decide to match with inventors who already appear to be particularly promising. Therefore, we are not able to fully disentangle the effect of collaboration with stars from the characteristics that make such collaborations more likely, nor can we isolate the underlying channels through which star collaborations can shape the transition to stardom.

Future research could build on these limitations in two complementary ways. First, it could expand the empirical basis of the analysis by combining patent data with other sources of evidence that make collaboration processes more directly observable. Surveys, interviews, focus groups, and linked organizational data could capture dimensions that patent records do not observe, while also making it possible to move beyond a binary gender classification. Second, future studies could strengthen causal identification through alternative empirical strategies. Quasi-experimental settings based on exogenous shocks to collaboration networks, such as the sudden death or unexpected exit of a star scientist (Awate et al., 2025; Azoulay et al., 2010, 2019; Khanna, 2021, 2023), could help separate the effects of star collaboration from selection into such collaborations. Randomized or structured interventions, designed to create mentoring or sponsorship relationships with high-performing inventors, would also be valuable, as they could provide clearer evidence on whether the observed patterns reflect learning, support, access to opportunities, or assortative matching.

These alternative data sources and methods could be particularly useful to understand the mechanisms through which star collaborations shape the transition to stardom. In particular, they could help clarify the role of general star spillovers (such as access to resources, reputation, knowledge, and networks) as well as the gender-specific channels highlighted in our framework, e.g., the gender-specific mentoring and role-model effects behind "window" and "mirror" effects.

In conclusion, this analysis shows that the path to inventive stardom is deeply embedded in collaboration patterns, and that understanding these gendered dynamics remains an important task for both innovation research and innovation policy in order to better explain and widen access to high-impact inventive careers.

Declaration of generative AI use

During the preparation of this work the authors used OpenAI's ChatGPT 5.5 in order to support the language editing, which was then checked by a professional English proofreader. After using this tool, the authors reviewed and edited the content as needed, and they take full responsibility for the content of the published article.

CRediT authorship contribution statement

Federico Caviggioli: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Alessandra Colombelli:** Writing – review & editing, Validation, Methodology, Investigation, Funding acquisition, Conceptualization. **Chiara Ravetti:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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Appendix

A. Variables and additional statistics

Table A1
Statistics across technological field (WIPO concordance table): share of females out of the total number of inventors; share of females out of the number of star inventors; average time necessary to become a star (in years); average delay in becoming a male star inventor relative to becoming a female star (years of difference).

WIPO code	Description	Female inv. (on tot. inv.)	Female stars (on stars)	Avg. time to become a star	Delay of a male star vs a female star
	Full sample	14.4%	10.3%	5.03	0.43
01	Electrical machinery, apparatus, energy	10.4%	9.1%	6.54	0.02
02	Audio-visual technology	11.9%	10.8%	6.08	0.24
03	Telecommunications	11.6%	10.4%	5.21	0.86
04	Digital communication	11.3%	10.4%	4.74	0.37
05	Basic communication processes	9.4%	9.5%	6.24	0.85
06	Computer technology	12.2%	10.0%	5.11	0.76
07	IT methods for management	13.5%	10.9%	3.72	1.17
08	Semiconductors	13.9%	10.1%	6.08	0.39
09	Optics	13.1%	10.8%	6.52	0.66
10	Measurement	10.5%	8.3%	6.46	0.31
11	Analysis of biological materials	21.4%	15.8%	7.34	0.81
12	Control	10.3%	8.9%	5.65	1.32
13	Medical technology	14.7%	9.6%	6.64	0.62
14	Organic fine chemistry	23.2%	16.1%	7.22	0.77
15	Biotechnology	25.8%	16.0%	7.48	1.18
16	Pharmaceuticals	25.9%	16.0%	7.00	0.79
17	Macromolecular chemistry, polymers	19.3%	14.6%	7.26	0.48
18	Food chemistry	22.2%	14.1%	7.32	0.48
19	Basic materials chemistry	19.2%	13.9%	7.41	0.01
20	Materials, metallurgy	13.0%	11.0%	6.82	0.49
21	Surface technology, coating	13.6%	11.1%	7.10	−0.13
22	Micro-structural and nano-technology	14.5%	12.9%	6.39	1.09
23	Chemical engineering	12.2%	9.5%	6.73	0.41
24	Environmental technology	10.2%	8.4%	6.46	−1.45
25	Handling	9.3%	7.0%	6.80	−0.44
26	Machine tools	8.1%	6.8%	6.87	1.87
27	Engines, pumps, turbines	7.7%	6.2%	6.10	0.55
28	Textile and paper machines	14.8%	11.9%	6.28	1.02
29	Other special machines	11.6%	9.7%	7.18	1.15
30	Thermal processes and apparatus	8.9%	7.8%	6.73	2.25
31	Mechanical elements	6.4%	5.8%	6.70	−1.11
32	Transport	8.4%	6.1%	6.15	0.85
33	Furniture, games	14.4%	8.1%	6.21	0.16
34	Other consumer goods	16.9%	10.9%	6.62	1.67
35	Civil engineering	7.9%	6.7%	6.72	0.38

Table A2
Definitions of the main variables calculated for each of the inventors under study.

Variable	Definition
Star dummy	Dummy variable equal to one if an inventor is both prolific and highly cited in at least one technological field in a given year, t. A prolific (or highly cited) inventor is ranked above the 95th percentile of the distribution in their field, from the year 1868 up to the considered year, in terms of number of patents (or citations received). Time-variant variable. Authors' elaboration from PatStat.
Female dummy	Dummy equal to one for female individuals (from PatentsView). Time-invariant variable.
N. of coinventors	Cumulative number of coinventors up to the observed year (Authors' elaboration from PatentsView). Time-variant variable.
Share of female coinventors	Share of female individuals in the cumulative number of coinventors up to year *t*, computed as the ratio between the total number of female coinventors and the total number of coinventors observed in all the patents of the focal inventor from the debut year up to year *t* (Authors' elaboration from PatentsView). Time-variant variable.
Share of male coinventors	Share of male individuals in the cumulative number of coinventors up to year *t*, computed as the ratio between the total number of male coinventors and the total number of coinventors observed in all the patents of the focal inventor from the debut year up to year *t* (Authors' elaboration from PatentsView). Time-variant variable.
Share of coinventors with>10yrs experience	A coinventor with >10 years of experience is a coinventor who filed at least one patent ten or more years earlier than the observed year. This variable is the share of senior individuals in the cumulative number of coinventors up to year *t*, computed as the ratio between the total number of senior coinventors and the total number of coinventors observed in all the patents of the focal inventor from the debut year up to year *t* (Authors' elaboration from PatentsView). Time-variant variable.
Share of female coinventors with>10yrs experience	A coinventor with >10 years of experience is a coinventor who filed at least one patent ten or more years earlier than the observed year. This variable is the share of female senior individuals in the cumulative number of coinventors up to year *t*, computed as the ratio between the total number of female senior coinventors and the total number of coinventors observed in all the patents of the focal inventor from debut year up to year *t* (Authors' elaboration from PatentsView). Time-variant variable.
Share of male coinventors with >10yrs experience	A coinventor with >10 years of experience is a coinventor who filed at least one patent ten or more years earlier than the observed year. This variable is the share of male senior individuals in the cumulative number of coinventors up to year *t*, computed as the ratio between

(*continued on next page*)

Table A2 (*continued*)

Variable	Definition
	the total number of male senior coinventors and the total number of coinventors observed in all patents of the focal inventor from debut year up to year *t* (Authors' elaboration from PatentsView). Time-variant variable.
Share of star coinventors	Share of star coinventors in the cumulative number of coinventors up to year *t*, computed as the ratio between the total number of star coinventors and the total number of coinventors observed in all patents of the focal inventor from debut year up to year *t* (Authors' elaboration from PatStat and PatentsView). Time-variant variable. An inventor is classified as a star in year *t* if they simultaneously belong to the top 5% of the distribution of patent counts and forward citations within their WIPO field and year.
Share of female star coinventors	Share female star coinventors in the cumulative number of coinventors up to year *t*, computed as the ratio between the total number of female star coinventors and the total number of coinventors observed in all patents of the focal inventor from debut year up to year *t* (Authors' elaboration from PatStat and PatentsView). Time-variant variable.
Share of male star coinventors	Share male star coinventors in the cumulative number of coinventors up to year *t*, computed as the ratio between the total number of male star coinventors and the total number of coinventors observed in all patents of the focal inventor from debut year up to year *t* (Authors' elaboration from PatStat and PatentsView). Time-variant variable.

Table A3
Correlation matrix considering the sample based on the definition of star (N = 1828,019).

	Variable	1	2	3	4	5	6	7	8	9	10
1	Star dummy	1.000									
2	Female dummy	−0.010	1.000								
3	N. of coinventors	0.164	0.011	1.000							
4	Share of female coinventors	0.002	0.131	0.092	1.000						
5	Share of male coinventors	0.023	−0.060	0.171	−0.340	1.000					
6	Share of coinv. with>10yrs exp.	0.017	−0.021	0.140	−0.056	0.316	1.000				
7	Share of female coinv. with>10yrs exp.	0.005	0.020	0.069	0.315	−0.101	0.217	1.000			
8	Share of male coinv. with >10yrs exp.	0.017	−0.027	0.128	−0.130	0.347	0.975	−0.006	1.000		
9	Share of star coinventors	0.082	0.002	0.172	−0.027	0.272	0.448	0.089	0.438	1.000	
10	Share of female star coinventors	0.031	0.038	0.076	0.347	−0.111	0.073	0.435	−0.025	0.271	1.000
11	Share of male star coinventors	0.076	−0.008	0.157	−0.113	0.324	0.455	−0.015	0.470	0.960	0.033

Table A4
Summary statistics for the sub-samples of male and female inventors in the last examined year.

Variables cumulated up to 2019 (mean values)	Subsample:Male inventors only *(N = 84,710)*	Subsample:Female inventors only *(N = 14,230)*
Portfolio size	5.969	4.632
N. of coinventors	17.775	15.934
Share of female coinventors	0.087	0.157
Share of male coinventors	0.771	0.699
Share of star coinventors	0.224	0.220
Share of female star coinventors	0.014	0.023
Share of male star coinventors	0.204	0.191
Share of coinventors with >10yrs experience	0.228	0.203
Share of female coinventors with >10yrs experience	0.013	0.017
Share of male coinventors with >10yrs experience	0.215	0.186

B. Robustness checks

B1. Definitions of stars

In this section, we assess the robustness of our results to alternative definitions of star inventors. Our baseline specification identifies stars as inventors who simultaneously belong to the top 5% of both patent output and forward citations within their technological field and for a given year, and this definition may be considered relatively stringent. Thus, to address this concern, we re-estimate our models using two alternative criteria: (i) a definition based exclusively on prolific inventors, defined as those in the top 5% of the distribution of patent counts, and (ii) a definition based exclusively on highly cited inventors, defined as those in the top 5% of the distribution of forward citations. The corresponding estimates are reported in Table B1.

The results obtained for these alternative definitions are consistent with those of the baseline model. In particular, the presence of star coinventors, regardless of whether defined in terms of productivity or citation impact, is associated with a significantly faster transition to stardom. Moreover, the interaction effects with the female dummy remain qualitatively similar, thereby confirming that female inventors benefit relatively more from collaborations with star coinventors. Slightly differently from the baseline model, the interaction between female inventors and female star coinventors becomes statistically significant for both alternative definitions. This suggests that, when adopting less restrictive criteria to identify star inventors, collaborations with female stars may also generate a measurable additional benefit for women. Overall, despite this nuance, the main patterns remain stable, thus indicating that our results are not driven by the specific operationalization of star inventors.

Table B1
Other definitions of star inventors. Maximum likelihood estimation for the parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star: prolific in models 1 and 2, highly cited in models 3 and 4, respectively (i.e., above the 95th percentile, according to the definition employed in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)	(3)	(4)
Definition of star inventor	Prolific		Highly-cited	
Female dummy	1.065***	1.038***	0.959***	0.862***
	(0.125)	(0.123)	(0.116)	(0.110)
Share of star coinventors	−2.848***		−6.004***	
	(0.056)		(0.042)	
Female dummy x Share of star coinventors	−0.669***		−0.860***	
	(0.191)		(0.146)	
Share of female star coinventors		−3.279***		−6.894***
		(0.177)		(0.113)
Female dummy x Share of female star coinventors		−0.978**		−0.959***
		(0.469)		(0.284)
Share of male star coinventors		−2.775***		−5.847***
		(0.057)		(0.043)
Female dummy x Share of male star coinventors		−0.587***		−0.681***
		(0.198)		(0.146)
N. of coinventors	−0.244***	−0.246***	−0.143***	−0.146***
	(0.005)	(0.005)	(0.003)	(0.003)
Technology field dummies	Yes	Yes	Yes	Yes
Constant	9.719***	9.703***	9.715***	9.647***
	(0.074)	(0.074)	(0.057)	(0.057)
lngamma	0.305***	0.309***	0.353***	0.366***
	(0.007)	(0.007)	(0.005)	(0.005)
Obs.	1828,019	1828,019	1828,019	1828,019
Log lik.	−41,334.089	−41,401.852	−58,661.540	−59,174.746
chi-squared	6861.977	6753.269	28,300.645	28,374.145

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

B2. Career stages

Models (1) and (2) in Table B2 are estimated considering the subsample of inventors who have not yet become stars within the first 5 years after their patenting debut and who are then followed during the growth stage of their careers, from year 6 up to year 10. In this subsample, 2.8% of the inventors attain star status. As in the baseline analysis, these specifications are estimated using a log-logistic distribution.

Models (3) and (4) are estimated on the subsample of inventors who have not yet become stars within the first 10 years of their careers and who are then observed during the mature stage, from year 11 to year 20 after their patenting debut. In this interval, 2.2% of the inventors become stars. We use a Gompertz model for these specifications, as it provides a better fit to the data, whereas log-logistic models do not converge.

Table B2
Subsamples by career stages. Maximum likelihood estimation of the parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). Models (1) and (2) are estimated with a log-logistic distribution, whereas models (3) and (4) use a Gompertz distribution.

	(1)	(2)	(3)	(4)
Subsample considered	Non-star inventors from years 6 to 10 of their careers (growth stage)		Non-star inventors from years 11 to 20 of their careers (mature stage)	
Female dummy	1.045***	1.063***	−0.558***	−0.556***
	(0.243)	(0.243)	(0.111)	(0.110)
Share of star coinventors	−2.240***		1.867***	
	(0.169)		(0.061)	
Female dummy x Share of star coinventors	−0.966**		0.233	
	(0.382)		(0.178)	
Share of female star coinventors		−2.859***		2.064***
		(0.434)		(0.233)
Female dummy x Share of female star coinventors		−0.441		0.088
		(0.949)		(0.449)
Share of male star coinventors		−2.200***		1.828***
		(0.171)		(0.064)
Female dummy x Share of male star coinventors		−1.067***		0.261
		(0.401)		(0.184)
N. of coinventors	−0.188***	−0.191***	0.013***	0.013***
	(0.019)	(0.020)	(0.001)	(0.001)
Technology field dummies	Yes	Yes	Yes	Yes
Constant	9.312***	9.365***	−0.729***	−0.802***
	(0.479)	(0.482)	(0.007)	(0.007)
Lngamma (for models 1 and 2) / gamma (for models 3 and 4)	0.073	0.083	−0.164***	−0.164***
	(0.064)	(0.064)	(0.009)	(0.009)
Obs.	457,299	457,299	889,189	889,189
Log likelihood	−6332.145	−6336.812	−6307.753	−6320.063
Chi-squared	243.474	242.177	4201.927	4207.798

Notes: In the Gompertz specifications (models 3 and 4), coefficients are reported on the log-hazard scale. A positive coefficient (e.g., "Share of star coinventors" in model 3) indicates a higher hazard of becoming a star, that is, a shorter expected time to stardom. A negative coefficient (e.g., "Female dummy") indicates a lower hazard of transition and, therefore, a longer time to reach star status. *p < 0.10, **p < 0.05, ***p < 0.01.

Overall, the results are consistent with the baseline findings and confirm their robustness across the different career stages. The female dummy remains positive and statistically significant in the growth stage (models 1 and 2), thus indicating that women take longer to become stars, while collaboration with star coinventors significantly shortens the time to stardom. The interaction terms are also broadly in line with the baseline evidence: the interaction between the female dummy and the overall share of star coinventors is negative and significant in model 1, while the interaction with male star coinventors is negative and significant in model 2, thus suggesting that women benefit in particular from collaboration with male stars at this stage; the interaction with female star coinventors is instead not statistically significant. The Gompertz estimates confirm the same qualitative pattern in the mature stage (models 3 and 4): the female dummy is negative and significant, thereby indicating a lower hazard of transition to stardom, whereas collaboration with star coinventors, both overall and separately by gender, is positively and significantly associated with the hazard of becoming a star. The interaction terms with the female dummy are no longer statistically significant, thus suggesting that star collaboration remains beneficial in later career stages, but its gender-differentiated effect weakens.

B3. Star inventors only

Table B3
Sample of star inventors only. Maximum likelihood estimation for parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)	(3)	(4)	(5)
Female dummy	−0.044	−0.089**	0.079	−0.018	−0.018
	(0.036)	(0.045)	(0.118)	(0.063)	(0.062)
Share of female coinventors		0.058			
		(0.074)			
Female dummy x Share of female coinventors		0.305			
		(0.202)			
Share of male coinventors			−0.052		
			(0.046)		
Female dummy x Share of male coinventors			−0.161		
			(0.142)		
Share of star coinventors				−1.045***	
				(0.034)	
Female dummy x Share of star coinventors				0.008	
				(0.101)	
Share of female star coinventors					−1.133***
					(0.103)
Female dummy x Share of female star coinventors					0.123
					(0.235)
Share of male star coinventors					−1.020***
					(0.035)
Female dummy x Share of male star coinventors					−0.007
					(0.109)
N. of coinventors	−0.054***	−0.054***	−0.054***	−0.039***	−0.040***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Technology field dummies	Yes	Yes	Yes	Yes	Yes
Constant	−0.728***	−0.728***	−0.729***	−0.802***	−0.799***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
lngamma	65,619	65,619	65,619	65,619	65,619
	−10,621.365	−10,618.496	−10,618.851	−10,012.481	−10,044.778
Obs.	1845.149	1840.108	1878.350	3727.590	3642.651
Log likelihood	−0.728***	−0.728***	−0.729***	−0.802***	−0.799***
Chi-squared	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

B4. Technological fields with high and low female prevalence

Table B4
Sample of inventors in fields where the presence of females is high (>19% of inventors): Analysis of biological materials; Organic fine chemistry; Biotechnology; Pharmaceuticals; Macromolecular chemistry; Food chemistry; Basic materials chemistry. Maximum likelihood estimation for parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)	(3)	(4)	(5)
Female dummy	1.015***	0.595***	2.675***	0.948***	0.974***
	(0.164)	(0.213)	(0.753)	(0.235)	(0.233)
Share of female coinventors		0.461			
		(0.368)			
Female dummy x Share of female coinventors		2.322**			
		(0.984)			
Share of male coinventors			−0.456*		
			(0.262)		
Female dummy x Share of male coinventors			−2.146**		
			(0.897)		
Share of star coinventors				−4.310***	

(*continued on next page*)

Table B4 (*continued*)

	(1)	(2)	(3)	(4)	(5)
				(0.159)	
Female dummy x Share of star coinventors				−0.127	
				(0.379)	
Share of female star coinventors					−5.115***
					(0.377)
Female dummy x Share of female star coinventors					1.602
					(1.028)
Share of male star coinventors					−4.093***
					(0.162)
Female dummy x Share of male star coinventors					−0.381
					(0.392)
N. of coinventors	−0.232***	−0.233***	−0.232***	−0.172***	−0.175***
	(0.013)	(0.014)	(0.013)	(0.010)	(0.010)
Technology field dummies	Yes	Yes	Yes	Yes	Yes
Constant	9.742***	9.696***	10.096***	10.177***	10.135***
	(0.276)	(0.278)	(0.340)	(0.259)	(0.258)
lngamma	0.439***	0.438***	0.437***	0.286***	0.295***
	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)
Obs.	430,920	430,920	430,920	430,920	430,920
Log likelihood	−7995.549	−7987.798	−7986.131	−7546.150	−7579.268
Chi-squared	574.437	569.988	581.566	1139.497	1129.197

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

Table B5
Sample of inventors in fields where the presence of females is very low (<10% of inventors): Handling; Machine tools; Engines, pumps, turbines; Thermal processes and apparatus; Mechanical elements; Transport; Civil engineering. Maximum likelihood estimation for parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)	(3)	(4)	(5)
Female dummy	0.713***	0.552***	0.540	1.009***	1.023***
	(0.161)	(0.188)	(0.521)	(0.261)	(0.259)
Share of female coinventors		0.882***			
		(0.327)			
Female dummy x Share female coinventors		1.093			
		(1.121)			
Share of male coinventors			−0.672***		
			(0.159)		
Female dummy x Share of male coinventors			0.160		
			(0.616)		
Share of star coinventors				−3.116***	
				(0.098)	
Female dummy x Share of star coinventors				−0.742*	
				(0.428)	
Share of female star coinventors					−3.595***
					(0.357)
Female dummy x Share of female star coinventors					−0.998
					(1.143)
Share of male star coinventors					−3.082***
					(0.101)
Female dummy x Share of male star coinventors					−0.786*
					(0.444)
N. of coinventors	−0.304***	−0.305***	−0.299***	−0.234***	−0.237***
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)
Technology field dummies	Yes	Yes	Yes	Yes	Yes
Constant	8.884***	8.835***	9.376***	9.086***	9.088***
	(0.164)	(0.165)	(0.198)	(0.160)	(0.160)
lngamma	0.399***	0.399***	0.397***	0.296***	0.299***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Obs.	557,595	557,595	557,595	557,595	557,595
Log likelihood	−13,739.933	−13,731.654	−13,728.393	−13,222.472	−13,236.735
Chi-squared	1065.315	1055.090	1120.852	1720.367	1686.826

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

B5. Technological complexity

As an additional heterogeneity test, we examine whether the effects of collaboration with star inventors vary across fields with different levels of technological complexity. To this end, we classify patents using the WIPO 35-field technology classification and construct a field-level indicator of technology intensity (Schmoch, 2008). Specifically, each WIPO field is assigned a technology-intensity level by aggregating the intensity classification of the IPC subclasses included in that field, where technology intensity follows the standard distinction between low, medium-low-, medium-high-, and high-technology activities (EUROSTAT, 2024). Based on this mapping, we define a dummy variable equal to one for fields classified as at least medium-high technology (i.e., medium-high or high technology), and zero otherwise. We then use this indicator as a moderating field characteristic in the baseline specifications to assess whether the gendered effects of star collaboration differ systematically between more technologically complex

fields and the rest of the technological space. The corresponding estimates are reported in Table B6.

Table B6
Maximum likelihood estimation for the parametric regression survival-time models. Multiple records per individual. "Failure" event: first time of becoming a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution. Models include interaction terms to control for the moderating role of technological complexity (High-tech field).

	(1)	(2)
Female dummy	1.269***	1.282***
	(0.260)	(0.258)
Share of star coinventors	−3.610***	
	(0.116)	
Female dummy x Share of star coinventors	−0.704*	
	(0.410)	
Share of female star coinventors		−3.823***
		(0.513)
Female dummy x Share of female star coinventors		−0.450
		(1.476)
Share of male star coinventors		−3.575***
		(0.119)
Female dummy x Share of male star coinventors		−0.757*
		(0.424)
High-tech field	0.211**	0.182*
	(0.105)	(0.105)
Female dummy x High-tech field	−0.077	−0.117
	(0.326)	(0.322)
Share of star coinventors x High-tech field	−0.649***	
	(0.143)	
Female dummy x Share of star coinventors x High-tech field	−0.247	
	(0.501)	
Share of female star coinventors x High-tech field		−1.159**
		(0.567)
Female dummy x Share of female star coinventors x High-tech field		−0.083
		(1.615)
Share of male star coinventors x High-tech field		−0.578***
		(0.147)
Female dummy x Share of male star coinventors x High-tech field		−0.212
		(0.518)
N. of coinventors	−0.239***	−0.242***
	(0.006)	(0.006)
Technology field dummies	Yes	Yes
Constant	11.117***	11.128***
	(0.123)	(0.123)
lngamma	0.413***	0.419***
	(0.009)	(0.009)
Obs.	1828,019	1828,019
Log lik.	−31,628.328	−31,699.463
chi-squared	5034.319	4955.593

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

The main coefficients of interest retain the same sign as those of the benchmark specifications and show a similar significance pattern: the female dummy remains positive and significant, thereby indicating women require a longer time to become star inventors; the share of star coinventors continues to display a negative and significant coefficient, thus confirming that collaboration with star inventors is associated with a shorter time to reach star status; the interaction between the female dummy and star collaboration remains negative in the overall and male-star specifications, in line with the baseline results.

Focusing on the moderating role of technological complexity, the coefficient of the high-tech field dummy is positive and statistically significant in both model (1) and model (2). This indicates that inventors operating in high-tech fields tend, on average, to experience a delay in the transition to star inventor status, compared to inventors in other fields. Instead, the Female dummy × High-tech field interaction is negative, but it is not statistically significant in either specification, thus suggesting that there is no robust evidence that the baseline gender gap in the time to stardom differs systematically for high-tech and non-high-tech fields.

The interaction between technological complexity and star collaboration is instead consistently negative and statistically significant. In model (1), the coefficient for the Share of star coinventors × High-tech field indicates that collaboration with star inventors in high-tech fields is associated with a further reduction in the time needed to become a star inventor. Model (2) confirms this pattern when the star collaborators are split by gender. Hence, although high-tech fields are on average associated with a longer path to stardom, collaboration with star inventors becomes even more beneficial in those technologically complex environments, and this holds for both female and male star collaborators.

Finally, the triple interaction terms are not statistically significant. This implies that, although technological complexity overall strengthens the accelerating role of star collaboration, there is no robust evidence that this moderating effect differs even more on the basis of the gender of the focal inventor. In other words, high-tech fields appear to intensify the beneficial role of star collaboration, but they do not significantly change the gender-specific pattern identified in the baseline model.

C. Notes on disambiguation and gender identification

In this section, we address some issues regarding the gender definitions adopted in our empirical setting and the employed dataset. First, the disambiguation algorithm cannot consider any change in surname of women who get married. The relationship between scientific productivity and surname changes has been noted in other studies (see, for example, Chaudhary, 2022): since women in some countries tend to change their maiden name upon marriage, female productivity may appear to be lost because some patents are allocated to two "different" individuals when, in reality, one is referring to only one woman, albeit with two different surnames. If women marry relatively early on in their career, this issue should mostly affect their initial career phases, which, as we saw in the Kaplan-Maier graph in Fig. 2, is a crucial time to achieve the patenting output to become a star. We are not able to compute how many women in our sample are affected by this issue, but the phenomenon is quite widespread in the general population, so much so that around 70% of women changed their surname in the USA in 2015 (NYT & Google Consumer Surveys, 2015). However, some studies have shown that the phenomenon is more limited among highly educated women, especially beyond the PhD level, and if the bride has already "made a name" for herself (Goldin & Shim, 2004; Gooding & Kreider, 2010). Overall, this is a possible limitation of our analysis, since part of the female disadvantage of becoming a star could be imputed to these surname changes, while the factors underlying the choice of surname retention could also enhance some of the selection mechanisms of working with a star.

As far as the gender identification in PatentsView data is concerned, 5% of our starting sample of inventors, who debut in the year 2000, has missing gender. We perform additional analyses on the subsample of inventors in which the gender of the coinventors can be identified: 80,881 inventors are included (82% of the main sample studied in this article). However, this approach introduces some bias against larger teams in which missing gender is more likely, especially when teams with multiple nationalities are involved, as the disambiguation of names could be harder for such teams. Indeed, dropping scientists who work with coinventors with missing gender indirectly affects the relative representation of stars in our sample. We have no elements to conjecture gender polarization (i.e., missing gender data biased toward one gender). Nonetheless, the summary statistics reported in Table C1 show that the restricted sample with no missing gender among the coinventors underestimates the presence of stars, as expected, due to the smaller team size and, albeit to a slightly lesser extent, of the fewer female stars.

Table C1
Comparison of the main sample and the sample with only coinventors of identified gender.

Sample	Inventors debuting in 2000 with identified gender (main sample)	Inventors debuting in 2000 with identified gender AND with all coinventors having identified gender
Size	98,940	80,881
Female inventors (%)	14.4	14.1
Avg. N. of coinventors (up to 2019)	17.51	9.67
Stars (% of sample)	15.2	10.6
Female stars (% of stars)	10.3	9.4

Table C2 provides the results of the baseline models tested on the subsample of inventors who only have coinventors with no missing gender. In order to become a prolific star, in this subsample, the female disadvantage seems more marked for women homophily matches (column 2), but the results are not very significant, and a male disadvantage can even be observed (column 3), probably because we over-index on inventors with just a few or no coinventors. However, the results pertaining to stars generally remain robust, even though the significance of the interaction of female and female stars is lost, although, as noted above, this subsample underrepresents female stars, compared with the full sample.

Table C2
Sample of inventors that only have collaborators of identified gender. Maximum likelihood estimation for parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)	(3)	(4)	(5)
Female dummy	0.801***	0.459***	1.618***	1.216***	1.216***
	(0.139)	(0.169)	(0.523)	(0.211)	(0.211)
Share of female coinventors		0.452			
		(0.297)			
Female dummy x Share of female coinventors		2.344***			
		(0.876)			
Share of male coinventors			−0.178		
			(0.161)		
Female dummy x Share of male coinventors			−1.025*		
			(0.609)		
Share of star coinventors				−4.239***	
				(0.100)	
Female dummy x Share of star coinventors				−0.871***	
				(0.315)	
Share of female star coinventors					−5.169***
					(0.309)
Female dummy x Share of female star coinventors					0.827
					(1.042)
Share of male star coinventors					−4.170***
					(0.103)
Female dummy x Share of male star coinventors					−1.020***
					(0.323)

(continued on next page)

Table C2 (*continued*)

	(1)	(2)	(3)	(4)	(5)
N. of coinventors	−0.400***	−0.402***	−0.399***	−0.301***	−0.300***
	(0.011)	(0.011)	(0.011)	(0.008)	(0.008)
Technology field dummies	Yes	Yes	Yes	Yes	Yes
Constant	13.104***	13.085***	13.227***	12.922***	12.916***
	(0.182)	(0.183)	(0.211)	(0.169)	(0.169)
lngamma	0.669***	0.669***	0.668***	0.535***	0.534***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Obs.	1533,960	1533,960	1533,960	1533,960	1533,960
Log likelihood	−20,494.956	−20,483.525	−20,490.809	−19,518.921	−19,513.715
Chi-squared	1989.592	1989.122	2029.139	2995.747	3009.643

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

Next, we exclude solo inventors who have portfolios of patents with no coinventors, and thus who make the calculation of the gender shares among the coinventors less symmetric. Table C3 shows that all the results are robust. It should be noted that if we were to combine the two restrictions and focus only on inventors who always have collaborators in their patents and whose gender is always defined, we would obtain similar results and identical coefficients for the share of male and female coinventors, albeit with opposite signs, since, in such a case, the two shares would sum up to one.

Table C3
Sample of inventors that always have at least one coinventor in all patents. Maximum likelihood estimation for parametric regression survival-time models. Multiple records per individual. "Failure" event: first time to become a star (prolific and highly cited, i.e., above the 95th percentile in the reference cohort). The survival models employ a loglogistic distribution.

	(1)	(2)	(3)	(4)	(5)
Female dummy	0.811***	0.452**	2.600***	1.298***	1.301***
	(0.150)	(0.186)	(0.829)	(0.238)	(0.238)
Share of female coinventors		0.853***			
		(0.326)			
Female dummy x Share of female coinventors		2.148**			
		(0.927)			
Share of male coinventors			−0.853***		
			(0.326)		
Female dummy x Share of male coinventors			−2.148**		
			(0.927)		
Share of star coinventors				−4.656***	
				(0.115)	
Female dummy x Share of star coinventors				−0.951***	
				(0.339)	
Share of female star coinventors					−5.206***
					(0.340)
Female dummy x Share of female star coinventors					0.866
					(1.143)
Share of male star coinventors					−4.617***
					(0.118)
Female dummy x Share of male star coinventors					−1.122***
					(0.345)
N. of coinventors	−0.411***	−0.413***	−0.413***	−0.315***	−0.315***
	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)
Technology field dummies	Yes	Yes	Yes	Yes	Yes
Constant	13.301***	13.242***	14.095***	13.380***	13.379***
	(0.204)	(0.205)	(0.372)	(0.199)	(0.198)
lngamma	0.677***	0.677***	0.677***	0.530***	0.529***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Obs.	1235,845	1235,845	1235,845	1235,845	1235,845
Log likelihood	−17,758.729	−17,744.234	−17,744.234	−16,753.267	−16,750.539
Chi-squared	1691.439	1688.747	1688.747	2470.161	2486.917

Notes: *p < 0.10, **p < 0.05, ***p < 0.01.

References

Adams, J. (2012). The rise of research networks. *Nature, 490*(7420), 335–336. https://doi.org/10.1038/490335a

Agrawal, A., Goldfarb, A., & Teodoridis, F. (2016). Understanding the changing structure of scientific inquiry. *American Economic Journal: Applied Economics, 8*(1), 100–128. https://doi.org/10.1257/app.20140135

Agrawal, A., McHale, J., & Oettl, A. (2017). How stars matter: Recruiting and peer effects in evolutionary biology. *Research Policy, 46*(4), 853–867. https://doi.org/10.1016/j.respol.2017.02.007

Allen, T. D., Day, R., & Lentz, E. (2005). The role of interpersonal comfort in mentoring relationships. *Journal of Career Development, 31*(3), 155–169. https://doi.org/10.1177/089484530503100301

Avin, C., Keller, B., Lotker, Z., Mathieu, C., Peleg, D., & Pignolet, Y.-A. (2015). Homophily and the glass ceiling effect in social networks. In *Proceedings of the 2015 conference on innovations in theoretical computer science* (pp. 41–50). https://doi.org/10.1145/2688073.2688097

Avolio, B., Chávez, J., & Vílchez-Román, C. (2020). Factors that contribute to the underrepresentation of women in science careers worldwide: A literature review. *Social Psychology of Education, 23*(3), 773–794. https://doi.org/10.1007/s11218-020-09558-y

Awate, K. S., Khanna, R., & Srikanth, K. (2025). Big shoes to fill: How star search behavior and network structure influence coinventor mobility and innovation performance upon star exit. *Organization Science, 36*(6), 2264–2283. https://doi.org/10.1287/orsc.2020.14415

Azoulay, P., Fons-Rosen, C., & Zivin, J. S. G (2019). Does science advance one funeral at a time? *American Economic Review, 109*(8), 2889–2920. https://doi.org/10.1257/aer.20161574

Azoulay, P., Zivin, J. S. G., & Wang, J. (2010). Superstar extinction. *Quarterly Journal of Economics, 125*(2), 549–589. https://doi.org/10.1162/qjec.2010.125.2.549

Bedi, G., Van Dam, N. T., & Munafo, M. (2012). Gender inequality in awarded research grants. *The Lancet, 380*(9840), 474. https://doi.org/10.1016/S0140-6736(12)61292-6

Bell, A., Chetty, R., Jaravel, X., Petkova, N., & Van Reenen, J. (2019). Who becomes an inventor in America? The importance of exposure to innovation. *The Quarterly Journal of Economics, 134*(2), 647–713. https://doi.org/10.1093/qje/qjy028

Bettinger, E. P., & Long, B. T. (2005). Do faculty serve as role models? The impact of instructor gender on female students. *American Economic Review, 95*(2), 152–157. https://doi.org/10.1257/000282805774670149

Blake-Beard, S., Bayne, M. L., Crosby, F. J., & Muller, C. B. (2011). Matching by race and gender in mentoring relationships: Keeping our eyes on the prize: Matching by race and gender in mentoring relationships. *Journal of Social Issues, 67*(3), 622–643. https://doi.org/10.1111/j.1540-4560.2011.01717.x

Bol, T., de Vaan, M., & van de Rijt, A. (2018). The Matthew effect in science funding. *Proceedings of the National Academy of Sciences, 115*(19), 4887–4890. https://doi.org/10.1073/pnas.1719557115

Breda, T., Grenet, J., Monnet, M., & Van Effenterre, C. (2020). Do female role models reduce the gender gap in science? Evidence from French high schools. *IZA Discussion Paper Series*, (No. 13163).

Carrell, S. E., Page, M. E., & West, J. E. (2010). Sex and science: How professor gender perpetuates the gender gap. *Quarterly Journal of Economics, 125*(3), 1101–1144. https://doi.org/10.1162/qjec.2010.125.3.1101

Caviggioli, F., Colombelli, A., & Ravetti, C. (2023). Gender differences among innovators: A patent analysis of stars. *Economics of Innovation and New Technology, 32*, 1000–1018. https://doi.org/10.1080/10438599.2022.2065634

Caviggioli, F., Colombelli, A., & Ravetti, C. (2026). Gender homophily and diversity in patenting: Academic and corporate assignees in inventor's collaborations. *Economics of Innovation and New Technology, 35*, 814–834. https://doi.org/10.1080/10438599.2026.2634911

Caviggioli, F., & Forthmann, B. (2022). Reach for the stars: Disentangling quantity and quality of inventors' productivity in a multifaceted latent variable model. *Scientometrics, 127*(12), 7015–7040. https://doi.org/10.1007/s11192-022-04328-3

Ceci, S. J., & Williams, W. M. (2011). Understanding current causes of women's underrepresentation in science. *Proceedings of the National Academy of Sciences, 108*(8), 3157–3162. https://doi.org/10.1073/pnas.1014871108

Charlesworth, T. E. S., & Banaji, M. R. (2019). Gender in science, technology, Engineering, and mathematics: Issues, causes, solutions. *The Journal of Neuroscience, 39*(37), 7228–7243. https://doi.org/10.1523/JNEUROSCI.0475-18.2019

Chaudhary, V. B. (2022). A scientist by any other name. *Nature Microbiology, 7*(3). https://doi.org/10.1038/s41564-022-01067-2, 351–351Article 3.

Costas, R., Nane, T., & Larivière, V. (2015). Is the year of first publication a good proxy of scholars' academic age?. In *Proceedings of ISSI 2015 Istanbul: 15th international society of scientometrics and informetrics conference* (pp. 988–998).

Del Carpio, L., & Guadalupe, M. (2022). More women in tech? Evidence from a field experiment addressing social identity. *Management Science, 68*(5), 3196–3218. https://doi.org/10.1287/mnsc.2021.4035

Dreher, G. F., & Cox, T. H. (1996). Race, gender, and opportunity: A study of compensation attainment and the establishment of mentoring relationships. *Journal of Applied Psychology, 81*(3), 297–308. https://doi.org/10.1037/0021-9010.81.3.297

DuBois, D. L., Portillo, N., Rhodes, J. E., Silverthorn, N., & Valentine, J. C. (2011). How effective are mentoring programs for youth? A systematic assessment of the evidence. *Psychological Science in the Public Interest, 12*(2), 57–91. https://doi.org/10.1177/1529100611414806

Duffy, R. D., Jadidian, A., Webster, G. D., & Sandell, K. J. (2011). The research productivity of academic psychologists: Assessment, trends, and best practice recommendations. *Scientometrics, 89*(1), 207–227. https://doi.org/10.1007/s11192-011-0452-4

Eby, L. T. D. T., Allen, T. D., Hoffman, B. J., Baranik, L. E., Sauer, J. B., Baldwin, S., Morrison, M. A., Kinkade, K. M., Maher, C. P., Curtis, S., & Evans, S. C. (2013). An interdisciplinary meta-analysis of the potential antecedents, correlates, and consequences of protégé perceptions of mentoring. *Psychological Bulletin, 139*(2), 441–476. https://doi.org/10.1037/a0029279

EPO. (2026). *Advancing women in stem - A data-driven assessment of the gender gap across europe's innovation ecosystem*. European Patent Office. https://doi.org/10.65216/20260303-0001

EUROSTAT. (2024). *High-tech industry and knowledge-intensive services (HTEC)* [Data set]. https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm.

Flory, J. A., Leibbrandt, A., & List, J. A. (2015). Do competitive workplaces deter female workers? A large-scale natural field experiment on job entry decisions. *The Review of Economic Studies, 82*(1), 122–155. https://doi.org/10.1093/restud/rdu030

Fox, M., Whittington, K., & Linkova, M. (2017). Gender, (In)equity, and the scientific workforce. *The handbook of science and technology studies (Fourth edition)*. The MIT Press.

Goldin, C., & Shim, M. (2004). Making a name: Women's surnames at marriage and beyond. *Journal of Economic Perspectives, 18*(2), 143–160. https://doi.org/10.1257/0895330041371268

Goldstein, E. (1979). Effect of same-sex and cross-sex role models on the subsequent academic productivity of scholars. *American Psychologist, 34*(5), 407–410. https://doi.org/10.1037/0003-066X.34.5.407

Gooding, G. E., & Kreider, R. M. (2010). Women's marital naming choices in a nationally representative sample. *Journal of Family Issues, 31*(5), 681–701. https://doi.org/10.1177/0192513X09344688

Grigoriou, K., & Rothaermel, F. T. (2014). Structural microfoundations of innovation: The role of relational stars. *Journal of Management, 40*(2), 586–615. https://doi.org/10.1177/0149206313513612

Groysberg, B., & Lee, L. E. (2009). Hiring stars and their colleagues: Exploration and exploitation in professional service firms. *Organization Science, 20*(4), 740–758. https://doi.org/10.1287/orsc.1090.0430

Guan, J., & Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. *Research Policy, 45*(1), 97–112. https://doi.org/10.1016/j.respol.2015.08.002

Halevi, G. (2019). Bibliometric studies on gender disparities in science. In W. Glänzel, H. F. Moed, U. Schmoch, & M. Thelwall (Eds.), *Springer handbook of science and technology indicators* (pp. 563–580). Springer International Publishing. https://doi.org/10.1007/978-3-030-02511-3_21.

Haseltine, F. P., & Chodos, M. (2017). Why' vs. 'what,' or 'the bad penny opera': Gender and bias in science. *Technology & Innovation, 18*(4), 275–279. https://doi.org/10.21300/18.4.2017.275

Heikkilä, J. (2019). IPR gender gaps: A first look at utility model, design right and trademark filings. *Scientometrics, 118*(3), 869–883. https://doi.org/10.1007/s11192-018-2979-0

Hein, P., Diehl, M.-R., & Kreutzer, K. (2025). Magic will happen if you gather us in one room: Gender homophily and women-only networking. *Journal of Management*. , Article 01492063251390850. https://doi.org/10.1177/01492063251390850

Higgins, M. J., Stephan, P. E., & Thursby, J. G. (2011). Conveying quality and value in emerging industries: Star scientists and the role of signals in biotechnology. *Research Policy, 40*(4), 605–617. https://doi.org/10.1016/j.respol.2011.01.006

Hinton, A. O., Termini, C. M., Spencer, E. C., Rutaganira, F. U. N., Chery, D., Roby, R., Vue, Z., Pack, A. D., Brady, L. J., Garza-Lopez, E., Marshall, A. G., Lewis, S. C., Shuler, H. D., Taylor, B. L., McReynolds, M. R., & Palavicino-Maggio, C. B. (2020). Patching the leaks: Revitalizing and reimagining the STEM pipeline. *Cell, 183*(3), 568–575. https://doi.org/10.1016/j.cell.2020.09.029

Holman, L., Stuart-Fox, D., & Hauser, C. E. (2018). The gender gap in science: How long until women are equally represented? *PLOS Biology, 16*(4), Article e2004956. https://doi.org/10.1371/journal.pbio.2004956

Huang, J., Gates, A. J., Sinatra, R., & Barabási, A.-L. (2020). Historical comparison of gender inequality in scientific careers across countries and disciplines. *Proceedings of the National Academy of Sciences, 117*(9), 4609–4616. https://doi.org/10.1073/pnas.1914221117

Hunt, J., Garant, J. P., Herman, H., & Munroe, D. J. (2013). Why are women underrepresented amongst patentees? *Research Policy, 42*(4), 831–843. https://doi.org/10.1016/j.respol.2012.11.004

Jadidi, M., Karimi, F., Lietz, H., & Wagner, C. (2018). Gender disparities in science? Dropout, productivity, collaborations and success of male and female computer scientists. *Advances in Complex Systems, 21*, Article 1750011. https://doi.org/10.1142/S0219525917500114, 03n04.

Jagsi, R., Griffith, K. A., Jones, R., Perumalswami, C. R., Ubel, P., & Stewart, A. (2016). Sexual harassment and discrimination experiences of academic medical faculty. *JAMA, 315*(19), 2120. https://doi.org/10.1001/jama.2016.2188

Jones, B. F. (2009). The burden of knowledge and the "death of the Renaissance man": Is innovation getting harder? *Review of Economic Studies, 76*(1), 283–317. https://doi.org/10.1111/j.1467-937X.2008.00531.x

Karimi, F., Génois, M., Wagner, C., Singer, P., & Strohmaier, M. (2018). Homophily influences ranking of minorities in social networks. *Scientific Reports, 8*(1), Article 11077. https://doi.org/10.1038/s41598-018-29405-7

Kegen, N. V. (2013). Science networks in cutting-edge research institutions: Gender homophily and embeddedness in formal and informal networks. *Procedia - Social and Behavioral Sciences, 79*, 62–81. https://doi.org/10.1016/j.sbspro.2013.05.057

Kehoe, R. R., Lepak, D. P., & Bentley, F. S. (2018). Let's call a star a star: Task performance, external status, and exceptional contributors in organizations. *Journal of Management, 44*(5), 1848–1872. https://doi.org/10.1177/0149206316628644

Kerr, S. P., & Kerr, W. R. (2018). Global collaborative patents. *The Economic Journal, 128*(612), F235–F272. https://doi.org/10.1111/ecoj.12369

Khanna, R. (2021). Aftermath of a tragedy: A star's death and coauthors' subsequent productivity. *Research Policy, 50*(2), Article 104159. https://doi.org/10.1016/j.respol.2020.104159

Khanna, R. (2023). Passing the torch of knowledge: Star death, collaborative ties, and knowledge creation. *Research Policy, 52*(1), Article 104649. https://doi.org/10.1016/j.respol.2022.104649

Kofoed, M. S., & McGovney, E. (2019). The effect of same-gender or same-race role models on occupation choice: Evidence from randomly assigned mentors at West Point. *Journal of Human Resources, 54*(2), 430–467. https://doi.org/10.3368/jhr.54.2.0416.7838R1

König, C. J., Fell, C. B., Kellnhofer, L., & Schui, G. (2015). Are there gender differences among researchers from industrial/organizational psychology? *Scientometrics, 105*(3), 1931–1952. https://doi.org/10.1007/s11192-015-1646-y

Kurtulus, F. A., & Tomaskovic-Devey, D. (2012). Do female top managers help women to advance? A panel study using EEO-1 records. *The ANNALS of the American Academy of Political and Social Science, 639*(1), 173–197. https://doi.org/10.1177/0002716211418445

Kwiek, M., & Roszka, W. (2021). Gender-based homophily in research: A large-scale study of man-woman collaboration. *Journal of Informetrics, 15*(3), Article 101171. https://doi.org/10.1016/j.joi.2021.101171

Larivière, V., Ni, C., Gingras, Y., Cronin, B., & Sugimoto, C. R. (2013). Bibliometrics: Global gender disparities in science. *Nature, 504*(7479), 211–213. https://doi.org/10.1038/504211a

Lawrence, B. S., & Shah, N. P. (2020). Homophily: Measures and meaning. *Academy of Management Annals, 14*(2), 513–597. https://doi.org/10.5465/annals.2018.0147

Lax Martinez, G., Raffo, J., & Saito, K. (2016). Identifying the gender of PCT inventors. In *World intellectual property organization economic research working paper* (No. 33).

Legewie, J., & DiPrete, T. A. (2014). The high school environment and the gender gap in science and engineering. *Sociology of Education, 87*(4), 259–280. https://doi.org/10.1177/0038040714547770

Lerchenmueller, M., Hoisl, K., & Schmallenbach, L. (2019). Homophily, biased attention, and the gender gap in science. *Academy of Management Proceedings, 2019*, Article 14784. https://doi.org/10.5465/AMBPP.2019.14784abstract. *2019*(1).

Li, D., Cui, F., & Li, Y. (2026). Two sides of the same coin: The dual effect of star inventors on team innovation. *Frontiers in Psychology, 16*, Article 1669363. https://doi.org/10.3389/fpsyg.2025.1669363

Lim, J., & Meer, J. (2017). The impact of teacher–Student gender matches: Random assignment evidence from South Korea. *Journal of Human Resources, 52*(4), 979–997. https://doi.org/10.3368/jhr.52.4.1215-7585R1

Maddi, A., & Gingras, Y. (2021). Gender diversity in research teams and citation impact in economics and management. *Journal of Economic Surveys, 35*(5), 1381–1404. https://doi.org/10.1111/joes.12420

Mayer, S. J., & Rathmann, J. M. K (2018). How does research productivity relate to gender? Analyzing gender differences for multiple publication dimensions. *Scientometrics, 117*(3), 1663–1693. https://doi.org/10.1007/s11192-018-2933-1

Meng, Y. (2016). Collaboration patterns and patenting: Exploring gender distinctions. *Research Policy, 45*(1), 56–67. https://doi.org/10.1016/j.respol.2015.07.004

Mindruta, D., Bercovitz, J., Mares, V., & Feldman, M. (2025). Stars in their constellations: Great person or great team? *Management Science, 71*, 2170–2191. https://doi.org/10.1287/mnsc.2021.01969. mnsc.2021.01969.

Morales, D. X., Grineski, S. E., & Collins, T. W. (2018). Effects of gender concordance in mentoring relationships on summer research experience outcomes for undergraduate students. *Science Education, 102*(5), 1029–1050. https://doi.org/10.1002/sce.21455

Morales, D. X., Grineski, S. E., & Collins, T. W. (2021). Effects of mentor–mentee discordance on Latinx undergraduates' intent to pursue graduate school and research productivity. *Annals of the New York Academy of Sciences, 1499*(1), 54–69. https://doi.org/10.1111/nyas.14602

Morales, D. X., Grineski, S. E., & Collins, T. W. (2023). Advancing understanding of discordant mentoring relationships in STEMM: A method and framework. *Annals of the New York Academy of Sciences, 1526*(1), 8–15. https://doi.org/10.1111/nyas.15035

Morrison, A. M., White, R. P., & Van Velsor, E. (1994). *Breaking the glass ceiling: Can women reach the top of america's largest corporations? (Updated ed., 1. paperback print)*. Addison-Wesley.

Mullen, C. A., & Klimaitis, C. C. (2021). Defining mentoring: A literature review of issues, types, and applications. *Annals of the New York Academy of Sciences, 1483*(1), 19–35. https://doi.org/10.1111/nyas.14176

National Academies of Sciences, Engineering, and Medicine. (2018). In P. A. Johnson, S. E. Widnall, & F. F. Benya (Eds.), *Sexual harassment of women: Climate, culture, and consequences in academic sciences, engineering, and medicine*. National Academies Press, Article 24994. https://doi.org/10.17226/24994.

Neumark, D., & Gardecki, R. (1998). Women helping Women? Role model and mentoring effects on female ph.D. Students in economics. *The Journal of Human Resources, 33*(1), 220. https://doi.org/10.2307/146320

Ni, C., Smith, E., Yuan, H., Larivière, V., & Sugimoto, C. R. (2021). The gendered nature of authorship. *Science Advances, 7*(36), Article eabe4639. https://doi.org/10.1126/sciadv.abe4639

Niederle, M., & Vesterlund, L. (2007). Do women shy away from competition? Do men compete too much? *The Quarterly Journal of Economics, 122*(3), 1067–1101. https://doi.org/10.1162/qjec.122.3.1067

NYT and Google Consumer Surveys. (2015). *About the maiden-name analysis*. The New York Times. https://www.nytimes.com/2015/06/28/upshot/about-the-maiden-name-analysis.html.

Oettl, A. (2012). Reconceptualizing stars: Scientist helpfulness and peer performance. *Management Science, 58*(6), 1122–1140. https://doi.org/10.1287/mnsc.1110.1470

Ohlott, P. J., Ruderman, M. N., & McCauley, C. D. (1994). Gender differences in managers' developmental job experiences. *Academy of Management Journal, 37*(1), 46–67. https://doi.org/10.2307/256769

Oldroyd, J. B., & Morris, S. S. (2012). Catching falling stars: A human resource response to social capital's detrimental effect of information overload on star employees. *Academy of Management Review, 37*(3), 396–418. https://doi.org/10.5465/amr.2010.0403

Oliveira, D. F. M., Ma, Y., Woodruff, T. K., & Uzzi, B. (2019). Comparison of National Institutes of Health grant amounts to first-time male and female principal investigators. *JAMA, 321*(9), 898. https://doi.org/10.1001/jama.2018.21944

Pohlhaus, J. R., Jiang, H., Wagner, R. M., Schaffer, W. T., & Pinn, V. W. (2011). Sex differences in application, success, and funding rates for NIH extramural programs. *Academic Medicine, 86*(6), 759–767. https://doi.org/10.1097/ACM.0b013e31821836ff

Porter, C., & Serra, D. (2020). Gender differences in the choice of major: The importance of female role models. *American Economic Journal: Applied Economics, 12*(3), 226–254. https://doi.org/10.1257/app.20180426

Powell, K. (2019). Breastfeeding mums are finally getting spaces to pump at some US institutions. *Nature*. https://doi.org/10.1038/d41586-019-01335-y. d41586-019-01335-y.

Puuska, H. M. (2010). Effects of scholar's gender and professional position on publishing productivity in different publication types. Analysis of a Finnish university. *Scientometrics, 82*(2), 419–437. https://doi.org/10.1007/s11192-009-0037-7

Ravetti, C., Sarr, M., Munene, D., & Swanson, T. (2019). Discrimination and favouritism among South African workers: Ethnic identity and union membership. *World Development, 123*, Article 104604. https://doi.org/10.1016/j.worlddev.2019.06.027

Reardon, S. (2022). Scientific collaborations are precarious territory for women. *Nature, 605*(7908), 179–181. https://doi.org/10.1038/d41586-022-01204-1

Reme, B.-A., Kotsadam, A., Bjelland, J., Sundsøy, P. R., & Lind, J. T. (2022). Quantifying social segregation in large-scale networks. *Scientific Reports, 12*(1), 6474. https://doi.org/10.1038/s41598-022-10273-1

Roper, R. L. (2019). Does gender bias still affect women in science? *Microbiology and Molecular Biology Reviews, 83*(3), e00018–e00019. https://doi.org/10.1128/MMBR.00018-19

Rua-Gomez, C., Carnabuci, G., & Goossen, M. C. (2023). Reaching for the stars: How gender influences the formation of high-status collaboration ties. *Academy of Management Journal, 66*(5), 1501–1528. https://doi.org/10.5465/amj.2021.0218

Schmoch, U. (2008). *Concept of a technology classification for country comparisons [Final report to the world intellectual property organisation (WIPO)]*. June. Fraunhofer Institute for Systems and Innovation Research.

Schmuck, C. (2017). *Women in stem disciplines*. Springer International Publishing. https://doi.org/10.1007/978-3-319-41658-8

She, M., Bachmann, J., Karimi, F., & Peel, L. (2025). Gender differences in collaboration and career progression in physics. *Royal Society Open Science, 12*(8), Article 241536. https://doi.org/10.1098/rsos.241536

Simcoe, T. S., & Waguespack, D. M. (2011). Status, quality, and attention: What's in a (Missing) name? *Management Science, 57*(2), 274–290. https://doi.org/10.1287/mnsc.1100.1270

Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality? *Management Science, 56*(1), 41–56. https://doi.org/10.1287/mnsc.1090.1072

Smith, J. W., Smith, W. J., & Markham, S. E. (2000). Diversity issues In mentoring academic faculty. *Journal of Career Development, 26*(4), 251–262. https://doi.org/10.1023/A:1022998106420

Sosik, J. J., & Godshalk, V. M. (2005). Examining gender similarity and mentor's supervisory status in mentoring relationships. *Mentoring & Tutoring: Partnership in Learning, 13*(1), 39–52. https://doi.org/10.1080/13611260500040138

Sugimoto, C. R., Ni, C., West, J. D., & Larivière, V. (2015). The academic advantage: Gender disparities in patenting. *PLOS One, 10*(5), Article e0128000. https://doi.org/10.1371/journal.pone.0128000

Szell, M., & Thurner, S. (2013). How women organize social networks different from men. *Scientific Reports, 3*(1), 1214. https://doi.org/10.1038/srep01214

Tahmooresnejad, L., & Turkina, E. (2022). Female inventors over time: Factors affecting female inventors' innovation performance. *Journal of Informetrics, 16*(1), Article 101256. https://doi.org/10.1016/j.joi.2022.101256

Tang, X., Patterson, P., MacKenzie-Shalders, K., Van Herwerden, L. A., Bishop, J., Rathbone, E., Honeyman, D., & Reidlinger, D. P. (2021). Workplace programmes for supporting breast-feeding: A systematic review and meta-analysis. *Public Health Nutrition, 24*(6), 1501–1513. https://doi.org/10.1017/S1368980020004012

Tomassini, C. (2021). Gender gaps in science: Systematic review of the main explanations and research agenda. *Education in the Knowledge Society (EKS), 22*, 22. https://doi.org/10.14201/eks.25437

USPTO. (2019). Progress and potential: A profile of women inventors on US patents. In Technical Report. In *IP Data Highlights* (Issue 2).

USPTO. (2020). Progress and potential: 2020 update on U.S. women inventor-patentees. Office of the chief economist IP data highlights https://www.uspto.gov/ip-policy/economic-research/publications/reports/progress-potential.

Van Den Besselaar, P., & Sandström, U. (2016). Gender differences in research performance and its impact on careers: A longitudinal case study. *Scientometrics, 106*(1), 143–162. https://doi.org/10.1007/s11192-015-1775-3

van Zeebroeck, N. (2011). The puzzle of patent value indicators. *Economics of Innovation and New Technology, 20*(1), 33–62. https://doi.org/10.1080/10438590903038256

Waldinger, F. (2016). Bombs, brains, and science: The role of Human and physical capital for the creation of scientific knowledge. *Review of Economics and Statistics, 98*(5), 811–831. https://doi.org/10.1162/REST_a_00565

Wang, J., & Maynard, A. (2025). Gender disparity in U.S. patenting. *Humanities and Social Sciences Communications, 12*(1), 1730. https://doi.org/10.1057/s41599-025-06038-6

Wang, Y., Yang, Z., Liu, L., & Wang, X. (2020). Gender bias in patenting process. *Journal of Informetrics, 14*(3), Article 101046. https://doi.org/10.1016/j.joi.2020.101046

Whittington, K. B. (2018). A tie is a tie? Gender and network positioning in life science inventor collaboration. *Research Policy, 47*(2), 511–526. https://doi.org/10.1016/j.respol.2017.12.006

Witteman, H. O., Hendricks, M., Straus, S., & Tannenbaum, C. (2019). Are gender gaps due to evaluations of the applicant or the science? A natural experiment at a national funding agency. *The Lancet, 393*(10171), 531–540. https://doi.org/10.1016/S0140-6736(18)32611-4

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science (New York, N.Y.), 316*(5827), 1036–1039. https://doi.org/10.1126/science.1136099

Wullum Nielsen, M., & Börjeson, L. (2019). Gender diversity in the management field: Does it matter for research outcomes? *Research Policy, 48*(7), 1617–1632. https://doi.org/10.1016/j.respol.2019.03.006