**Do Some Stars Shine Brighter than Others?**

**Knowledge Recombination in Teams with Female versus Male Stars**

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**KNOWLEDGE RECOMBINATION IN TEAMS WITH FEMALE VERSUS MALE STARS**

# Abstract

This paper focuses on female stars, an underrepresented and largely unexplored group of star knowledge workers, and their role in team knowledge recombination. We argue that gender differences between male and female stars can produce differential implications for the availability and integration of knowledge in teams. We hypothesize that the presence of a female star fosters the breadth of knowledge recombination in teams more than the presence of a male star. Empirically, we rely on a sample of star inventors, representing knowledge workers, and their patents filed at the US patent office in the period of 1990-2010. We match teams with a female star to similar teams with a male star and compare how broadly the teams recombine knowledge across technological boundaries in their patented inventions. We find that teams with a female star combine knowledge more broadly. Our findings emphasize the special role of female stars in teams and may thus help leverage the untapped potential of women in many knowledge-based and creative industries.

**Keywords**: stars, teams, gender differences, knowledge recombination, creativity

# Introduction

Substantial scholarly interest has been devoted to star knowledge workers, who disproportionately exceed their peers in terms of their contribution to organizational knowledge creation (e.g., Zucker & Darby, 1996). Stars profit knowledge creation in organizations by virtue of their unique individual contributions, knowledge spillovers (e.g., Azoulay, Zivin, & Wang, 2010), and superior access to resources (e.g., Groysberg, Lee, & Nanda, 2008). The creation of knowledge relies to a large extent on the recombination of diverse existing knowledge elements (Fleming, 2001; Nelson & Winters, 1982; Schumpeter, 1934) and is mostly a team endeavor (Kogut & Zander, 1992). The benefits of stars for the recombination of knowledge in teams, such as their creative synthesis abilities (Liu, Mihm, & Sosa, 2019), are well established. However, recent evidence suggest that stars might also induce adverse effects on knowledge recombination in teams, mainly due to increased focus on the star and development of star-centric routines (Chen & Garg, 2018; Grigoriou & Rothaermel, 2014; Kehoe & Tzabbar, 2015; Morris, Alvarez, & Barney, 2018). Considering these positive and negative effects of stars on knowledge recombination in teams, it is important to identify factors that determine the extent of both costs and benefits.

We identify the gender of a star as a determinant for how star knowledge workers affect knowledge recombination in teams. Much of the literature so far assumes that star effects generalize to all stars. Yet, what we know about stars does not account for differences resulting from salient star characteristics. In particular, since the majority of stars tend to be men, partly due to lower representation of women among the top ranks of many knowledge-based professions (Center for American Progress, 2018; U.S. Bureau of Labor Statistics, 2016), our understanding of stars’ contribution to creative knowledge work may very well be restricted to male stars. However, research from sociology and psychology suggests that male and female (star) knowledge workers play remarkably different roles in team settings. We therefore seek to answer the following research question: do teams with female versus male stars recombine knowledge more broadly? We focus on the breadth of knowledge recombination, as it captures the degree to which diverse knowledge elements are integrated and because it is crucial for creativity and innovation (Fleming, 2001; Nelson & Winter, 1982; Schumpeter, 1934b). Hargadon (1998), for example, suggests that the recombination of discoveries in electronic, crystal, and optics technologies resulted in the emergence of a completely new industry, namely optoelectronics. Knowledge recombination breadth is thus considered a key outcome in innovation and its importance for radical creativity and innovation is undisputed.

Whether the presence of a female star affects the breadth of knowledge recombination more positively or negatively than the presence of a male star is not obvious. On the one hand, a large body of research on status originating from sociology indicates that women are subject to discrimination and experience status discount compared to men (Ridgeway, 1991; Ridgeway & Diekema, 1992). This discount may put a female star’s entire team at a disadvantage by reducing access to networks, resources, and, consequently, knowledge available for recombination (Liu et al., 2019; Perry-Smith & Mannucci, 2017). On the other hand, findings in the discipline of psychology suggest that gender differences in the perception, characteristics, and behavior of women and men (Eagly, 1987; Eagly & Karau, 2002) may facilitate team processes that are crucial for the successful integration of diverse knowledge components (Harvey, 2014; Liu et al., 2019). We aim to investigate which of the two mechanisms may dominate, i.e., whether teams with a female star recombine knowledge more or less broadly than teams with a male star.

Integrating the sociological and psychological perspectives, we hypothesize that the breadth of knowledge recombination in teams should benefit more from the presence of a female than a male star. The combination of knowledge elements across categories requires the ability to integrate diverse information, expertise and perspectives into a common creative output (Harvey, 2014). The integration of these elements, which we expect to work better in teams with a female than a male star, should benefit knowledge recombination breadth more than the mere availability of knowledge (Hargadon & Bechky, 2006; Liu et al., 2019). Further, given that we look at stars, who are a special group of knowledge workers with exceptionally high productivity, gender differences in access to external resources and knowledge are likely not as pronounced as might generally be the case. These factors should, on the whole, benefit knowledge recombination breadth in teams with female versus male stars.

To investigate the research question, we look at US patent inventors. Inventors are highly representative of knowledge workers, since they are directly involved in the generation of new knowledge and represent a relatively homogenous group of employees engaged in creative tasks (Arrow, 1972; Drucker, 1999; Hoisl & Mariani, 2017). Our dataset consists of patents filed by inventor teams at the US patent office in the period of 1990-2010. We follow the literature and identify star knowledge workers based on their exceptional individual inventive performance (e.g., Tzabbar & Kehoe, 2014). We extract patents of teams that involved these star inventors and match teams involving a female star to similar teams involving a male star using coarsened exact matching (CEM). Finally, we compare how broadly the teams recombine knowledge across technological boundaries in their patented inventions, using knowledge recombination breadth as our dependent variable (Gruber et al., 2013) and the team as our level of analysis. We employ several robustness checks including an instrumental variable approach and alternative dependent variables to verify our results and test a moderation model to provide preliminary evidence in support of our theoretical arguments. We find robust empirical evidence suggesting that teams with female stars combine knowledge more broadly than teams with male stars.

Our research contributes to the theoretical understanding of the role played by stars in the creation of knowledge in teams in three ways. First, we examine how a distinct star characteristic, i.e., the star’s gender, influences the extent to which teams benefit from the presence of stars. While existing research on star performers is largely built around male stars, we examine gender differences that may impact how the beneficial and adverse effects of stars documented by prior literature manifest in the creation of knowledge. Second, we attempt to resolve a contradiction emerging from the literatures on status and findings in the discipline of psychology, to theorize how gender differences between stars may impact the availability and integration of diverse knowledge in teams. Third, we extend literature on the social perspective on creativity and knowledge creation, by showing that team members’ collaborations with female and male stars are likely to produce different knowledge outcomes due to differences in how team members communicate and interact with female and male stars.

# theoretical background and hypothesis

## The role of stars in the recombination of knowledge in teams

Recombination of existing knowledge and ideas is a critical part of knowledge creation in organizations (Fleming, 2001; Nelson & Winters, 1982; Schumpeter, 1934). Knowledge recombination comprises the development of new intellectual capital by exchanging and integrating knowledge elements, for instance, in the form of concepts, artefacts, perspectives and ideas (Grant, 1991; Nahapiet & Ghoshal, 1998). Recombining knowledge across boundaries can be conducive to increasing the quality and impact of an invention (Ferguson & Carnabuci, 2017; Fleming, 2001; Nerkar, 2003). Creative outputs that combine distant knowledge have been shown to possess greater potential for creating competitive advantage and driving varied applications (Nerkar, 2003).

In teams, the breadth of knowledge recombination can increase both when team members possess and have access to heterogenous knowledge bases (Singh & Fleming, 2010), and when team processes function in ways that facilitate the integration of such diverse knowledge through exchanges, synthesis, and cross-fertilization (Baer, Vadera, Leenders, & Oldham, 2014; De Vries, Van Den Hooff, & De Ridder, 2006; Paulus & Nijstad, 2003; Van Knippenberg, De Dreu, & Homan, 2004). This implies that a team’s capacity to recombine knowledge depends on both the overall knowledge stock available to the team, as well as the team processes that allow members to effectively integrate the available information (Faraj & Xiao, 2006; Harvey, 2014; Singh & Fleming, 2010).

As individuals with exceptionally high performance relative to their peers and broad external visibility (Groysberg et al., 2008; Oldroyd & Morris, 2012), stars exert significant influence on knowledge recombination in teams. In the following, we organize these effects based on whether they relate to the team’s stock of heterogenous knowledge available (*availability of knowledge*) or to the team’s capacity to successfully integrate this knowledge stock (*integration of knowledge*).

Stars increase teams’ available knowledge stock primarily in three ways. First, they contribute their own unique and superior skills, explicit and tacit knowledge, and expertise (e.g., Lacetera, Cockburn, & Henderson, 2004; Rothaermel & Hess, 2007; Zucker & Darby, 1996). Given stars’ superior productivity and impact, these are likely to be significant additions to the team. Second, due to their pronounced organizational status, reputation and social visibility, stars enjoy access to larger social networks and greater organizational resources. These resources can be used to access external knowledge that may otherwise not be readily available to teams (Li, Li, Li, & Li, 2020; Oldroyd & Morris, 2012). Finally, collaborating with stars leads to positive knowledge spillover to non-star team members, which can raise the cumulative knowledge stock of the team, albeit not necessarily enhance the diversity of knowledge available (Kehoe & Tzabbar, 2015; Oettl, 2012).

In addition, stars impact teams’ knowledge integration processes in two key ways. First, stars have been shown to play a central role in creative synthesis in teams, often by identifying and filling knowledge gaps, building consensus, and facilitating the simultaneous consideration of diverse ideas and specialized knowledge (Li et al., 2020; Liu et al., 2019). Second, stars can paradoxically also impede teams’ knowledge exchange and integration, due to the development of star-centric routines and information overload brought about by their excessive social visibility and organizational status (Chen & Garg, 2018; Li et al., 2020; Oldroyd & Morris, 2012; Tzabbar & Vestal, 2015).

To summarize, stars are known to affect team knowledge recombination in both positive and negative ways. In the subsequent sections, we review literature on gender differences to establish that these effects may not be homogenous for male and female stars.

## Gender differences in stars’ status

A large amount of evidence shows that, on average, women have lower status than men in organizational contexts. Gender serves as a diffuse status characteristic that leads to perceptions of higher competence and influence for men (Carli & Eagly, 1999; Ridgeway & Diekema, 1992). Because gender is a highly salient characteristic in organizations (Acker, 1990), status differences attributed to gender signify not only relative positioning in social hierarchies, but also access to prestige and power (Berger, Ridgeway, & Zelditch, 2002; Bunderson, 2003). Extending these findings to stars, male stars are likely to enjoy higher status and visibility than comparable female stars due to gender-driven discounting of female stars’ achievements. In turn, male stars’ higher status may imply greater control over teams’ resources and greater social prestige than comparable female stars would have (Anderson, John, Keltner, & Kring, 2001; Blau, 1964; Ridgeway & Erickson, 2000).

The gender difference in the external status of stars may affect knowledge recombination breadth by impacting teams’ ability to access remote external knowledge. This is because social network size and centrality as well as the capacity to undertake potentially time- and resource-intensive search processes are key determinants of the ability to obtain remote knowledge (e.g., Kneeland, Schilling, & Aharonson, 2020; Perry-Smith & Shalley, 2003). Moreover, status is believed to be transferable, such that an actor’s status “leaks to” or impacts that of her/his associates (Podolny, 2005). That is, association with high status actors routinely benefits the status and organizational outcomes of low status individuals who affiliate with them (e.g., Shapiro, 1983). Thus, gender differences in stars’ status are likely to leak to fellow team members, such that teams with male stars may enjoy cumulatively higher status than teams with female stars, thereby further exacerbating differences in access to resources and external knowledge.

Lower status of female stars compared to male stars may also have implications for internal team knowledge processes. Status-induced hierarchical differences in teams can be detrimental to team processes as they constrain the integration of knowledge, especially of knowledge that contradicts or diverges from that of the high-status individual (Anthony, 2018; Van der Vegt, de Jong, Bunderson, & Molleman, 2010). Large status differentials in teams with stars are associated with an increasing presence of star-centrism (Bendersky & Hays, 2012; Oldroyd & Morris, 2012; Tzabbar & Vestal, 2015). Due to smaller perceived status differentials between the star and the non-star team members, teams with female stars may be less constrained by the problem of star-centrism and hierarchical segregation than those with male stars, thereby avoiding excessive reliance on stars’ knowledge base and facilitating the integration of diverse knowledge across the team (Hargadon & Bechky, 2006; Harvey, 2014; Wuchty, Jones, & Uzzi, 2007)

## Gender differences in the perception, characteristics, and behavior of stars in teams

Literature in the field of psychology documents differences between men and women in terms of perception, characteristics, and behavior. Several meta-analyses and cross-cultural comparisons indicate significant gender differences in personality traits, with women reporting higher levels of agreeableness and warmth, and men reporting higher levels of assertiveness (Costa, Terracciano, & McCrae, 2001; Lippa, 2008, 2010; Schmitt, Realo, Voracek, & Allik, 2008). This is consistent with the gender roles literature, which demonstrates that women are routinely expected to behave in warm and communal rather than agentic ways, while the opposite is true for men (e.g., Eagly, 1987; Eagly & Karau, 2002). Similarly, women are, on average, found to be more interpersonally sensitive, exhibit greater perspective-taking, and have more people-oriented interests than men (Galinsky, Magee, Ena Inesi, & Gruenfeld, 2006; LePine, Hollenbeck, Ilgen, Colquitt, & Ellis, 2002; Su, Rounds, & Armstrong, 2009; Williams & Polman, 2015). These differences have also been found to generalize to women who occupy positions of power and visibility in organizations and who have advanced up the career ladder (Adams & Funk, 2012; Eagly, Johannesen-Schmidt, & Van Engen, 2003; Post, 2015; Rosette & Tost, 2010).

Extending these differences to stars, female stars can be expected, on average, to display more interpersonal and socially oriented characteristics and behaviors than male stars. In turn, female stars’ presumed display of such characteristics and behaviors may affect knowledge recombination breadth by strengthening team processes that play a major role in the integration of knowledge. Teams that undertake creative knowledge work often need to configure diverse knowledge, dissimilar expertise and potentially contradictory perspectives (Hargadon & Bechky, 2006). In order to do so, they must communicate and collaborate in ways that are conducive to both the relatively uninhibited sharing of unique knowledge as well as collective sensemaking (Harvey, 2014; Liu et al., 2019; Mannucci, 2017). In this respect, characteristics and behaviors that indicate mutual respect, social sensitivity and interpersonal competence have been repeatedly found to facilitate knowledge integration in teams (Grigoriou & Rothaermel, 2014; Hargadon & Bechky, 2006; Woolley, Chabris, Pentland, Hashmi, & Malone, 2010; Wuchty et al., 2007).

## Hypothesis

In the previous sections, we established that the benefits of male stars for knowledge recombination breadth in teams predominantly derive from their capacity to increase the overall knowledge available, while the benefits of female stars mainly relate to knowledge integration processes. Therefore, the question whether teams with male or female stars are better at recombining diverse knowledge components essentially depends on whether the availability of knowledge or effective knowledge integration processes are more important for knowledge recombination breadth. In the specific context of star knowledge workers in teams, we argue that knowledge integration should matter more for two main reasons.

First, team processes that facilitate knowledge integration are consistently recognized as essential for combining diverse knowledge, dissimilar expertise and potentially disparate perspectives into creative output (Hargadon & Bechky, 2006; Harvey, 2014; Staw, 2009). In contrast, excessively increasing levels of knowledge available to teams, without promoting its exchange, may lead to more rigid and confirmatory knowledge processes. Ultimately, this could lead to reliance on familiar or repetitive knowledge rather than exploration of new or diverse knowledge (Harvey, 2013; Perry-Smith & Mannucci, 2017; Uzzi & Spiro, 2005; Zhou, Shin, Brass, Choi, & Zhang, 2009).

Second, our arguments concern stars, who are a special group of knowledge workers that enact several times the productivity of others. Therefore, we expect that gender differences in external visibility and resource availability are unlikely to be as pronounced as would be the case if we were to consider the more general sample of knowledge workers. Accordingly, although gender differences in factors leading to knowledge availability likely exist between teams with male and female stars, the margin of difference may not be so large as to overpower the benefits stemming from the perception, characteristics, and behavior of female stars. Based on these arguments, we formulate the following hypothesis.

*Hypothesis: Teams with a female star recombine knowledge more broadly than teams with a male star.*

# MeTHODS

## Data and sample

We test our hypothesis in an empirical study of inventor teams and their patented inventions. We rely on patent data because it has proven useful for studying both star knowledge workers (Liu et al., 2019; Tzabbar & Kehoe, 2014) and knowledge recombination breadth (Agrawal, Cockburn, & McHale, 2006; Fleming, 2001; Gruber et al., 2013). To build our dataset, we combine data from the USPTO, PATSTAT and genderize.io.

We first build a sample of star inventors and the patents granted to them by the United States Patent and Trademark Office (USPTO) between 1990 and 2010[[1]](#footnote-1). We use inventor data of USPTO patents provided by the PatentsView initiative (http://www.patentsview.org). We complement this data with patent information at the patent family-level recorded in PATSTAT, the worldwide patent statistical database We use patent families to prevent double-counting and to better estimate patent-based measures of a single invention, particularly knowledge recombination breadth[[2]](#footnote-2) (cf. Martínez, 2011). We then infer the sex of the inventors from their forenames using the genderize.io database (<https://genderize.io/>). Because name-based gender designation is particularly challenging for certain countries and ethnicities, we conduct additional checks relying on US census data[[3]](#footnote-3) as well as independent raters. We exclude names and countries (e.g., China), for which gender designation is not reliable[[4]](#footnote-4). Finally, we match inventor teams with female stars to inventor teams with male stars to account for the gender imbalance in patenting and differences in inventor teams (Ding, Murray, & Stuart, 2006; Sugimoto, Ni, West, & Larivière, 2015). In the subsequent sections, we explain each of the abovementioned steps in depth, first elucidating how we identify female and male star inventors and then giving an overview of the matching approach employed.

***Identifying star inventors.*** Following the definition of stars, we identify star inventors based on their exceptional relative performance. To do so, we create a panel dataset covering the universe of inventors who have ever filed a patent at the USPTO and measure their inventive performance at different points in time. In a first step, we rely on the inventor disambiguation provided by the PatentsView initiative to identify unique inventors. The disambiguation is based on an algorithm outlined in Li et al. (2014) and allows for a robust identification of individual inventors of granted US patents since 1976 (Melero, Palomeras, & Wehrheim, 2020). In a second step, we link more than two million unique inventors to over seven million patents. Next, we identify star inventors based on the quantity and impact of their cumulative inventions, i.e., inventor performance, following the approach proposed by Tzabbar and Kehoe (2014). We calculate inventor performance as the product of two factors. The first is the number of patents (*InvPatij*) for which inventor *i* applied by year *t*, divided by the years since the inventor’s first patent filing (*IndTenureit*). This is multiplied by the second factor, the sum of forward citations to all patents filed by inventor *i* by year *t* (*ForwardCiteijt*) discounted by the years since the patents were granted (*YearsSincePatGrantijt*):

We update this inventor performance measure on a yearly basis once an inventor has entered the dataset through a first patent filing. We determine an inventor’s main industry based on the technology field (Schmoch, 2008) in which an inventor *i* has filed most of his or her patents by year *t*. This implies that the inventor’s main industry may vary over time as stars are conceptualized relative to their peers. Therefore, it is important to define and adapt the peer group in case stars switch between fields. As exemplified in Figure 1, we follow prior research (Tzabbar & Kehoe 2014) and consider every inventor with an inventor performance score of more than two standard deviations above the mean for a given year in a given industry as a star inventor.

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| Insert Figure 1 about here |

Altogether, we identify 91,762 star-inventor-years in the sample. These star-inventor-years can be attributed to less than one percent of inventors who ever filed a patent at the USPTO. Yet, they are responsible for more than 20% of all patents filed between 1990 and 2010. This underlines the disproportionate contribution of star inventors and lends credence to our star identification procedure.

Since we are interested in the difference in knowledge recombination breadth of inventor teams with one female versus one male star, we further limit the sample to patents filed by exactly one star inventor and at least one non-star coinventor. We exclude all private inventions, i.e., patents filed without an organization, as we aim to investigate team processes in organizational settings. For the observations retained in the sample, we derive the gender of the star based on the procedure described in Appendix 1 and only keep stars for whom we can reliably disambiguate gender. Following the outlined steps leaves us with approximately 55,000 teams that filed patents with roughly 7,000 distinct star inventors. Of these teams, 951 involved one of 189 female star inventors.

***Matching teams with female stars to teams with male stars.*** Even though the proportion of female stars has steadily increased over the years (see also USPTO, 2019), female stars continue to be substantially underrepresented among star inventors. As summarized in Appendix 2, women make up 2.64% of star inventors (from 1990-2010), with the highest shares in the fields of biotechnology (9.64%) and basic material chemistry (7.05%), i.e., fields which tend to have higher rates of female participation in general. Besides these differences in the representation of female versus male stars across fields and time, a comparison of the distribution of key covariates (see Appendix 3) suggests that there are other differences between the teams they work in. To account for these differences and the imbalance between male and female star inventors, we employ a matching approach.

Using coarsened exact matching (CEM), inventor teams with a female star are matched to inventor teams with a male star (Iacus, King, & Porro, 2011, 2012). The CEM technique ensures balance along a set of covariates between the treatment group, i.e., inventor teams with a female star, and the control group, i.e., inventor teams with a male star[[5]](#footnote-5). The CEM algorithm involves four steps (Blackwell, Iacus, King, & Porro, 2009). First, a set of covariates is selected and coarsened into meaningful categories. Next, treated- and non-treated observations are sorted into strata based on their values along the coarsened matching variables, or alternatively, on their exact original values (exact matching). Third, observations assigned to strata that do not have at least one treatment and one control observation are pruned. Lastly, weights are calculated and assigned to each observation to maintain balance within and across strata[[6]](#footnote-6). These weights are used in all later analyses.

We match our data at the team level along the following variables: *patent filing year* (21 years), *patent WIPO field* (35 fields), and *share of female inventors* (two categories: share above or below the median in the same year and field). By doing so, we obtain 26,793 matched patents of which 951 (3.6%) were filed by inventor teams with a female star. As illustrated in Appendix 3, the matching technique not only yields balance on the matching variables, but also on other key covariates, including team size, team inventive performance, team patenting experience, extent of prior collaboration, technological team diversity, and regional team diversity[[7]](#footnote-7). None of the means of these variables statistically differ between inventor teams with female stars and male stars after matching. To underline the comparability of teams with female and male stars, Table 1 presents a probit model, with having a female star in the inventor team (i.e., being treated) as the dependent variable, and team characteristics as independent variables. Before matching, the share of female inventors and regional team diversity are statistically significant predictors of the treatment, while none of the variables are significant after matching. We are, thus, confident that the sample of 26,793 patents filed by 5,017 different star inventors is balanced and allows for a thorough analysis of our hypothesis.

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| Insert Table 1 about here |

## Measures

***Dependent variable****.* The dependent variable in our analysis is *knowledge recombination breadth*. We operationalize this variable as per Gruber et al. (2013). The measure is an adapted Herfindahl index, which captures the distribution of a focal patent’s backward citations across different technological domains. Technological domains are represented by four-digit International Patent Classification (IPC) subclasses. The IPC system emerged as a result of the Strasbourg Agreement in 1971 and helps patent authorities around the globe to group patents in technology classes and retrieve prior art when examining patent applications[[8]](#footnote-8). A patent filed at the USPTO cites prior patents. The referenced patents are assigned to differenttechnological domains (IPC subclasses). The share of a specific technology domain in one referenced patent is captured in. The cumulative number of references to technological domains by all cited patents is captured in . Based on these parameters, *knowledge recombination breadth* is calculated as follows:

Knowledge recombination breadth is bound between one and zero and increases when a patent references a larger number of distinct technological domains. It decreases when it references the same technological domain multiple times (Ferguson & Carnabuci, 2017). A distribution of the variable is depicted in the histogram in Figure 2. The average knowledge recombination breadth in our sample is 0.867, with a standard deviation of 0.195. Many patents report a knowledge recombination breadth of zero because they only reference patents from one technological domain. Running our analyses on a subsample where these patents are excluded does not change our results.

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***Independent variable.*** Our main independent variable is an indicator for *female star inventor*. The variable takes the value of one when a patent was filed by an inventor team with a female star and zero when it was filed by an inventor team with a male star. As we excluded patents with multiple stars and patents without any gender-designated star, these categories are mutually exclusive. In our matched sample, approximately 3.6% percent of the patents were filed by inventor teams with a female star.

***Control variables.*** Several controls are applied at the team, star, and patent level that are likely to influence knowledge recombination breadth.

*Team-level controls.* At the team level, we control for *team size* since larger teams tend to have a broader knowledge stock to draw from for knowledge recombination. *Team size* is measured by the number of inventors appearing on a patent. We control for the *share of female inventors*, i.e., the share of female non-star team members of all non-star team members for whom we were able to designate the gender. We control for *team inventive performance*, measured as the average non-star team members’ inventor performance as of the year prior to the focal patent’s filing date. This is the same measure we used to identify star inventors and encompasses the quantity and impact of the inventors’ prior patents. Next, we control for *team patenting experience* by looking at both the average number of years and the average number of patents since the non-star team members’ first patent filing. Having more experienced team members will likely increase a team’s knowledge stock. To account for the possibility that team members already know each other, which might enhance the extent to which they share knowledge, we further control for the *extent of prior collaboration*. This is measured as the share of non-star team members who have previously filed a patent with at least one other team member on the focal patent. While patenting experience and team size may account for the size of a team’s knowledge stock, we control for the diversity of a team’s knowledge stock via *technological team diversity* and *regional team diversity. Technological team diversity* captures the number of distinct WIPO fields (Schmoch, 2008) the non-star team members have filed most of their patents in. *Regional team diversity*, on the other hand, is a count of the different countries the team members come from.

*Star-level controls*. At the level of the star, we employ four control variables. Since the star inventors are already pre-selected according to their exceptional relative performance, they can all be assumed to bring an exceptional set of skills and abilities to the team. To still account for differences in this right tail of the inventor performance distribution, we control for *star inventive performance*, which reflects the impact and quantity of the star inventor’s prior performance. We further control for *star patenting experience (years)* and *star* *patenting experience (patents)* to account for the time spent inventing and the number of patents previously filed, presumably increasing stars’ individual knowledge stocks. Next, we control for *star technological diversity*, which counts the number of different WIPO fields (Schmoch, 2008) the star inventor has previously patented in. Lastly, we add *country fixed effects* for the country of the star inventor based on the location that was recorded in the patent application process.[[9]](#footnote-9)

*Patent-level controls.* Finally, we also control for patent characteristics. The *number of patent claims* controls for the scope of the invention that is protected by the patent. The broader the scope of a patent, the more likely it combines different bodies of knowledge. The *size of the patent family* controls for the different patent applications that belong to the same simple DOCDB family. The size of the patent family can be an indicator for the invention’s value as patent families also cover patent applications for the same invention with patent offices other than the USPTO. Given the costs associated with patenting, applications will only be filed in multiple jurisdictions if deemed worthy. The *number of backward citations* captures the number of references a patent makes to other patents and accounts for the fact that our dependent variable knowledge recombination breadth and the precision of its measure increase with more backward citations (Gruber et al. 2013). The *number of patent applicants* controls for the number of distinct applicants, who appear on the patent filing and are not listed as inventors. As we excluded private patents from the sample, the applicants are firms or organizations. We employ *patent filing year* fixed effects to account for time trends in the data, such as more knowledge being recombined in recent years and increased female patenting activity. Lastly, we use 131 *technology class fixed effects* based on the 3-digit IPC subclasses a focal patent has been assigned to. These fixed effects control for heterogeneity in patenting behavior across technological fields.

Table 2 lists summary statistics and descriptions for each of the presented variables. Table 3 further presents bivariate correlations. Correlations between the independent variables are relatively low, indicating that collinearity should not be a concern.

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# Results

To test our hypothesis, we run multivariate linear regression models and estimate how broadly teams with female stars recombine knowledge compared to teams with male stars. Table 4 presents five linear regression models testing the hypothesis that teams with female stars recombine knowledge more broadly than teams with male stars. In Model 4.1 we start with the main independent variable female star inventor, without including any controls, and observe a positive and statistically significant relationship with knowledge recombination breadth (*β* = 0.060, *p* < 0.01). We then subsequently add the weights obtained from the CEM matching that ensure a balanced sample between patents filed by inventor teams with male stars and patents filed by inventor teams with female stars (Model 4.2), the team-level controls (Model 4.3), the star-level controls (Model 4.4) and patent-level controls (Model 4.5).

Across these model specifications, we see a positive and statistically significant relationship (*p* < 0.01) between having a female star on the team and knowledge recombination breadth, on average. Importantly, the effect size decreases from 0.060 to 0.025 when moving from the first to the second model, indicating that our matching achieves the goal of improving balance in the sample and that it is important to control for inherent team differences. The effect size remains robust as more controls are added, with only a slight decrease to 0.023 in the final model that includes all controls. At the same time, the model’s explanatory power increases with the inclusion of the control variables, resulting in an adjusted R-square of 0.228 in the final model.

To illustrate the magnitude of the effect, we benchmark the coefficient of female star inventor against other coefficients in the model. Adding one additional member to the team, for example, is associated with an increase in knowledge recombination breadth by 0.003 on average, holding everything else constant. We can extend this comparison to variables, which we normalize by their standard deviation to ease interpretability (as indicated in Table 2). An increase in a stars’ technological diversity by one standard deviation, for example, is related to an increase by 0.018 in knowledge recombination breadth, on average. Similar effect sizes can be observed for one standard deviation changes in star inventive performance and prior collaboration. Only for technological team diversity we find a slightly larger point estimate of 0.027. Altogether, we interpret the results summarized in Table 4 as support for our hypothesis and as an indication for a meaningful and relevant effect.

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| Insert Table 4 about here |

## Robustness checks and additional analyses

We test the robustness of our findings and refute alternative explanations in a series of post-hoc analyses. First, we discuss and address concerns regarding endogeneity and sample selection bias. We then provide suggestive evidence in support of the proposed mechanism. Finally, we show that our results are robust to using alternative specifications of the dependent variable and an alternative estimation strategy.

***Endogeneity.***A central concern that may threaten the validity of our findings is that team composition and project choice are not random. In other words, the presence of female stars may not be exogeneous with regard to team or project characteristics, which may bias the OLS regression estimates (Wooldridge, 2002). Despite our rich set of control variables, the examined relationship between the presence of a female star and team knowledge recombination may be biased by endogeneity from two main sources. First, reverse causality might occur as anticipated outcomes may affect the likelihood that female stars are assigned to specific types of teams or projects. If female stars were, for instance, assigned to teams that are *better* at recombining knowledge, we would obtain biased coefficients in the OLS regression. Second, omitted variables may influence both the independent and the dependent variable, since through the matching and controls we only ensure that there are no differences on observables between teams with female and male stars. Teams or projects with female stars may, however, differ from those with male stars on unobserved factors that could also relate to knowledge recombination. For instance, one possibility could be that teams with female stars work on broader, more interdisciplinary topics with higher potential for knowledge recombination, and this may not fully be captured by our team- and patent-level controls such as technological team diversity.

To mitigate these concerns, we use an instrumental variable (IV) regression as a robustness check. We use the *share of female inventors per industry, year and country/state*[[10]](#footnote-10) as an instrument. A valid instrument needs to be relevant, i.e., correlated with the endogenous variable (female star), and exogenous, i.e., not correlated with the dependent variable (knowledge recombination breadth) or the error term capturing unobserved factors in ways other than though the endogenous variable (Wooldridge, 2002). The share of female inventors per industry, year and country/state can be considered relevant because the likelihood of having a female star on a team is determined by the pool of active female inventors in the peer group (same year, industry and country/state). A higher share of female inventors in the peer group increases the likelihood of one of them becoming a star and working on a patent in that industry, year, and country/state. The relevance of the instrument is also validated by our data as the instrument exhibits a positive correlation with the endogenous variable female star (correlation *=* 0.072, *p* < 0.01). Conditional on the controls, especially those for team characteristics including the share of women on the team, exogeneity is given, as the share of women in the peer group is theoretically unrelated to the focal team’s knowledge recombination other than through the focal female star.

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| Insert Table 5 about here |

First- and second-stage results of the IV regression are shown in Table 5. First-stage IV results (dependent variable: female star) indicate that the instrument coefficient is highly significant and positive (β = 0.275; *p* < 0.001). The Cragg–Donald Wald *F*-statistic takes the value of 205.34 and thus rejects the null hypothesis of weak model identification (i.e., that the instrument explains only a small part of the variance in the endogenous regressor), indicating sufficiently strong instruments (Bound, Jaeger, & Baker, 1995; Staiger & Stock, 1997)[[11]](#footnote-11).

Second-stage results corroborate the baseline results from Table 4, as the coefficient of female star is positive and significant (*β* = 0.596; *p* < 0.01). The size of the coefficient in the second stage of the instrumental variable regression is larger than in the OLS regression. This change in the coefficient size can be attributed to the use of a continuous instrumental variable to instrument a binary endogenous variable. As the instrumented variable represents the probability of having a female star (not a dummy), the interpretation of the coefficient size has changed.). Overall, the IV regression confirms our main results.

***Sample selection bias.*** Employing a matching technique increases the balance between treatment and control units in the later analyses but might also introduce bias by focusing on a very special set of observations. In our analysis, we use approximately 27,000 (49%) of about 55,000 patents which would theoretically qualify for the analysis. Even one step earlier, in the gender designation process, we lose roughly 15% of observations because the stars’ gender cannot be determined accurately (see Appendix 1). To address potential concerns that our final sample is not representative, we estimate a probit model that predicts an inventor team’s likelihood to end up in the final sample based on its characteristics. Model A4.1 in Appendix 4 shows that the inventor teams we analyze are, on average, smaller with a lower share of female inventors but a higher level of inventive performance as compared to inventor teams which are not included. While there is no difference in terms of star characteristics between these teams, the related patents tend to have more claims, more backward citations and more applicants, on average. Most of these differences are small and can be explained by the employed matching approach which, by construction, changed the composition of patents in the sample. For example, many older patents and patents from fields with only male stars could not be matched. To ensure that our findings are generalizable, we rerun the analysis on the full sample for which the gender of the star is available. As shown in Model A5.1 in Appendix 5, which summarizes the robustness checks, the findings remain stable. We are, thus, confident that sample selection bias introduced via the matching approach is not an issue and that our findings generalize to the broader population of inventor teams. We also obtain similar results with different numbers of categories and thresholds used for coarsening the matching variables in the CEM procedure.

***Mechanism.*** Our main argument for the hypothesized positive effect of female stars on the recombination of knowledge rests on the assumption that the integration of knowledge in teams (where teams with female stars are likely to have an edge over teams with male stars) is more important than the availability of knowledge (where teams with female stars are likely to be disadvantaged). Unfortunately, our data does not allow us to unequivocally test and establish mechanisms. Nevertheless, we attempt to provide suggestive evidence for our theoretical arguments by conducting an indirect test. We identify two situations between which the relative importance of knowledge synthesis is likely to vary, while the importance of access to external knowledge does not. Specifically, we distinguish between teams which have never worked together and those that have a collaboration history.

Teams which have never worked together before might experience both a higher need for and more difficulty in integrating knowledge. Team members in newly formed teams likely lack established systems of organizing and exchanging knowledge, which are built through a history of interaction (Argote, Aven, & Kush, 2018; Majchrzak, Jarvenpaa, & Hollingshead, 2007). Hence, they are likely to find knowledge integration more challenging than teams that have collaborated before. In new teams, the role of the star as facilitator and “synthesizer” of knowledge exchanges (Liu et al., 2019) thus becomes even more important. Status differences also tend to be more pronounced in the early phases of collaboration (Bunderson, 2003), potentially hindering communication and free exchange of knowledge. Therefore, the influence of knowledge integration on knowledge recombination outcomes is likely to be more pronounced for newly formed teams, compared to those with a history of collaboration. This suggests that the presence of a female star, via the knowledge integration channel, should have greater influence on knowledge recombination breadth in newly formed teams. At the same time, we do not expect that access to external knowledge is more or less important in teams without prior collaboration history as compared to teams who have worked together before.

Accordingly, we test these arguments by interacting a dummy labeled one if the team has *no prior collaboration experience* (i.e., if the extent of prior collaboration is zero, such that none of the team members have worked together on a team before) with the female star variable in the regression. As shown in Model 6.1 of Table 6, the main effect of not having collaborated before is negative. In line with our arguments, the interaction of female star and no prior collaboration is positive and significant (*β* = 0.035; *p* < 0.01). This indicates that the effect of a female star on the team’s knowledge recombination is more positive when the team has never worked together before. We obtain similar results for the interaction when using *no prior collaboration with the star inventor* as an alternative variable, taking the value one if the star has never worked together with any of the non-star team members, as shown in Model 6.2.

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| Insert Table 6 about here |

***Alternative estimation strategy.***Our dependent variable knowledge recombination breadth is bound between 0 and 1. We choose weighted OLS in our main analyses because it makes the interpretation of the results simple and straightforward. Yet, to investigate possible issues of model dependence, we also run a Tobit model censored at 0 and 1 (Tobin, 1958). As shown in Model A5.2 in Appendix 5, our results remain robust.

***Alternative variable specification.***Our dependent variable measures the diversity of technology classes reported in a patent’s backward citations. The reliability of this approach hinges on the assumption that backward citations qualify as an objective indicator for an invention’s knowledge recombination breadth. As opposed to the patent examination process at the European Patent Office (EPO), the patent application process at the USPTO allows not only examiners but also applicants to reference prior knowledge. Specified in the duty of disclosure, patent applicants are required to disclose all information known to the individual. If individuals fail to cite a reference, they put their patent’s validity at risk (Kuhn, Younge, & Marco, 2020). Thus, in theory, all applicants have the same incentive to cite prior work when applying for a patent. Still, one may argue that personal characteristics, such as willingness to take risks or time and resources available for searching prior patents, influence the referencing process.

To rule out this alternative explanation, we create a second measure of knowledge recombination breadth, which excludes all backward citations made by the applicants themselves (on average, 40% of all citations). As shown in the Model A5.3 of Appendix 5, our results remain stable when using this adapted measure of knowledge recombination breadth. We are, therefore, confident that our results are not driven by different referencing behavior between inventor teams with female and male stars. Furthermore, we also use a traditional Herfindahl index (e.g., Tunzelmann, 1998) as an alternative measure for knowledge recombination breadth. This index is invariant to how broadly each of the referenced patents were distributed across technological areas. We again obtain consistent results, as reported in Model A5.4 of Appendix 5.

# Discussion and Conclusion

Our study aims to investigate differences in knowledge recombination breadth between teams including a female star versus a male star. Extending prior research, we characterize potential differences between male and female stars that may lead to differences in the recombination of knowledge in the teams they are a part of. Drawing from literature on status and psychological differences regarding the perception, characteristics, and behavior of women and men, we elucidate how gender differences between stars translate into differences in the breadth of knowledge recombination in teams.

We view knowledge recombination breadth as a function of the amount of knowledge available for recombination as well as of teams’ knowledge integration processes. Specifically, we argue that male stars enhance teams’ access to external knowledge due to their greater status in organizations, while female stars demonstrate behaviors and characteristics which facilitate knowledge integration processes in teams. We also theorize that teams’ benefits from superior knowledge integration outweigh those associated with accessing external knowledge. Our empirical analysis of inventor teams with female and male star inventors provides support for the hypothesis that teams with female stars recombine knowledge more broadly than teams with male stars.

## Theoretical implications

Our research extends knowledge on the role of female star performers in knowledge-intensive activities and contributes to current research debates in three main ways. First, we contribute to the star literature (Groysberg et al., 2008; Lacetera et al., 2004; Rothaermel & Hess, 2007; Zucker, Darby, & Brewer, 1998), where our knowledge to date is largely built around male stars. In particular, prior work has established both benefits and costs of stars’ presence on teams. Complementing this existing research, which indicates the organizational value of stars in knowledge work is contingent upon their collaborations with others (Chen & Garg, 2018; Grigoriou & Rothaermel, 2014; Kehoe & Tzabbar, 2015; Oettl, 2012), we highlight the importance of considering the star’s individual characteristics. Here, our findings indicate that the gender of the star matters and that female and male stars play different roles in teams, leading to systematic differences in knowledge outcomes.

Second, we attempt to address a contradiction emerging from literatures on gender differences related to status and gender differences related to psychological perceptions, characteristics, and behaviors. We disentangle the relevance of increasing available knowledge as raw material for recombination in teams, and the processes that ultimately allow this diverse material to be integrated into creative output (Hargadon & Bechky, 2006; Harvey, 2014; Liu et al., 2019). Here, our findings suggest not only that stars can differentially impact these two determinants, but that the relative importance of knowledge integration processes is a key driver of teams’ knowledge recombination outcomes.

Finally, our findings also contribute to the social perspective on team creativity and knowledge creation, which considers the importance of interaction and collaboration within teams as a central determinant of breakthrough creativity (Perry-Smith & Shalley, 2003). By arguing that teams interact and communicate with female and male stars in varied ways, our findings suggest that non-star team members’ collaboration with female and male stars does not yield identical knowledge outcomes. We, thus, contribute to the literature that examines the role and functioning of team social processes as key determinants of knowledge recombination (e.g., Harvey, 2014; Li et al., 2020; Mannucci, 2017).

## Practical implications

Our findings are also of high practical relevance. First, our findings imply that a special emphasis on identifying and advancing the progress and special skills of female knowledge workers may be fruitful for organizations and society. Our study shows that the characteristics and behaviors displayed by female stars, on average, present advantages for teams’ knowledge recombination outcomes. By better understanding where these differences come from, organizations can leverage the untapped potential of women who are largely underrepresented among star knowledge workers.

Second, consistent with prior work (Chen & Garg, 2018; Kehoe & Tzabbar, 2015; Tzabbar & Kehoe, 2014), our findings emphasize that stars represent a double-edged sword for organizations in that they can both facilitate and hinder different aspects of knowledge recombination. Our study draws particular attention to stars’ gender. To fully utilize the potential of stars in teams, organizations should strive to balance the benefits that male versus female stars represent against their potential limitations. For example, knowledge recombination in teams with male stars may benefit from systematic measures designed to enhance the integration of knowledge (Li et al., 2020). Managers may improve knowledge recombination breadth in such teams by encouraging stars to more frequently display behaviors that express interpersonal sensitivity and approachability.

Third, our findings suggest that organizations should pay particular attention to the knowledge bases of non-star team members as sources of new and unique ideas. Prior work has highlighted the danger of overreliance on stars’ knowledge bases in teams (Chen & Garg, 2018; Kehoe & Tzabbar, 2015; Tzabbar & Kehoe, 2014). Our findings suggest that, especially when the team includes a male star, special emphasis should be placed on exploring and integrating the unique knowledge bases of all team members, since novel ideas and diverse knowledge may not otherwise be exchanged and integrated in such teams to the same extent as in teams with female stars.

## Limitations and directions for future research

As with most empirical undertakings, our study comes with limitations that provide opportunities for future research. First, the usual concern with using patent data is that only patented inventions can be observed and not projects that failed. Since failed patents are not captured by our dependent variable, a systematic difference in the failing rate between teams with female and male stars could be problematic but seems unlikely given our focus on highly successful inventors.

Although we use a matching approach to minimize differences in team composition, include several star-related controls in our analyses, and provide an instrumental variable analysis, our data do not offer a random treatment allocation which would allow us to uncover causal relationships. Therefore, the potential to infer causality from our study is constrained by the data and design, and future research may aim to confirm our findings using data from random or quasi-random designs.

The measures we used to identify stars and to capture knowledge recombination breadth have some limitations. While being in line with prior literature, finding a cut-off point beyond which the performance of an individual qualifies for stardom is always arbitrary. Also, while we consider our choice of the measure for knowledge recombination breadth justified based on prior literature, this is not the sole way of measuring the breadth or diversity of knowledge recombined, nor is the combination of technological classes in patents itself the only way to proxy knowledge categories integrated in creative outputs. Therefore, it is important that future work replicates our results in different contexts, using different creative outputs and strategies for identifying stars knowledge workers.

We discuss various potential differences regarding the perception, characteristics, and behavior of male and female stars and provide some tentative evidence on potential mechanisms. Our main goal is to manifest the observed differences in outcomes by running a large-scale analysis across industries, years and geographical areas. However, our data do not allow us to fully disentangle the mechanisms that may lead to the observed difference in knowledge recombination breadth. Furthermore, in reality, the mechanisms may be interrelated, such that knowledge integration and knowledge availability are not completely independent. Future research may aim at closely examining the underlying mechanisms to better understand the dynamics and differences between teams with female and male stars, potentially by conducting qualitative studies at the micro-level or laboratory experiments.

To designate the gender of star inventors, we rely on their first names. Common problems in the gender designation of Asian names force us to exclude Asian inventors from the sample (see Appendix 1 for details). The generalizability of our findings is therefore limited to non-Asian inventors, which at the same time opens the door for future research to investigate how cultural norms and different gender roles across countries might influence processes and outcomes in teams with female versus male star knowledge workers.

Finally, it would be insightful to identify additional contingencies, such as situational factors (e.g., time pressure) or network characteristics (e.g., centrality of stars in knowledge networks) that influence whether teams with female or male stars perform better. Getting closer to these contextual forces may advance our general understanding of team dynamics with stars and the role of star characteristics including but not limited to the star’s gender.

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**Appendix**

Appendix 1: Gender designation process

Appendix 2: Representation of female star patents across time and fields

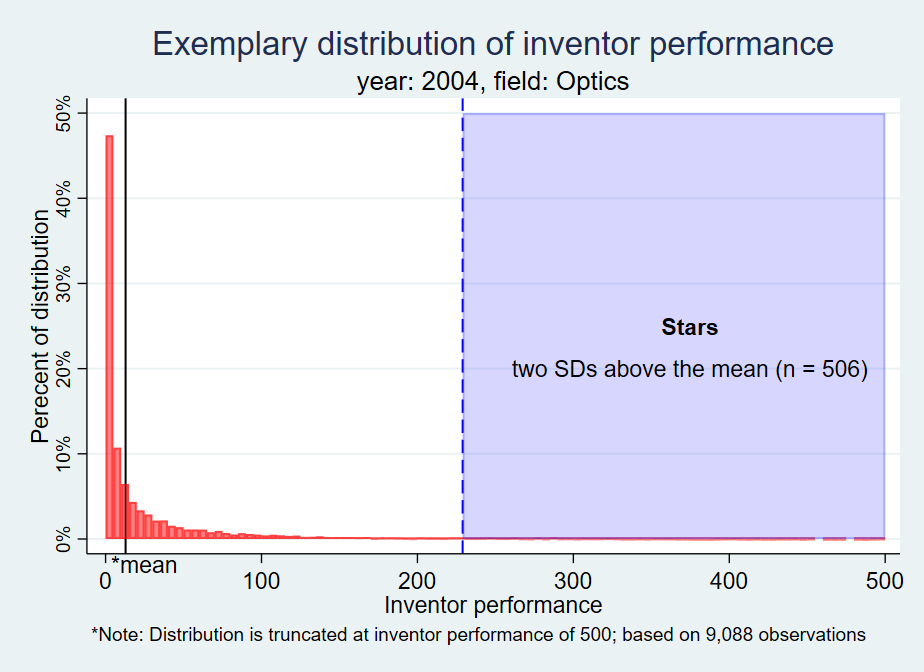
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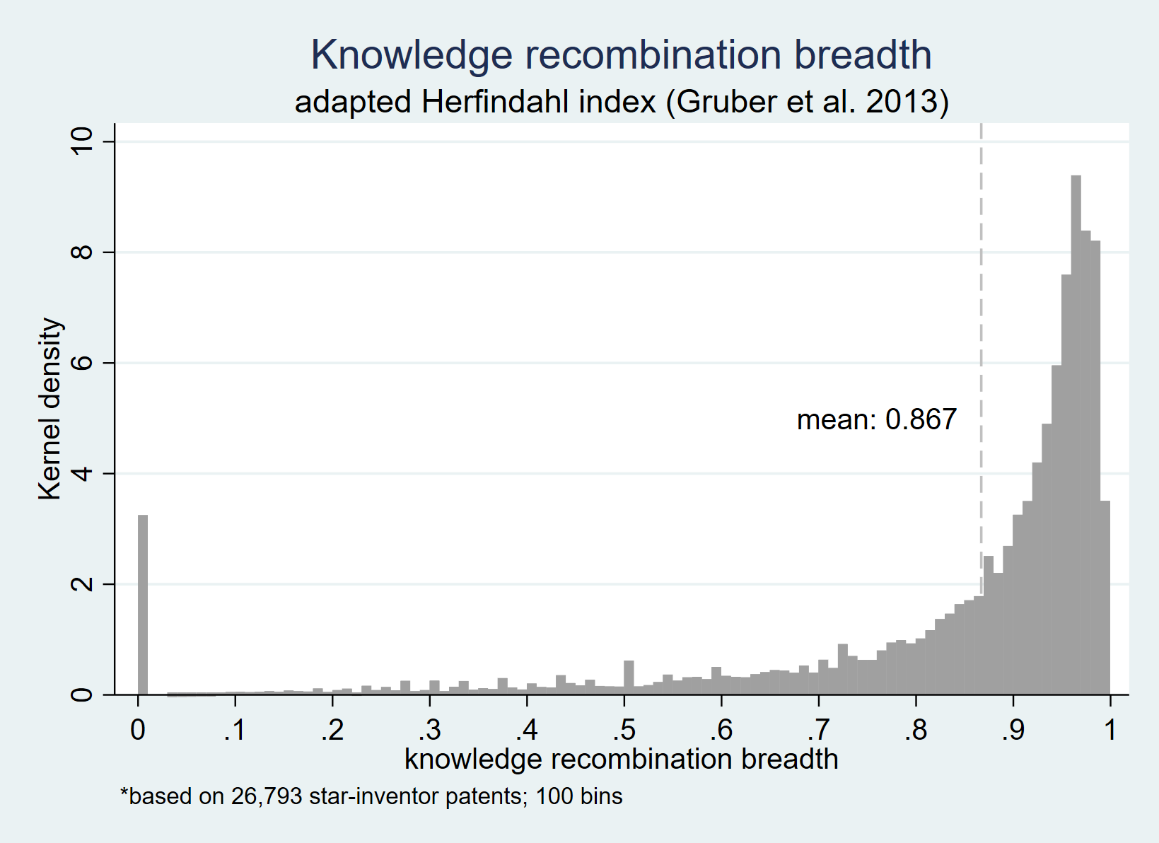
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# Figures and tables

**Figure 1: Exemplary identification of star inventors**



**Figure 2: Distribution of knowledge recombination breadth**



**Table 1: Probit regression of female star on inventor team characteristics before and after matching**



**Table 2: Descriptive statistics and variable overview**

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# Appendix

**Appendix 1: Description of the gender designation process**

The accuracy and value of our analysis hinges on the correct designation of the inventors’ gender. In general, there are two possible mistakes one can make: i) identify stars as male even though they are female and ii) identify stars as female even though they are actually male. While both mistakes would lead to the true effects being underestimated, the second case is more concerning in our setting. If we consider female stars as the treatment and male stars as a control group, it would imply that we falsely sort units from the control to the treatment group. Given that the treatment group is much smaller than the control group (see Appendix 1), these “false treatments” would have a stronger effect on the average effect size estimated for the treatment group as a “false control” would have on the effect size estimated for the control group. We therefore employ several steps to reduce the risk that we make the second mistake, i.e. classify stars as female even though they are actually male. These steps will be outlined in the following.

The USPTO collects limited information on patent inventors (full name, city and state). The main available information that allows us to identify gender is the inventors’ first name(s), and potentially his or her country of residence. Various name-to-gender inference methods exist and are used for research purposes. These algorithms can predict a person’s gender from their name with the help of large labeled datasets, sometimes enriched with information from social media, cultural background, and sociolinguistic insights (Santamaría & Mihaljević, 2018).

We use the genderize.io API (https://genderize.io/) to designate the star inventor’s gender based on his or her first name(s). A useful feature of the genderize.io API is that it not only provides a gender prediction but also two indicators for the prediction’s reliability. Genderize.io uses social network profiles linked to specific first names to report a gender as well as name count and an accuracy score. While the name count states how often a social network profile was linked to a particular name, the accuracy score reports the percentage of profiles for which the name was associated with the predicted gender (Wais, 2016). Due to these advanced frequency and accuracy indicators and because of its global and continuously growing reach, genderize.io has been shown to offer strong advantages in comparison to other gender designation algorithms (Wais, 2016).

A problem inherent in name-to-gender designation methods is that gender may depend on the language spoken or the country of origin. For some countries and ethnicities, it is difficult to derive a person’s gender from their first name, particularly if the first name is not written in Latin script and for languages for which meaning is derived from characters and diacritics (e.g., Mandarin, Japanese). In addition, there is a difference in the name order, commonly known as the Eastern versus Western name order, as some Asian cultures typically use their family name first, which can increase inconsistencies for translated names (Jacques, 2009). This generally results in less confident predictions for names of Asian origin (Santamaría & Mihaljević, 2018).

In the patent application process, names of Asian origin are often translated by patent officers and hence are not reliable as different examiners might write names in different ways. Additionally, if transliterated to Latin script, it is no longer possible to deduct gender. The high number of inventors with Asian names makes this particularly problematic (USPTO, 2019). This issue affects inventors living in Asian countries as well as inventors from Asian origin residing elsewhere.

For these reasons, we carefully assessed the accuracy of the gender designation for Asian countries as well as for any inventors with names that are likely to be of Asian origin. The results of these checks are presented in Table A3. First, we checked the prediction accuracy of the algorithm for Asian countries (China, Japan, South Korea, and Taiwan) by relying on the judgment of experts, i.e., two locals from each of the respective countries, in a random draw of up to 300 names. We found that for these countries, no more than 60% of female inventors were correctly predicted by the algorithm, on average. Second, we ran similar checks to assess the problem for people of Asian ethnicity living in foreign countries. We used US census data[[12]](#footnote-12) to determine inventors most likely ethnicity based on their last name (Kerr & Lincoln, 2010). Again, we drew a random sample of US inventors whose ethnicity was Asian with a probability of more than 50% and detected a similar pattern as for inventors from Asian countries. No more than 31% of inventors classified by genderize.io as female were also coded female by our local experts. As a benchmark, we can compare these ratios of accuracy as well as the correlation coefficient to non-Asian US investors for whom the algorithm designated almost 86% of the female inventors correctly.

To circumvent the high likelihood of misidentification for inventors from Asian countries, with names of Asian origin, and with rare names, we restrict the sample used in our analysis to inventors for whom we can reliably assess gender. To construct the sample, we therefore first select exclusively inventors who do not come from China, Japan, South Korea, or Taiwan and for whom US census data does not indicate that they are of Asian ethnicity. Doing so we can identify 8,344 female and male star inventors. In a next step, we rely on the frequency indicators (how many times the name is recorded in the database) and accuracy scores (percentage of data records that are associated with the predicted gender) of the genderize.io database. We retain inventors if their first name is recorded at least 10 times and if the gender prediction is based on an accuracy of 99% or more.[[13]](#footnote-13) This reduces the sample by roughly 15% so that we are left with 7,151-star inventors who qualify for our analyses.

Our restrictive approach leaves us confident that we only retain (female) stars in the analysis for whom we can correctly and reliably assess gender. However, we are aware that this approach limits the generalizability of our findings to non-Asian inventors. There might be cultural differences between Asian and non-Asian countries, also in relation to the role of women, which require us to interpret the findings exclusively for non-Asian inventor teams. We invite further research to verify if these effects also translate into Asian cultures and countries.

**Table A1: Accuracy of gender designation**



**Appendix 2: Representation of female star patents across time and fields**

**Figure A2.1: share of female star patents over time**

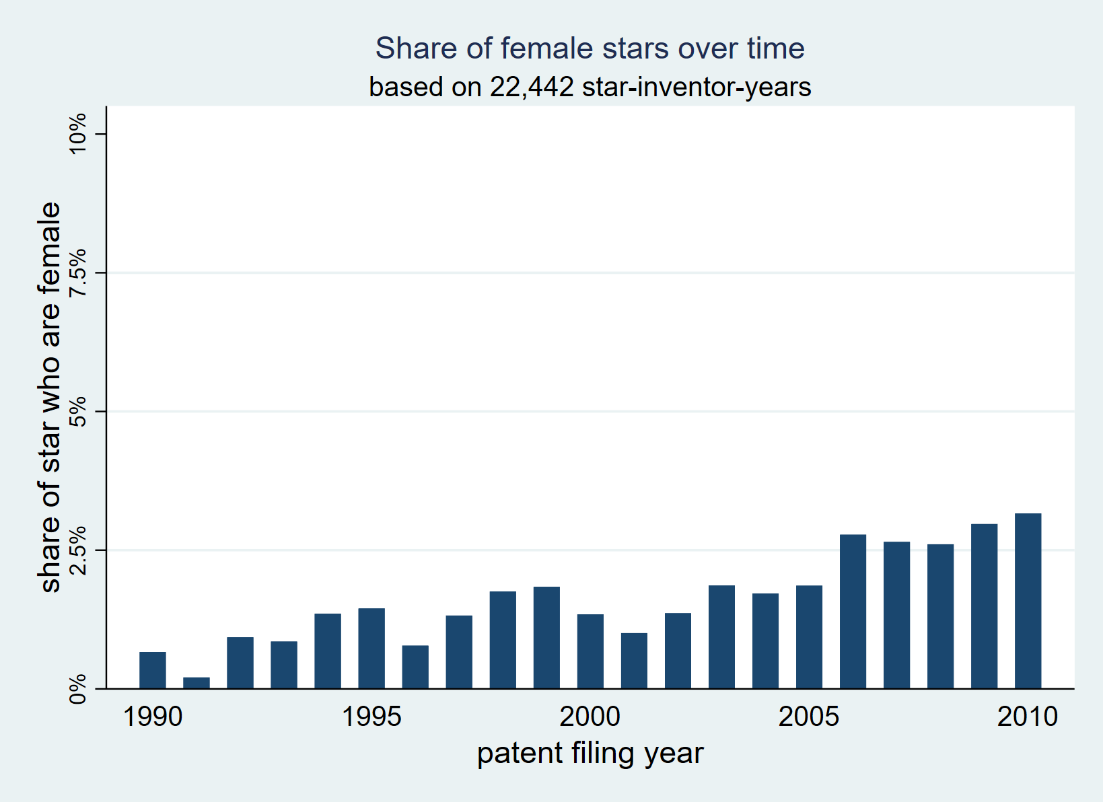


Figure A2.1 depicts the share of unique female stars from all unique stars, for whom we were able to designate the gender in a particular year. For example, in 2010 3.16% of all unique gender-designated stars were female.

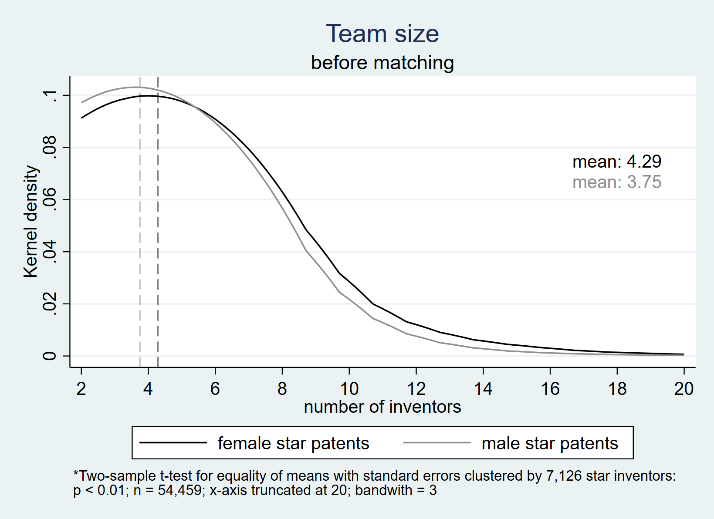
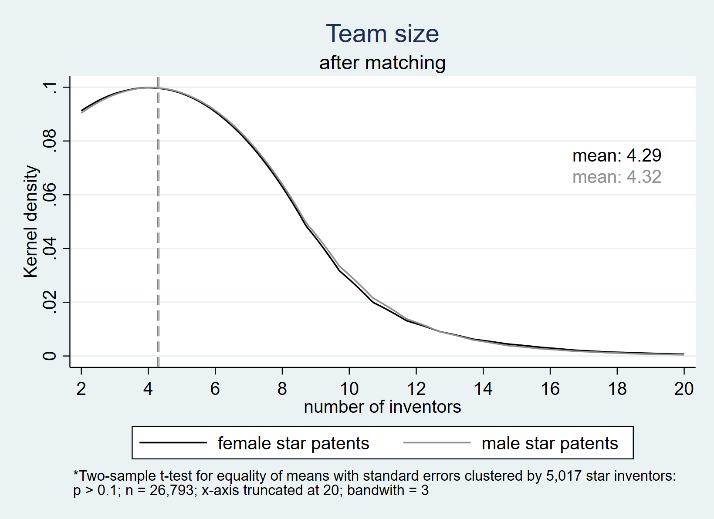
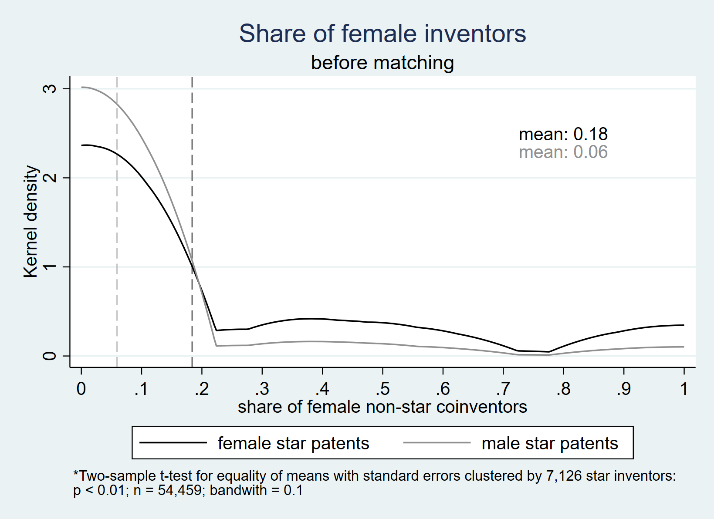
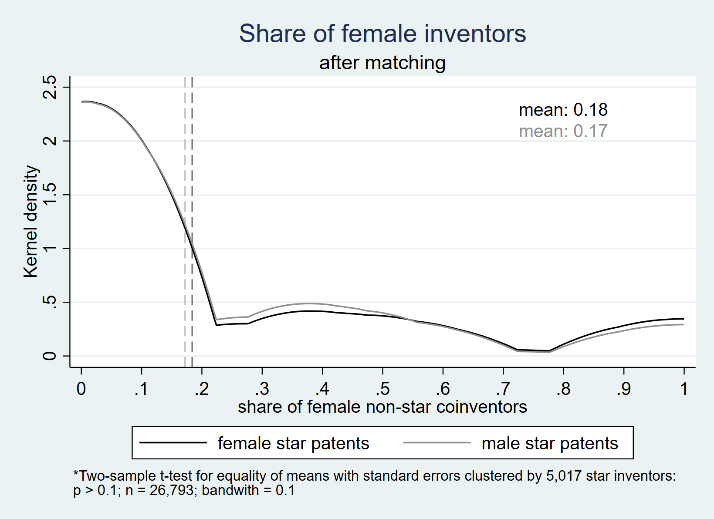
**Table A2.2: share of female (star) inventors across fields**

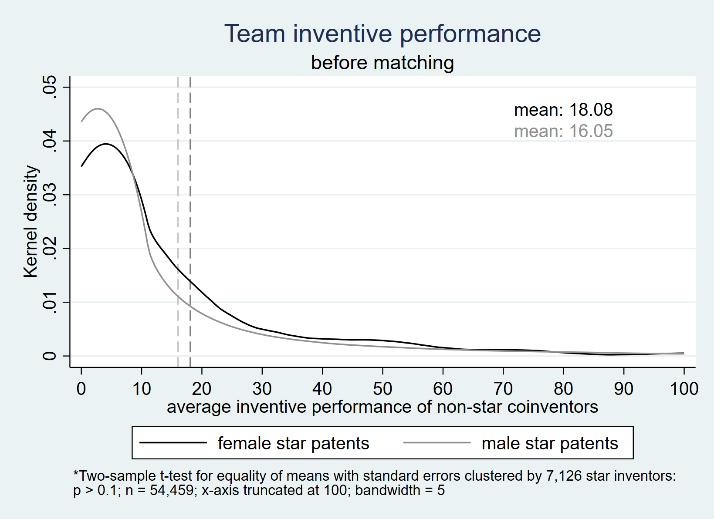
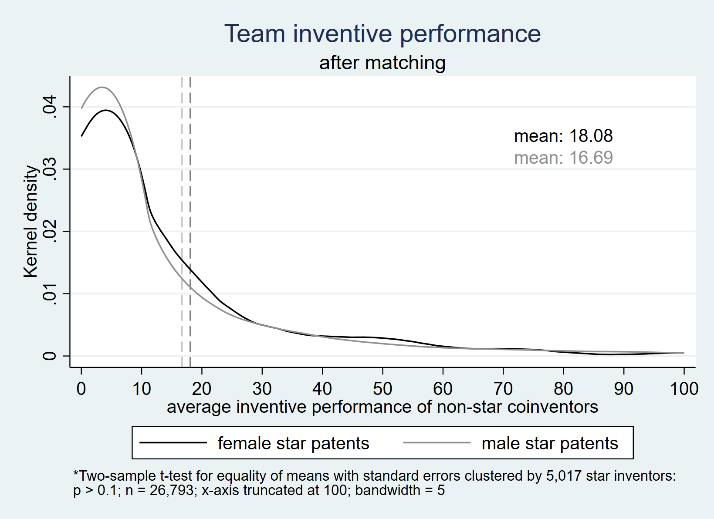


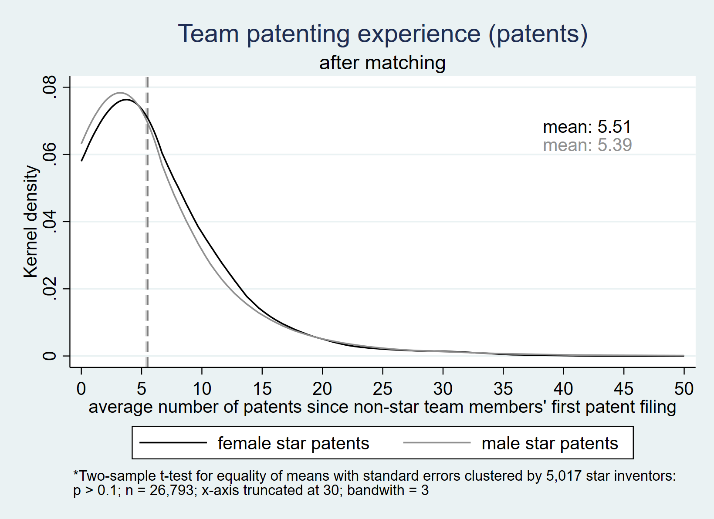
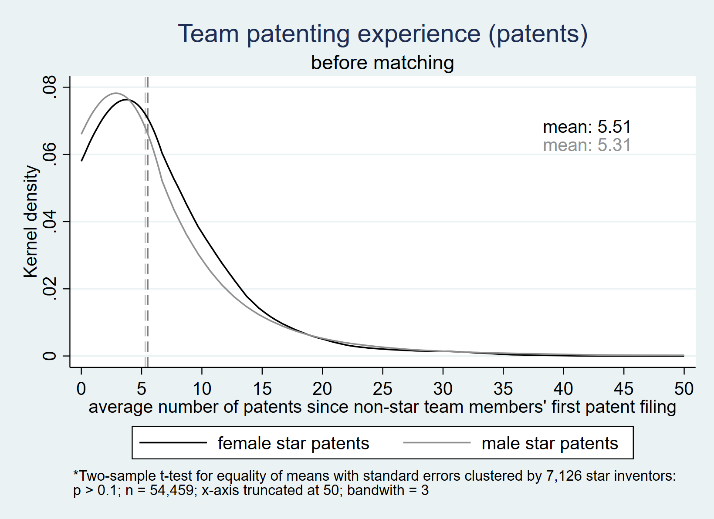
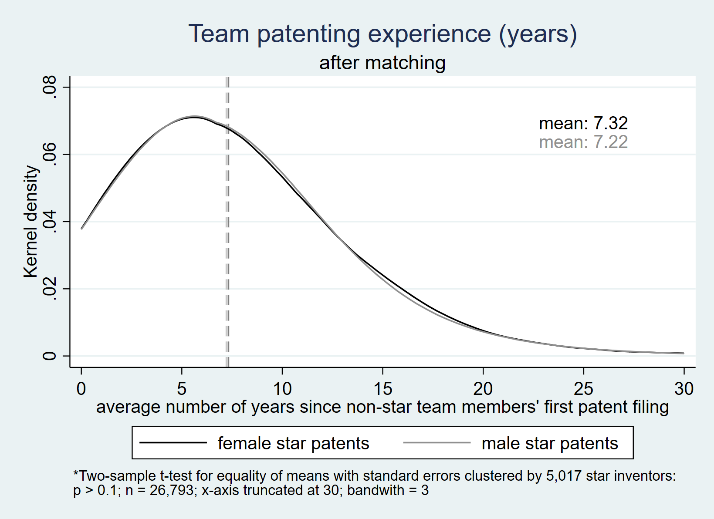
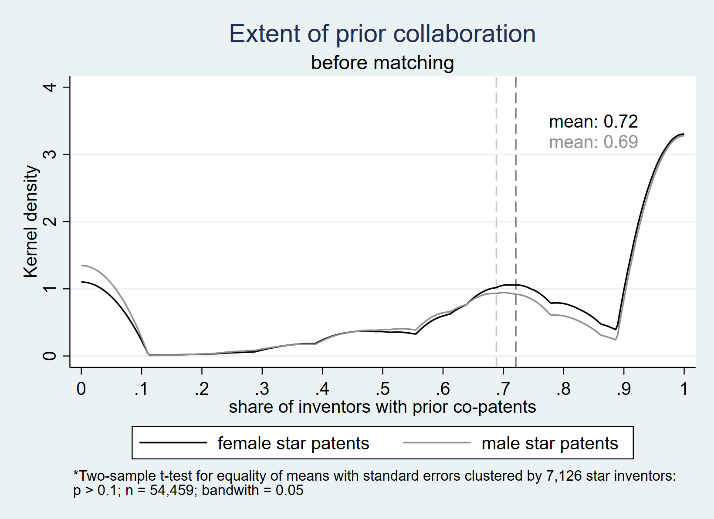
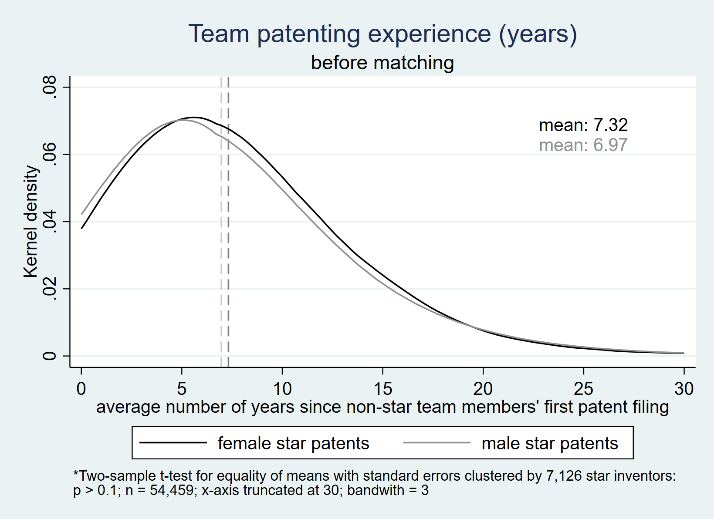
Table A2.2 summarizes the share of unique female (star) inventors of all unique gender-designated (star) inventors across fields between 1990 and 2010. For example, 9.64% of all gender-designated star inventors who have filed most of their patents in biotechnology are female. Similarly, 17.16% of all unique gender-designated inventors in biotechnology are female.

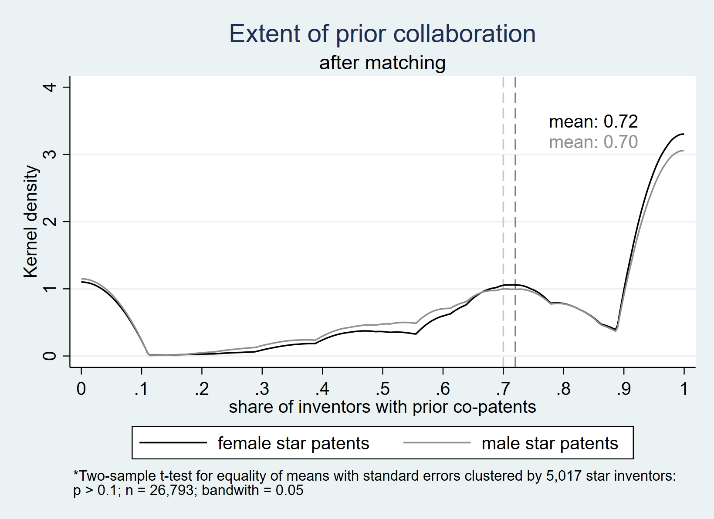
**Appendix 3: Distribution of inventor team and patent characteristics for female versus male star team before and after matching**

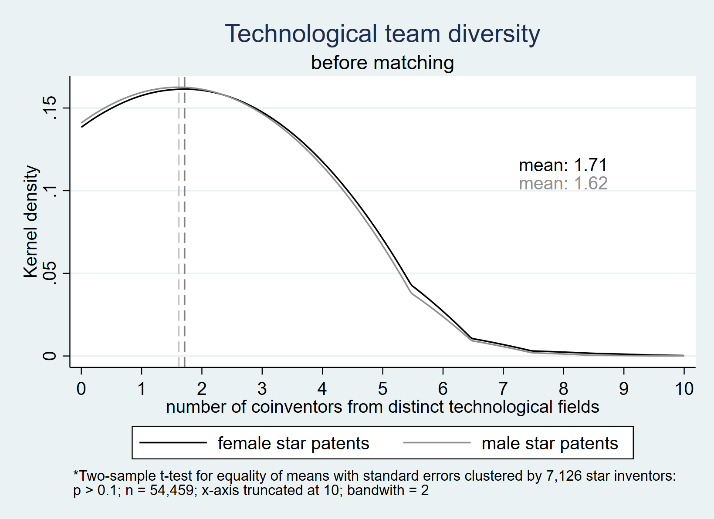
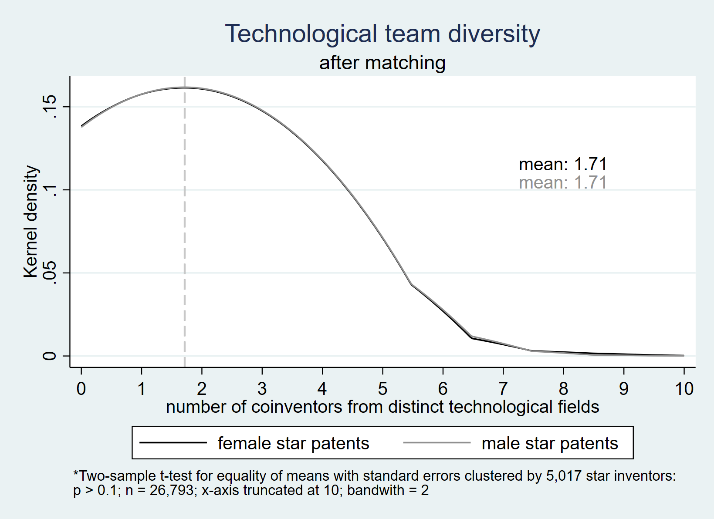
The graphs show the kernel density distribution of inventor team characteristics for teams with female and male stars. Graphs on the left-hand side show the distribution on the full sample (n = 54,459) while graphs on the right-hand side show the post-matching distribution (n=26,793), accounting for the matching weight obtained from CEM.

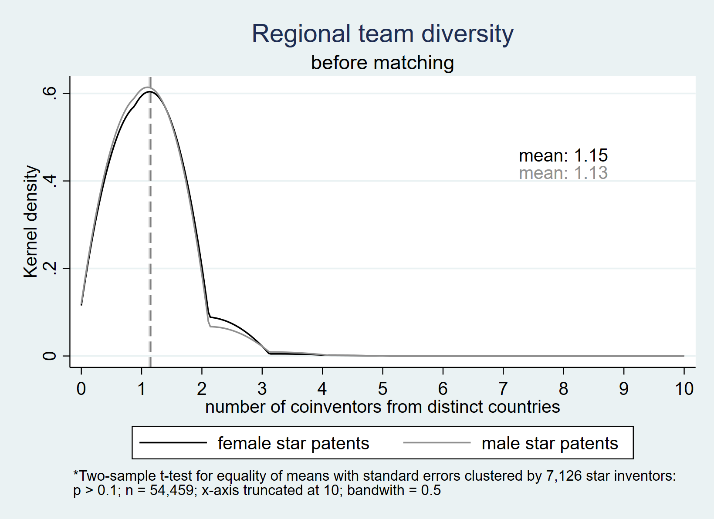
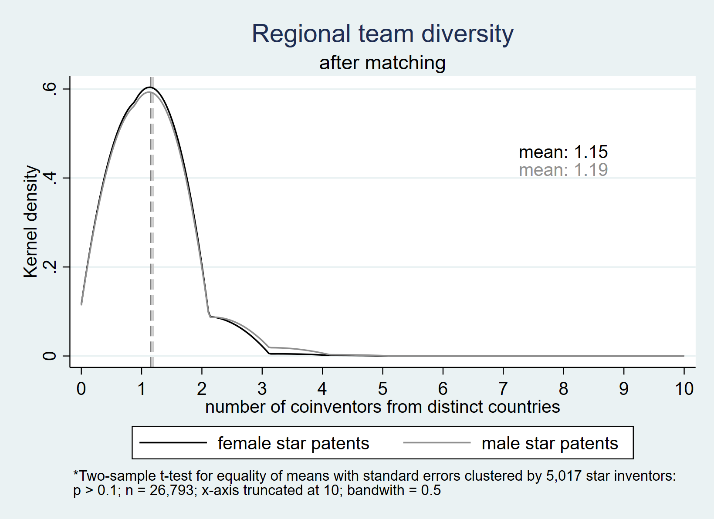


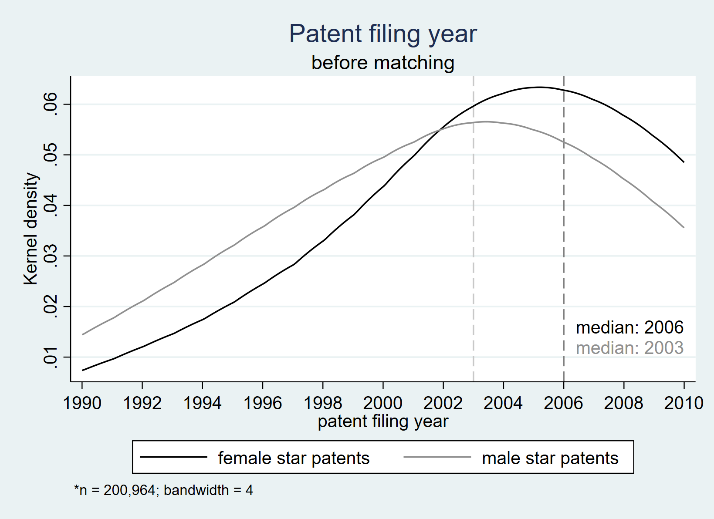
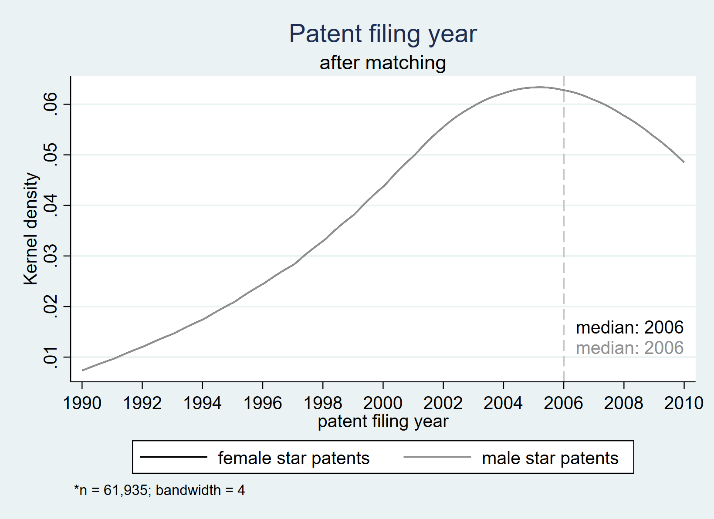


**Appendix 3: Distribution of inventor team and patent characteristics for female versus male star teams before and after matching (continued)**



**Appendix 3: Distribution of inventor team and patent characteristics for female versus male star team before and after matching (continued)**





**Appendix 4: Representativeness of the sample**



Model A4.1 shows a probit regression estimating the likelihood of an observation appearing in the final sample. The independent variables represent team, star, and patent characteristics. The dependent variable is a dummy variable indicating whether an observation was used in the final analysis. The final sample constitutes observations, which meet the gender designation requirements (see Appendix 3) and are selected in the coarsened exact matching.

**Appendix 5: Robustness checks**



Model A5.1 replicates the main analysis on the full sample. Model A5.2 employs a tobit regression bound between 0 and 1, the natural limits of the dependent variable. In Model A5.3 the dependent variable is based only on non-applicant backward citations. In Model A5.4 the traditional Herfindahl index measuring the breadth of cited technology classes is used as a dependent variable.

1. We rely on granted patents since the USPTO started recording patent applications only in 2001. Additionally, more than 97% of patent applications filed by the inventor teams in our sample as of 2001 were granted. This is not surprising given that we look at teams with star inventors. [↑](#footnote-ref-1)
2. A patent family represents the entire set of patents and applications filed across different countries protecting a single invention (OECD, 2015). In this article, when we refer to “patent”, we are referring to the simple DOCDB patent family. [↑](#footnote-ref-2)
3. Open source dataset, available here: <https://github.com/rflynn/pro-file/tree/master/data> (accessed on December 12, 2020) [↑](#footnote-ref-3)
4. The gender designation procedure is outlined in detail in Appendix 1. [↑](#footnote-ref-4)
5. For a recent application of CEM matching to inventors and patent data, see also Le Gallo & Plunket (2020). [↑](#footnote-ref-5)
6. A detailed explanation of CEM weights was published by Gary King in 2012 and can be accessed here: <https://docs.google.com/document/d/1xQwyLt_6EXdNpA685LjmhjO20y5pZDZYwe2qeNoI5dE/edit> (accessed on December 3, 2020). [↑](#footnote-ref-6)
7. We achieve similar results by matching on additional covariates and adopt the approach described above as it represents the most parsimonious approach to achieving covariate balance for our data. [↑](#footnote-ref-7)
8. <https://www.wipo.int/treaties/en/classification/strasbourg/> (accessed on December, 3 2020). [↑](#footnote-ref-8)
9. This information comes from PatentsView as the detailed locations of inventors and patent-owning entities are recorded when a patent is granted: see <https://www.patentsview.org/web/#viz/locations> (accessed on November 11, 2020). [↑](#footnote-ref-9)
10. For the United States, we use the share per industry, year, and U.S. federal state. This information also comes from the inventor location retrieved from PatentsView. [↑](#footnote-ref-10)
11. Post-estimation tests also reject the null hypothesis that the model was under-identified (Kleibergen–Paap rk LM statistic = 19.39, χ2 p-value = 0.000) or overidentified (Sargan–Hansen J-statistics = 0.000), with the latter indicating that the model was exactly identified. [↑](#footnote-ref-11)
12. Open source data, available here: https://github.com/rflynn/pro-file/tree/master/data [↑](#footnote-ref-12)
13. We obtain similar in our analysis if we adapt the threshold to 95%, for example. However, manual inspection of the data showed that even then we include stars falsely classified as female inventors. Results are available from the authors. [↑](#footnote-ref-13)