# GENDER INEQUALITY IN KNOWLEDGE-BASED ORGANIZATIONS: EVIDENCE FROM R&D SCIENTISTS IN STEM FIELDS 1985 – 2010

by

Carla Rua-Gomez

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***To Women in Science.***

*To those who have created the path to us that transit it next. And to the ones that will come in the future, who hopefully will enjoy a fairer world. This dissertation is dedicated to all of YOU!*

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miss you so much, and I am so sorry I did not have the time to hug you both for the last time. I hope whenever you are now you feel proud of who I became!

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# 1. INTRODUCTION

## 1.1.BACKGROUND

*"Through countless generations, from the very beginning, the social subservience of women resulted naturally in the partial atrophy or at least the hereditary suspension of mental qualities which we now know the female sex to be endowed with no less than men. But the female mind has demonstrated a capacity for all the mental acquirements and achievements of men, and as generations ensue that capacity will be expanded; the average woman will be as well educated as the average man, and then better educated, for the dormant faculties of her brain will be stimulated to an activity that will be all the more intense and powerful because of centuries of repose. Women will ignore precedent and startle civilization with their progress."*

*(Nikola Tesla, 1926)*

The *Times up* movement, along with other women's empowerment movements, have revived awareness of historical gender gaps within organizations across different industries and settings. Notably, these movements renewed the efforts of both organizational decision-makers as well as policymakers to reduce gender-based inequalities in the workplace. For example, quotas systems, diversity, and inclusion training, as well as mentorship and sponsorship programs, have been part of the exercise organizations have dedicated to the reduction of gender inequality. In terms of policymakers, the German government introduced 12 months of paid leave to increase women's workforce participation one year after a child's birth. Similarly, Canadian Prime Minister Justin Trudeau promoted gender equality in his cabinet by appointing 50 percent women. Taken together, these observations suggest that the reduction of different gender gaps has become an essential topic in the labor market agenda in recent years.

In the last few decades, several milestones have been accomplished. For example, a record number of women have finished graduate school (National Science Foundation, 2014); the proportion of women in the labor force has increased by 23 percent since 1950 (Hipple, 2016); and within the scientific field, up to 2019, 19 women have been awarded Nobel Prizes (The

Nobel Prize, 2019). Furthermore, there has been a significant increase in the participation of women in middle management positions, and a number record of women who are also mothers are now employed – i.e., 34.2 percent – (Leopold, Zahidi, & Ratcheva, 2017). Despite these and other advances, women still confront several disadvantages within the workplace. In STEM academic fields, for instance, despite the increased representation of women in graduate programs and assistant professorship positions, only 25% of the full professors are women (The World University Rankings, 2017). Similarly, in top managerial positions, women are still severely under-represented (Catalyst, 2014, 2018a); for example, only 6.6% of women are CEOs at Fortune 500 companies (Fortune, 2019). Furthermore, gender wage gaps are still highly salient in most industries and across different occupations (Catalyst, 2018b).

Although several factors are driving those gender differences in the workplace, prior work shows that gender bias plays a central role. In male-typed jobs, particularly, gender stereotypes penalize women by underestimating their ability (Correll & Ridgeway, 2003; Gorman, 2005, 2006; Gorman & Kmec, 2009; Joshi, Son, & Roh, 2015; Ridgeway & Walker, 1995). For example, when employers evaluate candidates for a position in a male-typed job, gender stereotypes bias the selection process because employers tend to regard male candidates as more qualified even when no difference in quality exists (Handley, Brown, Moss-Racusin, & Smith, 2015; Moss-Racusin, Dovidio, Brescoll, Graham, & Handelsman, 2012; Tinkler, Bunker Whittington, Ku, & Davies, 2015). This kind of biases effectively results in women having to meet higher standards than men to reach similar career outcomes (Handley et al., 2015; Tinkler et al., 2015). This affects how women are perceived, evaluated and rewarded at work, and accounts for part of the disadvantages that women face inside organizations (Gorman, 2005, 2006; Grams & Schwab, 1985; Joshi, Neely, Emrich, Griffiths, & George, 2015).

Gender biases may also shape the kind of workplace networks women and men build (Brass, 1985; Burt, 1998; Ibarra, 1992, 1997; Moore, 1990; Van Emmerik, 2006). Social network research proposes that network connections provide individuals with a valuable source of social capital that can determine individuals' career outcomes and success (Burt, 2000; Lincoln & Miller, 1979; Miller, 1986). Consistent with this view, social networks research attempts to explain gender differences in career outcomes. This research concurs that within organizations, women have reduced access to valuable sources of social capital compared to men (Brass, 1985; Ibarra, 1992; Lutter, 2015). For example, women tend to have fewer connections with important sponsors relative to men (Ibarra, 1992; McPherson, Smith-Lovin, & Cook, 2001); they need to borrow social capital from strategic partners (Burt, 1998; Ibarra, 1992), and they face greater difficulties in mobilizing social capital (Lin, 2001). These arguments add to gender bias explanations on gender inequality, leaving an open the door to explore how individuals' networks influence the gender gap in organizations.

In my dissertation, I complement this line of inquiry by building on social networks theories and exploring the social capital perspective of gender inequality. To this end, this dissertation examines how intra-organizational networks interact with individual and macro-level characteristics to affect men's and women's innovativeness and access to social capital in knowledge-based organizations. Many organizations aim to reduce gender disparities by increasing gender diversity and inclusiveness of their workplace (BCG, 2019, 2020). To promote workplace gender balance, several studies have provided consistent evidence on the positive association between a higher degree of women in organizations and the overall organizational performance (Cumming, Leung, & Rui, 2015; Joshi, Liao, & Jackson, 2006; Lyngsie & Foss, 2017; Richard, Barnett, Dwyer, & Chadwick, 2004). These studies, however, have overlooked

how the collaboration networks employees build within their organization play an essential role in explaining different individual and organizational outcomes. The goal of this dissertation, therefore, is to illuminate the importance of employees' networks in explaining gender differences in knowledge-based firms. By so doing, I aim to contribute new insight into the antecedents of gender inequality in knowledge-based firms.

In the following sections, I describe the main goals and structure of this dissertation, as well as the major constructs used in each chapter.

## 1.2.AIMS OF THE DISSERTATION

The goal of this dissertation is to improve our understanding of gender inequality within the workplace. To this end, this dissertation focuses on individual-, organizational-, and regional-level factors, with a focus on how workplace networks perpetuate or limit gender inequality within research-intensive corporations. I first examine whether gender influences how scientists form first-time collaborations with high-status colleagues (**Chapter 2**). Second, I look at how organizational-level gender diversity affects individual-level innovative performance (**Chapter 3**). Finally, I analyze how gender attitudes in the broader society affect gender performance gaps (**Chapter 4**). I focus on employees working in the forty largest pharmaceutical companies worldwide and academic scientists working in STEM (Science, Technology, Engineering, and Mathematics) fields. Empirically, I rely on a dataset, which combines patent data, LinkedIn data, data on academic scientists working at top-ranked US universities, and data from the General Social Survey (GSS) of the United States.

### 1.2.1. Understanding differences in men's and women's ability to form connections with high-status colleagues

With my dissertation, I first aim to understand differences in men's and women's ability to form collaboration ties with high-status colleagues. In **Chapter 2**, we argue that although women's human capital endowments have equalized or surpassed those of men in many knowledge-based sectors, research consistently shows that women underperform relative to men along most dimensions of career success (Burt, 1998; Kay & Wallace, 2009; Lutter, 2015; O'Neill & Gidengil, 2013; Singh, Hansen, & Podolny, 2010). A growing body of literature suggests that a major reason for this persistent disparity lies in women's reduced access to valuable sources of social capital within their organization (Adler & Kwon, 2002; Burt, 1997, 1998). **Chapter 2** contributes to this line of inquiry by examining differences in men's and women's access to high-status colleagues. To do so, we focus on the R&D labs of the forty largest pharmaceutical firms globally from 1985 until 2010. **Chapter 2** argues and shows that female and male scientists face systematically different conditions when attempting to form collaboration ties with so-called "star scientists" – an exemplar of high-status actors within pharmaceutical R&D labs. Our analyses indicate that it is harder for women than for men to initiate high-status collaborations; that women's path to high-status colleagues is more indirect, and hence more difficult than men's; and that such difficulties are amplified, rather than reduced, when the high-status actor is a woman.

**Chapter 2** extends the current understandings of the antecedents of gender inequality in knowledge-based organizations. To start, in **Chapter 2**, we provide novel theory and evidence to show that female scientists are less likely to form high-status relationships within their organizations and, consequently, have reduced access to the social capital inhering in those

relations. This finding is especially relevant because it might help us explain why, despite women's noticeable increases in human and educational capital, men still fare significantly better than women across most career outcomes. Furthermore, **Chapter 2** offers a novel insight into relational strategies and organizational policies that may help to reduce this gender inequality

### 1.2.2. Understanding who benefits from gender diversity

Extant research has shown that gender-diverse organizations tend to be more innovative than gender homogenous ones (Cumming et al., 2015; Herring, 2009; Joshi et al., 2006; Lyngsie & Foss, 2017; Richard et al., 2004) but has left unaddressed the question of who, among an organization's knowledge workers, becomes more innovative as gender diversity increases. **Chapter 3** addresses this question by examining how gender diversity affects individual-level innovative performance, measured through patent-based indicators, within the R&D labs of the forty largest pharmaceutical companies over the period 1985-2010. We argue that higher levels of gender diversity increase the performance of three categories of knowledge workers – women, rookies, and brokers –. In contrast, men, long-tenured employees, and employees embedded in constrained networks experience limited or no performance benefits. By demonstrating that gender diversity has a heterogeneous effect across different segments of an organization's knowledge workers, **Chapter 3** both deepen and qualify current understandings of how gender diversity affects innovation within organizations.

**Chapter 3** extends current knowledge on the performance effect of gender diversity within knowledge-based organizations. The goal of **Chapter 3** is to unpack the differential benefits of gender diversity for different types of knowledge workers. In particular, we seek to improve our understanding of how widely knowledge workers within organizations benefit from increased gender diversity and who exactly benefits from it. We provide novel theory and evidence to

show that gender diversity does not only affect the overall performance of the organization; it also affects how performance (and hence the material and symbolic resources associated with it) are distributed within the organization.

### 1.2.3. Understanding how gender-equity attitudes affect gender performance gaps

Building on prior work that has found a positive association between the level of gender bias in broader society and the size of gender productivity gaps (Charles & Guryan, 2008; Charles, Guryan, & Pan, 2009; Janssen, Sartore, & Backes-Gellner, 2016). In **Chapter 4**, I combine data on attitudes and behaviors in contemporary US society with information on the background and training of academic scientists at top-ranked US universities over the period 1985-2010. Because this setting includes men's and women's training and quality, I can control for the possibility of labor-market sorting by men and women (i.e., selection effects). Based on this, **Chapter 4** underlines two possible explanations: first, it is possible that employers' and coworkers' actions in less gender-equal regions somehow lower the productivity of female employees (i.e., treatment effects). Second, an alternative explanation could be that broad social attitudes influence where men and women choose to work in the first place. For example, if higher-qualified women choose to work in less gender-biased areas from the start, the observed correlation between attitudes and gender-performance gaps would be the product of a "selection effect." If this is the case, broader social attitudes widen the gender-productivity gap not by making women employees less productive in the workplace, but by affecting which jobs women of different levels of productivity are willing to take.

In **Chapter 4**, I find that in regions characterized by a stronger bias against gender equality, gender performance gaps are larger. This effect largely disappears, though, when I control for selection – i.e., when I account for the fact that women can self-select into specific workplaces.

These findings suggest that gender bias within a society mostly affects productivity gaps by influencing where workers of different quality choose to work. Therefore, I argue that distinguishing between selection and treatment effects is essential for understanding different gender gaps.

Table 1-1 summarizes the main constructs for the empirical analyses (**Chapters 2-4**). The last chapter (**Chapter 5**) of this dissertation summarizes the main findings and conclusions from the presented empirical studies. In the remaining of the chapter, I discuss scope conditions and limitations as well as future research.

**Table 1-1.** Outline of the empirical chapters

| Chapter | Dependent variable | Main independent variables | Level of analysis | Theoretical focus |
|---|---|---|---|---|
| **Chapter 2:** Reaching for the stars: How gender influences the formation of high-status collaboration ties | First-time collaboration | Scientists' gender<br>Third-party ties | Individual-level | The difference in men's and women's access to social capital |
| **Chapter 3:** Who benefits from gender diversity? How organization-level gender diversity affects the innovative performance of different kinds of employees | Innovative performance | Scientists' gender<br>Scientists' tenure<br>Scientists' constraint<br>Organizational-level gender diversity | Individual-level | The heterogeneous effect of gender diversity on employees' innovative performance |
| **Chapter 4:** How gender-equity attitudes affect gender performance gaps | Research output | Scientists' gender<br>Social bias toward gender equality | Individual-level | Gender bias in region and difference in men's and women's performance |

## 2. REACHING FOR THE STARS: HOW GENDER INFLUENCES THE FORMATION OF HIGH-STATUS COLLABORATION TIES[1]


### Abstract

Although women's human capital endowments have equalized or surpassed those of men in many knowledge-based sectors, research consistently shows that women underperform relative to men along most dimensions of career success. A growing body of literature suggests that a major reason for this persistent disparity lies in women's reduced access to valuable sources of social capital within their organization. We contribute to this line of inquiry by examining differences in men's and women's access to high-status colleagues. Focusing on the R&D labs of the forty largest pharmaceutical firms globally, we argue and show that female and male scientists face systematically different conditions when attempting to form collaboration ties with so-called "star scientists" – an exemplar of high-status actors within pharmaceutical R&D labs. Our analyses indicate that it is harder for women than for men to initiate high-status collaborations; that women's path to high-status colleagues is more indirect, and hence more difficult than men's; and that such difficulties are amplified, rather than reduced, when the high-status actor is a woman. The theory and evidence we present illuminate previously unknown social capital mechanisms underpinning the gender gap, and they bear important theoretical and managerial implications.



**Keywords:** Social capital, Status, Gender, Star scientists, Pharmaceutical industry


[1] Paper co-authored with Gianluca Carnabuci and Martin Goossen.

## 2.1. INTRODUCTION

Women's educational and human capital endowments have equalized or surpassed those of men in many knowledge-based sectors (DiPrete & Buchmann, 2013; Gayle, Golan, & Miller, 2012; Goldin, Katz, & Kuziemko, 2006; Lips, 2013), yet research consistently shows that women still lag behind men along most dimensions of career success (Brass, 1985; Catalyst, 2014; Fernandez-Mateo, 2009; Fernandez & Sosa, 2005; Forret & Dougherty, 2004; Gayle et al., 2012; Ibarra, 1992, 1997). For example, Davison and Burke (2000) found that women are less likely to be hired given equal records and Gorman (2006) noted that equivalent work done by women receives lower evaluations from managers. And while the share of females in leadership positions has increased in many sectors and countries, women remain dramatically underrepresented among upper echelon executives (e.g., Catalyst, 2014). Similarly, within the natural sciences, female scientists represent about half of all academic staff employed at universities, but their share drops to about one-third for all permanent faculty and to only one-fifth for the highest academic ranks (European Union Open Data, 2015; Hill, Corbett, & St Rose, 2010; The World University Rankings, 2017). Taken together, these observations suggest that women's increasing levels of educational attainment and human capital do not generally convert into commensurable improvements in career progress. This indicates that human capital explanations provide at best a partial explanation for the persistent gender disparity observed in many contemporary organizations (Ceci, Ginther, Kahn, & Williams, 2015; Merluzzi & Dobrev, 2015).

Complementing the human capital perspective, a growing body of literature suggests that a major reason for such persistent gender disparity lies in women's reduced access to valuable sources of social capital within the organization (Burt, 1998; Kay & Wallace, 2009; Lutter, 2015;

O'Neill & Gidengil, 2013; Singh et al., 2010). Inspired by the view that informal networks are critical for furthering employees' performance and career outcomes, scholars examined whether men and women differ in how they build or use their workplace networks (Forret & Dougherty, 2004; Ibarra, 1992; Singh, Hansen, & Podolny, 2010). Preponderantly, this research has shown that such differences do exist, and that women's workplace networks are generally less effective than men's at providing access to the social capital needed to advance their careers (Burt, 1998; Lutter, 2015; Ragins & Sundstrom, 1989; Van Emmerik, 2006). Consistent with these findings, Lyness and Thompson (2000) report that women are more likely to feel excluded from informal networks within the organization and perceive this to be a significant barrier to their success and career advancement.

We contribute to this line of inquiry by examining whether an employee's gender may affect his or her likelihood to build collaborative relations with high-status colleagues within the organization. Extant theory posits that high-status connections are a key source of social capital that may affect employees' success and career outcomes (Adler & Kwon, 2002; Burt, 1997; Inkpen & Tsang, 2005). Consistent with this view, evidence shows that affiliating with high-status colleagues enhances employees' internal visibility and facilitates access to organizational resources (Baron & Pfeffer, 1994; Ely, 1994; Huffman, Cohen, & Pearlman, 2010; Petersen, Saporta, & Seidel, 2000). Furthermore, high-status connections help employees gain organizational influence, and it results in positively biased evaluations of one's worth (e.g. Sauder, Lynn, & Podolny, 2012). Taken together, these findings lend support to the view that high-status colleagues are an important source of social capital within organizations and that, accordingly, employees who form collaborative ties with high-status colleagues have noticeable advantages over those who do not.

Forming collaborative relations with high-status colleagues is inherently difficult. On the one hand, the nature of status hierarchies is such that, typically, many low-status employees vie for the attention and favor of few high-status employees (Magee & Galinsky, 2008). On the other hand, high-status actors tend to be highly selective when considering low-status relationships because such relationships dilute their own status (Gould, 2002) while increasing the relational demands high-status actors must manage (Oldroyd & Morris, 2012). This asymmetry has two implications that are especially relevant for our study. First, high-status actors have a great deal of discretion in choosing which lower-status colleagues they include in their collaboration network. Second, in most organizations, only a minority of employees eventually succeed in forming high-status connections and gaining access to that important source of social capital.

Although forming high-status connections is difficult for everyone, in the present paper we argue and show that it is considerably more difficult for women than for men. Following extant theory (Castellucci & Ertug, 2010; Podolny & Lynn, 2009), the starting point of our argument is that high-status actors are motivated to form collaborative relationships with lower-status colleagues only if they expect those relationships to generate enough value to offset its associated costs. Prior to establishing a collaborative relationship, however, high-status actors face significant ex-ante uncertainty about the "true" value of their lower-status colleagues (Castellucci & Ertug, 2010). Research has shown that, under conditions of uncertainty, social categories based on visible cues become a salient signal from which people infer others' attributes through stereotypical association (Dahlander & McFarland, 2013; McPherson et al., 2001; Murphy & Ross, 1994). When jobs are male-typed, gender may act as a salient cue that negatively influences high-status actors' assessment of potential female collaboration partners.

As we articulate in the remainder of the paper, this argument bears several testable implications concerning men's and women's differential access to high-status colleagues.

To test our hypotheses, we collected data on the R&D laboratories of the forty largest pharmaceutical companies from 1985 until 2010. This setting is ideal for our test because pharmaceutical R&D labs are an exemplar case of knowledge-based organization where high-status employees are both easily observable and highly influential for the career advancement of their colleagues (Cohen & Huffman, 2003; England et al., 1994; Leslie et al., 2015; Valantine & Collins, 2015). We focus specifically on a set of high-status actors that have been shown to play a highly relevant role within R&D laboratories – so-called "star scientists" (Groysberg, 2010; Oettl, 2012; Oldroyd & Morris, 2012). Star scientists have received a great deal of scholarly and managerial attention because, in most large R&D labs, scientific productivity tends to be heavily skewed. Accordingly, a few star scientists are typically responsible for a disproportionable share of the laboratory's output (Groysberg, Lee, & Nanda, 2008; Oldroyd & Morris, 2012). In addition to being widely regarded as aspirational role models, star scientists enjoy a disproportionate amount of organizational influence and resources (Merton, 1968; Tzabbar, 2009), making them critical gatekeepers for any scientist wanting to advance his or her career (Schiffauerova & Beaudry, 2011). In short, they represent a clear-cut and contextually meaningful case of high-status actors who hold substantial social capital and with whom other scientists strive to affiliate (Groysberg, 2010; Oettl, 2009; Oldroyd & Morris, 2012, p. 396).

To examine whether a scientist's gender affects the likelihood that s/he enters a collaborative relationship with a star scientist, we trace each organization's internal R&D collaboration network longitudinally throughout the observation period using co-patenting data (e.g., Carnabuci & Operti, 2013). We estimate panel logit models predicting the likelihood that a focal

scientist is included in a collaborative R&D project with a star scientist for the first time. Our empirical analyses lend strong support to the argument that it is harder for women to form collaborative relationships with their organization's star scientists. Specifically, we find that women are 20 percent less likely than men to become part of star scientists' R&D collaboration networks. Importantly, this difference remains sizeable even after accounting for scientists' past performance records. Furthermore, in line with the view that gender matters most under conditions of uncertainty, we find that the gender gap is especially large among scientists who have no third-party connection, i.e. a shared contact within the organization with the star scientist. Hence, the star has less information to assess scientists' potential as R&D collaborators. Lastly, we find that that the gender gap is amplified, rather than reduced, when the star scientist is a woman.

Our study extends current understandings of the antecedents of gender inequality in knowledge-based organizations. To start, we provide novel theory and evidence to show that female scientists are less likely to form high-status relationships within their organizations and, consequently, have reduced access to the social capital inhering in those relations. This finding is especially relevant because it might help us explain why, despite women's noticeable increases in human and educational capital, men still fare significantly better than women across most career outcomes. Furthermore, our analyses offer novel insight into relational strategies and organizational policies that may help reducing this gender inequality.

## 2.2. THEORETICAL DEVELOPMENT

Research has shown that productivity in knowledge-based organizations tends to be heavily skewed, meaning that a small fraction of knowledge workers (dubbed "star employees") produce the majority of a firm's knowledge-based output (Groysberg et al., 2008; Oldroyd & Morris,

2012). This pattern has also been observed in the context of R&D laboratories, across several industries and in both basic and applied R&D (Narin, 1994), leading to a sizeable body of research on "star scientists" (Groysberg, 2010; Oettl, 2012; Oldroyd & Morris, 2012). Star scientists represent an unambiguous case of high-status employees within R&D-based organizations (e.g., Wry, Lounsbury, and Greenwood 2011). Not only are they exceptionally productive, they are also highly visible. Because their scientific output results in patents and publications, their exceptional productivity is observable to everyone and, as such, confers a solid and largely undisputed basis for status (Merton, 1968). In addition, star scientists typically command a great deal of influence and organizational resources, which further accentuates their "stardom" status (Oldroyd & Morris, 2012). As a result, star scientists invariably occupy the highest positions within the status hierarchy of R&D laboratories and they "amass exponentially high levels of social capital" within the organization (Oldroyd & Morris, 2012, p. 397).

Four reasons suggest that forming a collaborative relationship with star scientists may help non-star scientists[2] gain access to a source of social capital that is crucial for their career success. First, by being part of a star scientist's network, non-star scientists are more likely to become involved in high-visibility projects that are core to the company strategy (Huselid, Becker, & Beatty, 2005). For instance, Paruchuri (2010) shows that central inventors receive more exposure to other inventors in the firm, which results in their projects having a greater influence on the company's trajectory of technological development. Complementing this finding, Tzabbar and Kehoe (2014) show that the departure of star scientists leads to a change in the firm's technological core. Second, non-star scientists may improve their standing within the

[2] For simplicity, in the remainder of the paper we use the label "non-star scientist" to indicate all scientists within a firm who are not stars. This is consistent with prior work (Kehoe and Tzabbar, 2015, p. 712; Hess and Rothaermel, 2011; Oettl, 2012; Subramanian, Lim, and Soh, 2013).

organization because connections with star scientists represent a credible signal of a non-star scientist's value (Merton, 1973; Simcoe & Waguespack, 2011). Consistent with this view, prior work found that when a lower-status person affiliates with a higher status one, status spills over from the latter to the former (Podolny & Phillips, 1996; Stuart, 2000). Third, being connected with a star scientist may provide access to valuable strategic information and influence over scarce organizational resources (Oettl, 2012; Tushman, 1977). For example, prior research has shown that star scientists attract and control key resources both from inside and outside the organization's boundaries (Zucker, Darby, & Torero, 2002). Finally, non-star scientists may enhance their productivity because by being part of a star's network, non-stars can learn about the latest developments in their area and can quickly familiarize themselves with the best procedures for working in a particular topic area (Burke, Fournier, & Prasad, 2007; Katz & Allen, 1985; Lacetera, Cockburn, & Henderson., 2004). For instance, Katz and Allen (1985) showed that star employees tend to create exceptional value for their organizations because they are a crucial source of technical knowledge for non-star scientists.

Whereas non-star scientists have much to benefit from becoming part of star scientists' collaboration network, forming a collaboration tie with star scientists is inherently difficult. First, since the number of star scientists within an R&D lab is by definition very small, many non-star scientists are competing to become part of a star scientist's collaboration network. Second, organizational star scientists carefully choose their collaborators in order to optimize the use of time, resources, and attention (Oldroyd & Morris, 2012) as well as to reduce the possibility of status dilution (Gould, 2002). For these reasons, star scientists typically enjoy significant autonomy and discretion in selecting non-stars scientists to include in their collaboration network (Liebeskind, Oliver, Zucker, & Brewe, 1994; Oldroyd & Morris, 2012).

In what follows, we develop a model of how star scientists go about this decision.

### 2.2.1. How star scientists choose who to include in their collaboration network

We are interested in understanding whether men and women face different conditions when attempting to become part of the collaboration network with a star scientist within their firm. For that reason, we focus on the selection problem star scientists face when considering whom, among their non-star colleagues, they will include in their collaboration network *for the first time*. Our argumentation builds upon a few common assumptions. First, we assume that star scientists selectively seek to form collaborative relationships with non-star colleagues based on the latter's "expected quality" (Beckman, Haunschild, & Phillips, 2004; Castellucci & Ertug, 2010; Shipilov, Li, & Greve, 2011). However, and second, prior to collaborating with a particular non-star scientist, star scientists lack specific information about that non-star colleague; consequently, they face ex-ante uncertainty about his or her "true quality" (Bidwell & Fernandez-Mateo, 2010; Sorenson & Waguespack, 2006; Srivastava, 2012). Third, in the face of ex-ante uncertainty, salient social categories, such as gender, act as cues affecting stars' assessment of the quality of non-stars (Kanter, 1977b; Tajfel, Turner, Austin, & Worchel, 1979).

Prior research found that gender stereotypes shape quality expectations (Correll & Ridgeway, 2003). Building on this argument, we propose that gender stereotypes may differently affect the chances of male and female non-stars to enter the collaboration network of a star. Extant research has found that in male-typed jobs, gender-based inferences prompt a negative bias in evaluative judgment of women (Heilman, 2001). Over the past decades, a large stream of literature found that women tend to be systematically undervalued in predominantly male-typed jobs (Gorman, 2005, 2006; Gorman & Kmec, 2009; Grams & Schwab, 1985; Joshi, Neely, et al., 2015; Kanter, 1977b). When a star scientist evaluates a non-star scientist with whom s/he has not collaborated

before, gender stereotypes bias star's perceptions and judgments about women. In psychology, for example, Moss-Racusin *et al*. (2012) ran an experiment manipulating the resumés of job applicants for a lab technician job. In otherwise similar resumes, the authors manipulated the applicant's first name and observed that "John" was significantly more likely to get hired than "Jennifer". This kind of biases results in star scientists underrating female non-star scientists' competences relative to male's. Similarly, we propose that, holding other things constant, star scientists may have greater expectations of quality for male than for female non-stars with whom they have never collaborated before. Thus, star scientists may favor male non-star scientists even if no differences in true "quality" exist (Handley et al., 2015; Moss-Racusin et al., 2012; Tinkler et al., 2015). Consequently, star scientists will be more likely to form collaboration ties with a male non-star scientist than with a female one. We, therefore, propose the following hypothesis:

> *H1: Star scientists are less likely to form collaboration ties with female non-star scientists than with male non-star scientists.*

We argued that star scientists face ex-ante uncertainty about the true quality of non-star scientists with whom they never collaborated before. Having no first-hand collaboration experience with those non-star colleagues, star scientist lack person-specific information about those colleagues' competences and value as collaborators. However, social network theory emphasizes the role of third-party ties – a common contact between two actors – as key channels for information about colleagues with whom a focal actor is not directly connected (Ellwardt, Labianca, & Wittek, 2012; Obstfeld, 2005; Wittek & Wielers, 1998; Singh, Hansen, & Podolny, 2010). Building on this argument, we propose that third-party ties may reduce the ex-ante uncertainty faced by star scientists when choosing whom to include in their collaboration network. Third-party ties may convey credible person-specific information about non-star colleagues in several ways (Argote & Ren, 2012; Borgatti & Cross, 2003; Jarvenpaa &

Majchrzak, 2008; Singh et al., 2010). For instance, a star scientist may proactively ask his or her contacts if they know somebody with particular skills or to advance suggestions for non-star scientists on a specific project (Newman, 2001). Similarly, valuable information may accrue to the star scientist by the initiative of the third-party tie, for example, the third-party tie may recommend one of his or her contacts. Regardless of the specific mechanism through which information accrues to the star scientist, star scientists are more likely to retrieve person-specific information about non-star colleagues with whom they share third-party ties than about those with whom they have no contacts in common. Because detecting quality is harder under conditions of high uncertainty, we argue that star scientists are more likely to form collaboration ties with non-star scientists with whom they have common third-party ties (Fernandez & Sosa, 2005).

By arguing that third-party ties increase the likelihood that a non-star will form a tie with a star scientist, we do not mean to suggest that third-parties only provide stars with positive information about their non-star contacts. In some cases third parties may withhold relevant information (Smith, 2005) or even convey explicitly negative information about a particular non-star colleague (Zhelyazkov, 2018), thereby reducing the chances that a collaboration tie will form. However, there are theoretical reasons to believe that, on average, the presence of third-party ties should increase the likelihood of tie formation. First, third-party ties are more likely to refer colleagues of whom they have a good opinion; lacking a referral, these colleagues would probably not even enter the consideration set of the star scientist because they are not part of his or her network of direct collaborators (Van Hoye, 2013). Second, even under the assumption that third-party ties convey information about colleagues of whom they have a high opinion just as frequently as they convey information about colleagues of whom they have a low opinion, the

presence of third-party ties should still have an average positive effect on the likelihood of tie formation because people are more likely to make investments (e.g., enter a collaborative relation) when the ex-ante uncertainty is lower (Abdellaoui, Baillon, Placido, & Wakker, 2011). These arguments lead to the following hypothesis:

> *H2: Star scientists are more likely to form collaboration ties with non-star scientists with whom they have a common third-party tie, than with those with whom they have no common third-party.*

We argued that gender is a salient trait from which star scientists infer non-stars' quality under conditions of *ex-ante* uncertainty, that is, when the star scientist has limited information about non-stars' "true" quality as scientific collaborators. However, the salience of gender stereotypes should be lower when a star scientist has more granular, person-specific information about the non-star (Cook, 2005; Falkenberg, 1990; Simon & Warner, 1992). Since third-party ties may provide star scientists with just such person-specific information, the presence of third-party ties should reduce the effect of gender on tie formation. In other words, although third-party ties should be beneficial to all non-star scientists, they should be more beneficial for female non-star scientists than for male ones because, by providing star scientists with person-specific information about the non-star, third-party ties help star scientists override the negative bias against women resulting from stereotypical associations (Ellwardt, Labianca, & Wittek, 2012; Obstfeld, 2005; Wittek & Wielers, 1998; Singh, Hansen, & Podolny, 2010). Consequently, a common third-party tie between a star and a non-star scientist should be more beneficial for women than for men, i.e., it should reduce the gender inequality women face when trying to form connections with stars. As a result, we would expect:

> *H3: The positive effect of common third-party ties on forming ties to star scientists is stronger for female non-star scientists than for male ones, such that the gender gap is*

*largest among non-star scientists who have no third-party ties to the star scientist and smallest among those who have many common third-party ties*

### 2.2.2. How star scientist gender matters

Prior research suggests that many practices associated with gender inequality are related to decision makers' gender (Baron, Mittman, & Newman, 1991; Cohen, Broschak, & Haveman, 1998; Huffman, Cohen, & Pearlman, 2010; Kalev, Dobbin, & Kelly, 2006; Shenhav & Haberfeld, 1992). In particular, over the past decades, a large stream of literature has examined how high-status women influence the career attainment of their lower-status female counterparts (Baron et al., 1991; Cohen, Broschak, & Haveman, 1998; Hultin & Szulkin, 2003). This research has focused on two opposing explanations to examine the effect that high-status women have on their female colleagues. The first line of argument posits that high-status women act as "*agents of change"* helping their lower-status female colleagues to improve their career outcomes in terms of hiring, wages and promotions (Huffman et al., 2010; Hultin & Szulkin, 1999; Kurtulus & Tomaskovic-Devey, 2012; Stainback, Ratliff, & Roscigno, 2011). Conversely, the second line of argument, titled the "*cogs-in-the-machine*" perspective, posits that women who make it to the top tend to underestimate the "true" value of their female colleagues even more than men do (Derks et al., 2011; Ellemers et al., 2004; Maume, 2011). In what follows, we draw from these two distinct lines of argument to theorize how star scientists' gender may influence the likelihood of initiating collaborative relations with female non-stars.

#### 2.2.2.1. The agents-of-change view

A considerable body of theoretical and empirical research suggests that female star scientists, as many women in high-status positions, may act as *"agents of change"* serving as advocates for female non-star scientists, hence reducing the impact of potentially biased valuations made by majority members (i.e., male scientists) related to hiring and promotion decisions (Ibarra, 1995;

Ragins & Scandura, 1989). Two key arguments suggest that female star scientists may empathize with, and therefore favor, female non-stars. The first is that individuals are homophilous and prefer to interact more often with those they perceive to be similar to themselves. Prior research suggests that in the absence of information about attitudinal similarity, people rely on salient social categories, such as gender, as cues of underlying similarities (George & Chattopadhyay, 2002; McPherson & Smith-Lovin, 1987). Work following this theoretical development posits that individuals find members of the same social category to be more trustworthy, honest and cooperative than members of a different category (Brewer, 1979). Since gender is a salient social category, especially in the organization, "it can create a common bond between same-gender employees", i.e. female star/female non-star (Srivastava & Sherman, 2015, p. 1780).

The second argument asserts that female star scientists tend to be more sympathetic with female non-stars because female stars, like many women who have made it to the top, have experienced gender-based difficulties in their career advancement (Fagenson, 1993; Wallen, 2002). For example, in predominantly male-type jobs (e.g., R&D scientists), women's perceived competencies tend to be downgraded due to pervasive gender stereotypes (Moss-Racusin et al., 2012). Furthermore, women report suffering from unfair treatment in the workplace and hostility from colleagues in academia (Seymour, 2000). To the extent that they recognize such gender disparities and empathize with same-gender colleagues, female stars may use their status to favor other women by exhibiting behaviors that aim to overcome gender inequality in the workplace. In line with this view, Gorman (2005) found that high-status women tend to hire other women in large American law firms. Additionally, research shows that women in top managerial positions are associated with an increase of other women's promotions to middle management positions (Kurtulus & Tomaskovic-Devey, 2012) and a reduction in gender wage gaps (Hultin & Szulkin,

1999; Shenhav & Haberfeld, 1992). Furthermore, women in managerial roles tend to implement organizational policies that help to reduce gender inequality in the workplace (Stainback et al., 2011).

Given these arguments, female star scientists are likely to create a positive bond with female non-stars, leading them to judge female non-stars more favorably than male ones (Elliott & Smith, 2004; Gorman, 2005; Kanter, 1977b). Consistent with this view, several studies have shown that, compared to men, women in the upper echelons of organizations provide a more positive evaluation of female subordinates (Konrad & Pfeffer, 1991; Kulis, 1997; Pfeffer, Davis-Blake, & Julius, 1995). As female star scientists are less susceptible to gender bias in the first place, they are less likely to underestimate female non-stars based on stereotypical associations. Therefore, female star scientists may tend to assign a similar value to the person-specific information derived from third-party ties regardless of the gender of the non-star scientist. As a consequence, female star scientists are more likely to form ties with female non-star scientists independent of the presence of third-party ties. We, therefore, advance the following hypotheses:

> *H4a: The effect postulated by H1 (Star scientists are less likely to form collaboration ties with female non-star scientists than with male non-star scientists) is weaker when the star scientist is a woman.*
>
> *H5a: The effect postulated by H3 (The positive effect of common third-party ties should be stronger for female non-star scientists than for male ones) is weaker when the star scientist is a woman.*

#### 2.2.2.2. The cogs-in-the-machine view

Although there are reasons to believe that female star scientists might use their status to favor female non-star scientists, an alternative line of argument suggests that female stars may hold even more severe biases than male stars towards female non-star scientists (Cohen & Huffman, 2007; Derks et al., 2011; Ellemers et al., 2004; Maume, 2011). The social identity literature

describes this phenomenon as the “queen bee syndrome” (Staines, Tavris, & Jayaratne, 1974). For instance, Steinpreis et al. (1999) found that, in an academic environment, both female and male decision-makers prefer to hire male candidates rather than female candidates, even when controlling for human capital factors such as education and experience. Furthermore, Maume (2011) found that male employees received more job-related support than female employees when reporting to a female supervisor.

Research on the queen-bee phenomenon posits that women who have succeeded in male-typed jobs tend to be less inclined than men to show a preference for other women (Garcia-Retamero & Lopez-Zafra, 2009). A primary reason is that when women have made it to the top, they adopted an alternative identity that provides them with higher status (e.g., being a star scientist) (Chatman & O’Reilly, 2004; Ely, 1995), therefore, they tend to de-identify from their demographic groups (i.e., being a woman) (Derks, Van Laar, and Ellemers, 2016; Elsbach and Bhattacharya, 2001). For example, evidence suggests that high-status women are less likely to interact with other women because they no longer want to be perceived as in-group members (Chattopadhyay, Tluchowska, & George, 2004). Because women from the high-status group set themselves apart from other women, they tend to underrate lower-status female colleagues even more strongly than men (Paustian-Underdahl, King, Rogelberg, Kulich, & Gentry, 2017). Consistent with this view, several studies have found that compared with high-status men, high-status women are less supportive of the advancement of other women (Garcia-Retamero & Lopez-Zafra, 2009). They tend to give less support to equality programs that may improve opportunities for their female subordinates (Ely, 1994), and display more gender-biased perceptions about other women’s commitment to their career. For example, Ellemers et al.

(2004) found that female faculty tends to perceive female doctoral students as less committed to their careers, while male faculty perceives both male and female students as equally committed.

By arguing that women who make it to upper echelons of male-typed jobs have internalized male schemas and stereotypes even more intense than men have (Srivastava & Sherman, 2015; Staines, Tavris, & Jayaratne, 1974), this line of reasoning suggests that female star scientists are even more susceptible to gender stereotypes than male star scientists. In line with this view, prior work shows that high-status women tend to be more critical towards lower-status women than towards their male counterparts and make gender-stereotyped inferences about, for example, women's lack of ambition or professional commitment (Derks et al., 2011; Ellemers et al., 2004). Similarly, Stroebe et al. (2009) found that women who became successful in male-typed jobs perceived selection procedures as legitimate even when there is clear evidence of gender bias. Applied to the context of our study, this line of argument suggests that female star scientists may underrate the true value of female non-stars even more than male stars do. Furthermore, this negative bias should be particularly pronounced when female stars lack the person-specific information provided by third-party ties and, therefore, gender stereotypes are particularly salient. These arguments lead to the following hypotheses:

> *H4b: The effect postulated by H1 (Star scientists are less likely to form collaboration ties with female non-star scientists than with male non-star scientists) is even stronger when the star scientist is a woman.*
>
> *H5b: The effect postulated by H3 (The positive effect of common third-party ties should be stronger for female non-star scientists than for male ones) is even stronger when the star scientist is a woman.*

## 2.3. METHODOLOGY

### 2.3.1. Setting and data

We test our hypotheses in the context of American R&D departments of the forty largest pharmaceutical companies. Three features make this setting appropriate to test our predictions. First, collaboration networks are an essential determinant of productivity and career development for R&D scientists in the pharmaceutical industry and forming collaboration ties with high-status colleagues, e.g., star scientists, is critical to one's career advancement and success (Azoulay, Graff Zivin, & Wang, 2010; Waldinger, 2012). Second, there is compelling evidence that gender matters for R&D scientists. R&D scientists tend to have backgrounds in the natural sciences, engineering and life sciences (Eccles, 2007). Even though women have met or surpassed men regarding their human and educational capital in those academic areas, gender differences are still reflected in the demographics of R&D scientists, particularly among the hierarchical ranks (Frietsch, Haller, Funken-Vrohlings, & Grupp, 2009). Furthermore, preexisting implicit biases in these academic domains tend to result in lower hiring opportunities for women, compared to men (Moss-Racusin et al., 2012). Third, we have selected this industry because R&D activities of scientists in pharmaceutical firms are observable through archival data. Pharmaceutical firms tend to protect all their relevant inventions via patents (Brouwer & Kleinknecht, 1999), which leaves a fine-grained paper trail of who collaborated with whom at different moments in time.

Our research context consists of the forty members of the Pharmaceutical Research and Manufacturing Association (PhRMA) in 1985, which are the largest global pharmaceutical firms. We focused on these firms' R&D laboratories located within the United States because scientist gender is based on demographic data from the U.S. Social Security Administration (SSA), which is only available for the US. We collected financial, operational and patent data for these firms

from 1975 until 2010. Financial and operational data were obtained from Mergent WebReports, while we used EPO patent data to trace a firm's R&D activities. EPO patent data are preferred as they do not only include patents granted, but all patent applications (including the 50 percent of rejected applications), thereby reducing concerns of sample selection inherent in studies that use only patent grants (Ferguson & Carnabuci, 2017). Due to the global nature of the industry, pharmaceutical firms aim to protect their inventions in each possible region (Criscuolo, 2005), which reduces concerns about possible geographic selection biases.[3]

To trace a firm's R&D scientists, we examined the names appearing on that firm's patent applications (similar to McFadyen & Cannella, 2004; Paruchuri & Eisenman, 2012). Though not all R&D employees appear on patents, those who are involved in the creative stage of R&D projects must legally be mentioned as inventors on patent applications (Haeussler & Sauermann, 2013). We inferred scientists' gender based upon the demographic data provided by the U.S. Social Security Administration (SSA), which provides annual overviews of all first names, by gender, for American newborns. We compared the first name of each scientist to the name register of the U.S. Social Security Administration and used the dominant gender to classify scientists as male or female. From the complete sample of scientists (57,848 inventors), we could not identify the gender of 4.1 percent. These scientists are often immigrants. To be as conservative as possible in our estimates of gender effects, and in light of the fact that most scientists in our sample are males, we arbitrarily classified the unidentified scientists as male. We

[3] In order to protect inventions globally, pharmaceutical firms apply for patent protection in each state and can do so at different moments in time. However, nearly all firms use the Patent Cooperation Treaty process to get global patent protection in a single process whereby one patent application is filed at multiple offices within a limited time frame. This ensures that nearly all patents filed with any other patent office will also be filed with EPO.

also ran robustness checks classifying them as female and obtained qualitatively identical results (the results of these additional tests are discussed in the robustness checks section).

To define what constitutes a star scientist, we relied on prior studies that have examined the role of star scientists in knowledge-based organizations. Following Azoulay, Graff Zivin, and Wang (2010), Moretti and Wilson (2017), and Oettl (2012), we identified the 5 percent most productive R&D scientist within each firm based upon their five-year count of patent applications as stars.[4] This is similar to a frog-pond model where social comparison of individuals is based on the people around them, i.e., within the same laboratory (McFarland & Buehler, 1995). This fits well with the setting of R&D departments within pharmaceutical firms where both the development and use of knowledge through R&D projects takes place largely within firm boundaries (Giuri et al., 2007).

As the focus of this study is the initial formation of a collaboration tie between a star and a non-star scientist, our risk set comprises all possible dyads between all star scientists and all non-star scientists within each firm that have not collaborated before. We examined such dyads for each year, resulting in an unbalanced panel of star/non-star/year observations. We excluded cases in which (a) the star and non-star have collaborated before or (b) either the star or non-star left the firm or stopped being technologically active (which we assume to be the case when a scientist has not applied for any patents for five or more years).[5] Finally, we considered only star scientists who applied for a patent in a given year, since these are the particular time periods in which we could observe a collaboration between a star and a non-star scientist. We eliminated

[4] Results based on other thresholds - top-2 percent and top-10 percent - are presented in the robustness checks section.

[5] The probabilities that an inventor will file again for a patent are significant, but decrease rapidly over time: 60 percent of all inventors with subsequent patents apply within one year and another 20 percent in the year thereafter. The probability that an inventor will file another patent but not in the next five years, is around 1 percent. We therefore consider the five-year time window appropriate.

firms with less than twenty scientists in their R&D departments and those where star scientists never collaborate with non-stars, which account for 5 percent of the observations.

### 2.3.2. Measures

#### 2.3.2.1. Dependent variable

*First-time collaboration.* Our dependent variable is a dichotomous variable set to one when a non-star scientist collaborates with a star scientist for the first time (Dahlander & McFarland, 2013).

#### 2.3.2.2. Explanatory and moderating variables

*Female.* This is a dummy variable set to one to indicate female non-star scientists. The reference category is male non-star scientist.

*Third-party ties*. This is a dummy variable indicating if a star and a non-star scientist have at least one connection in common within the firm, that is, they independently both collaborated with the same scientist before. To identify third-party collaborators, we focus on the five years prior to the focal year.

#### 2.3.2.3. *Control variables*

Our models include factors that may drive systematic differences in the likelihood that a non-star scientist enters a collaborative relationship with a star scientist. Our control variables are operationalized into three categories: attributes of the star, attributes of the non-star, and dyadic attributes.

**Attributes of the Star.** Heterogeneity among star scientists, including their visibility and involvement in organizational projects (Oldroyd & Morris, 2012) or their willingness to collaborate (Oettl, 2012), influence a non-star's likelihood of collaborating. Hence, we control

for *Star scientists' Tenure*, measured as the number of years from the first patent that a star scientist has within the firm. Star scientists with a larger number of ongoing projects in a given year may need more colleagues to assist them and have an incentive to create new collaborations. Accordingly, we control for the number of ongoing projects a star scientist has in a given year, measured as the number of the patent applications a star has in each focal year *(Star scientists' Current projects).* Star scientists who have been highly productive in the past may be less likely to form new collaborations with non-star scientists because they already have a productive network of recurrent collaborators. Therefore, we control for *Star scientists' Prior productivity*, by counting their successful patent applications during the five years before the focal year.

**Attributes of the Non-Star.** Non-star scientists who have spent a long time within a firm are more likely to have already collaborated with a star scientist. Thus, we include the variable *Non-star scientist's Tenure*, which is calculated from the first time a non-star scientist appears on a patent in a given firm. Because a non-star scientist's likelihood of forming a new collaboration with a star scientist may reflect differences in non-star scientists' inherent ability, we control for *Non-star scientists' Prior productivity*, which is measured by the number of successful patent applications during the five years prior to the focal time period.

**Dyadic Attributes**. Because scientists who have a similar technological profile are more likely to collaborate, we control for the *Technological distance* between a star and a non-star scientist. We use the additive inverse of the Blau concentration index (1977) ranging from 0 to 1. It takes on the value of 0 when a star and a non-star scientist are specialized in the same main patent subclass(es) and it approaches 1 when a star and a non-star scientist are specialized in different, non-overlapping patent subclass(es). We also include the variable *Spatial distance*, which reflects scientists' geographical proximity, as the spatial distance between a star and a

non-star decreases the probability of forming a collaboration tie. Finally, non-star scientists vary in the degree to which they already have collaborated with other star scientists. To capture the remaining opportunities to form new collaborative ties with star scientists, we include *Collaboration opportunity* as the number of stars in the firm that the non-star scientist has not previously collaborated with.

## 2.4. RESULTS

Figure 2-1 shows the proportion of star and non-star scientists by gender throughout the years of analysis. In the period 1985–2010, the share of female R&D scientists among our sample firms increased by 15.9 percentage points, growing from 8.4 percent in 1985 to 24.3 percent in 2010. Among star scientists, the proportion of females increased during the period of analysis from 5 percent (in 1985) to 10 percent (in 2010). These differences suggest that the gender gap concerning stardom remains noticeable. Table 2-1 provides descriptive statistics and pairwise correlations. The probability of a star and non-star scientist forming a collaborative relation is around 0.1 percent, indicating that from all the potential collaborations between star/non-star scientists, only a few non-star scientists manage to form a collaborative tie with a star. Star and non-star scientists have a third-party collaborator in common in 4.4 percent of all potential dyads. However, third-party collaborators are present in 52.1 percent of all cases in which a collaboration tie between star and non-star is actually formed. This provides *prima facie* evidence for our second hypothesis. Moving to the attributes of the scientists, the average organizational tenure of a male star scientist (nine years) is larger than the average tenure of a female star scientist (seven years). Similarly, the average tenure of a male non-star scientist (five years) is larger than the average organizational tenure of a female non-star scientist (four years). There are no gender differences in the prior productivity of star and non-star scientists. However,

as expected, star scientists are much more productive than non-star scientists, with an average 18 patents in the prior five years compared to two patents for non-stars. The descriptive statistics from our dyadic attributes indicate that whereas 37 percent of all dyadic observations between a star scientist and male non-star scientist have no experience in the same technological classes, only 9 percent of all dyadic observations between a star scientists and female non-star scientists have no experience in the same technological classes. There are no gender differences in the average spatial distance between star and non-star scientists. On average, star and non-star scientists live a thousand kilometers radius (about six hundred miles) away from each other. Finally, while a male non-star scientist has not collaborated yet on average with seventy-two star scientists within each firm, a female non-star has not collaborated with seventy-five star scientists.

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Insert Table 2-1 and Figure 2-1 about here
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We used a binary logistic regression approach to test our hypotheses. To control for unobserved firm- and time-specific heterogeneity, we added firm and year fixed effects. Modeling inventor-fixed effects is not possible because gender does not vary over time. To deal with the interdependence of our observations, we employed a three-way clustering method (Colin, Gelbach, & Miller, 2011; Kleinbaum, Stuart, & Tushman, 2013) at the level of the star scientists, of the non-star scientist, and of the star/non-star dyad to obtain robust standard errors. We performed extensive robustness checks to address possible alternative explanations for our results, such as unobserved heterogeneity among scientists, sample bias, estimation bias among others. We discuss these results in the robustness checks section. As some of our control variables are highly skewed, we entered their log-transformed values in the analysis.

Table 2-2 reports results of logistic regression models predicting the formation of a first collaboration tie between a non-star and a star scientist. We began by estimating a baseline model including only control variables (Model 1). In line with the view that star scientists with a larger number of ongoing projects have more opportunities to create new collaboration ties, the effect of *Star scientists' Current projects* on *First-time collaboration* is positive and strongly significant ($p<.001$). Corroborating the view that non-star scientists' prior productivity increases their chances of building a collaborative relationship with star scientists, the effect of *Non-star scientists' Prior productivity* is positive and significant ($p<.001$). The negative coefficient of *Non-star scientist's Tenure* suggests that the larger the time a non-star spends within an organization, the lower tend to be his/her chances of initiating a collaboration with a star scientist ($p<.001$). As expected, we also find that star/non-star scientists who have a greater *Technological distance* or *Spatial distance* are less likely to form a collaborative relation ($p<.001$).

Turning to our covariates of interest, we introduce *Third-party ties* in Model 2, *Female* in Model 3 and their interaction term in Model 4. H1 predicts that star scientists are less likely to form collaboration ties with female non-star scientists than with male non-star scientists. In line with this hypothesis, a star scientist is nearly 20 percent less likely to initiate a collaboration with a female non-star scientist than with an otherwise-equivalent male non-star ($\beta=-0.220$; $p<.001$). H2 states that having *Third-party ties* increases the probability of initiating a collaboration tie. Corroborating this hypothesis, we find that star scientists are six times more likely to build a collaborative relation with a non-star scientist when they have common third parties ($\beta=1.872$; $p<.001$). H3 predicts that the positive effect of common third-party ties be larger for female non-star scientists than for male ones; consequently, the gap between female and male non-star scientists is smaller when non-star scientists have third-party ties in common with the star

scientist than when they have no third-party ties. The interaction term of *Female* and *Third-party ties*, included in model 4, is positive and significant ($\beta$=0.242; p<.001), providing support for this hypothesis. In terms of marginal effects, having a third-party tie increases the likelihood of collaboration six-fold for male non-stars, but this is over eight-fold for females. When visualizing these effects, we observe that the disadvantage faced by female non-stars disappears entirely with the presence of a third-party tie.

We further presented two alternative hypotheses is based on the "cogs in the machine" view, and the other on the "women as agents of change view," about how a star's gender influences the likelihood of male and female non-stars forming a collaboration tie. To adjudicate between these hypotheses, we created four dummy variables partitioning our risk set of possible dyads depending on the genders of the star and the non-star scientists, resulting in four combinations: male-star/male-non-star, male-star/female-non-star, female-star/male-non-star, and female-star/female-non-star. We enter these dummies in model 5, using male-star/male-non-star as our reference group. Overall, male star scientists are 20 percent less likely to start collaborations with female non-star scientists than with male non-stars. Compared with male star scientists, female star scientists are 19 percent less likely to form ties with male non-stars. Furthermore, female stars are even less likely, namely 30 percent, to include female non-stars in their collaboration networks compared to male non-stars. Model 6 adds the interaction between each of these three dummy variables and *Third-party ties*. These interactions enable us to test whether the effect hypothesized by H1 (that star scientists are less likely to form collaboration ties with female non-star scientists than with male non-star scientists) is reduced (H4a) or amplified (H4b) when the star scientist is a woman relative to when the star scientist is a man. Similarly, we construct a set of interaction terms to test if the effect postulated by H3 (that the positive impact of common

third-party ties is larger for female non-star scientists than for male ones) is reduced (H5a) or amplified (H5b) when the star scientist is also female relative to when the star scientist is a man. Using a Wald test on the relevant regression coefficients, we find that female star scientists are even less likely than male star scientists to build a collaborative relation with female non-star scientists ($\chi^2$=33.02; p<.001), which supports H4b rather than H4a. Furthermore, supporting H5b and contrary to H5a, women's need for third-party connections is larger if the star scientist is female than if he is male ($\chi^2$=22.70; p<.001). Hence, both these sets of results provide support for the "cogs in the machine view," indicating that female non-star scientists face even greater hurdles when attempting to form collaborative relations with female stars than with male stars.

Figure 2-2 displays the marginal effects of our four dyadic dummies and their interaction with third-party ties on the likelihood of initiating a collaboration. Several points are worth noting. First, the probability of forming a collaboration tie is largest between male star scientists and male non-star scientists and lowest between female star scientists and female non-star scientists. Thus, consistent with the "cogs in the machine" view and despite a generalized tendency towards homophily, female stars are even less likely than male ones to form a tie with female non-stars. Second, common third-party ties increase the likelihood of forming ties with stars by roughly one order of magnitude regardless of gender; furthermore, third-party ties are even more important for female than for male non-star scientists. For example, forming a collaboration *Female-star/Female-non-star* becomes about 10 times more likely with the presence of common third-party collaborators, while this is around 7 times for a collaboration between *Male-star/Female-non-star*. Indeed, this effect is so large that, among the subset of non-stars who have third-party ties with a star scientist, the likelihood of forming a collaboration tie is highest for the female-star/female-non-star combination. Furthermore, within this subsample, male star

scientists are almost as likely to form a collaboration tie with a female as with a male non-star in the presence of a third-party tie. These findings suggest that most of the gender disparity happens among the 96 percent of non-star scientists who have no third-party ties with stars. By contrast, there is little evidence of a gender gap among the small minority of non-star scientists who do have third-party tie connections with a star.

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Insert Table 2-2 and Figures 2-2 and 2-3
about here
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**Robustness Checks**

We performed a number of robustness checks regarding our measures, methods and sample. All relevant tables are reported in the Appendix. First, we checked the sensitivity of our results to changes in key measures. In our main analyses, we classified scientists whose first name could not be linked to a gender as male. To check whether our results may be affected by this choice, we classify these scientists as female, recreate all sample variables, and re-run the entire analysis. Results reported in Appendix Table 2-A3 remain similar to those presented before. Likewise, we earlier defined star scientists as the top 5 percent most productive inventors based on patent applications. We reconstructed the sample and repeated the analysis narrowing the definition to the top 2 percent and also widening it to the top 10 percent most productive inventors. The results, included in Appendix Table 2-A4 and Table 2-A5, are qualitatively identical to our earlier findings.

Unobserved heterogeneity among scientists may affect their likelihood of being chosen by a star scientist as a collaboration partner. As stated before, we cannot rely on fixed-effect regressions as they perfectly correlate with the key independent variable, scientist gender, and use multiway clustering instead. We performed two alternative robustness checks to address such

concerns further. First, we partially captured the unobserved heterogeneity of scientists by adding random effects at the star/non-star dyad level. The results of this random-effects logit regression, included in Table 2-A6, are similar to those reported in Table 2-2. Second, we employed a matched-sample design where female non-star scientists are matched to male non-star scientists based on observable characteristics. Specifically, each dyadic observation involving a female non-star scientist is matched to a dyadic observation of a non-star male scientists of the same firm in the same year related to the same star scientist, with similar non-star scientist *Tenure* and *Productivity* and with similar *Spatial* and *Technological distance* to the star, using a nearest-neighbor matching approach (Stuart, 2010). We found a close matches for 25 percent of our observations, resulting in a sample of 2.4 million observations: 1.2 million for female non-stars, each matched to a male non-star. When looking at their observable characteristics, both groups are very similar and within a 1 percent-range. Yet, there are slight differences between the 1.2 million matched and 1 million non-matched female non-star scientist observations, with the non-matched observations having a higher tenure and productivity and being geographically and technologically more distant, though all differences are within an acceptable 10 percent-range. When estimating our models on this matched sample, we obtain outcomes very similar to our main results, as Table 2-A7 shows. However, while the first three hypotheses are strongly supported, the effect of star gender is no longer significant.

Another concern we addressed pertains to the low probability of a first-time collaboration, which can bias the estimated coefficients of the logit regression. We used two alternative methods to check the robustness of our findings with respect to this concern. First, we estimated a rare-event logit model where each observed tie formation is linked to nine non-observed ties (King & Zeng, 2001). The regression outcome reveals very comparable results, as displayed in

Appendix Table 2-A8. Second, we limited the risk set of each star scientists to the set of non-star scientists who live within a hundred kilometers radius (about sixty miles) because nearly all created ties are within this distance. The results in Appendix Table 2-A9 are similar to those observed earlier.

Finally, we re-examined the hypotheses about initiating collaborations with a star scientist using an event history model, which simultaneously models the likelihood of and time until tie formation. For this analysis, we only kept the star/non-star/year observations in which the non-star inventor files a patent application, as these are the moments we can observe the (non-) collaboration between the star and non-star scientist. Using a Cox proportional hazards regression model, results support the hypotheses (see Appendix Table 2-A10). First, we observe that having third-party ties increases the probability of forming collaborations between a star and a non-star scientist. We also notice that the positive effect of third-party ties is larger for female non-star scientists than for male non-stars. Second, this analysis also confirms the role of star scientists' gender as we observe that female stars are less likely to initiate collaboration ties with female non-star scientists than male stars. Yet, third-party ties are more needed for female non-star scientists when the star scientist in question is a woman.

## 2.5. DISCUSSION AND CONCLUSION

Social network theory has helped us gain important new insights on the mechanisms generating gender inequality in organizations (Fernandez & Sosa, 2005; Merluzzi & Sterling, 2017; Ibarra, 1992, 1997; Burt, 1998; Van Emmerik, 2006). In this paper, we illuminated the conditions that facilitate or hinder women's access to a source of social capital that is disproportionably concentrated among a minority of high-status colleagues, so-called star scientist. First, confirming the hypothesis that access to the social capital of high-status actors is

gendered, we showed that star scientists are significantly less likely to form collaboration ties with female non-star scientists than with male ones. Second, we showed that whereas having common collaborators (i.e., third-party ties) who may connect a non-star to a star increased the likelihood of forming a collaboration tie in general, this effect varies markedly depending on the gender of the non-star. Specifically, we found that having third-party ties is critically important for female non-stars but comparatively less important for male non-stars; or, said differently, not having third-party ties represents a greater hurdle for female non-stars than for male ones. Insofar as women's ability to connect to stars depends more heavily on the intermediation of third parties than is the case for men, this finding suggests that women's path to entering a star scientist's collaboration network is more indirect, and hence more complicated, than men's. Third, we explored whether women's disadvantages in forming collaborative ties with stars are amplified or reduced when the star scientist is a woman. We found that female stars are even less likely than male stars to form collaboration ties with female non-stars, providing support to the so-called "cogs in the machine" line of argument (Cohen & Huffman, 2007; Srivastava & Sherman, 2015). We also found that the positive effect of common third-party ties is larger for female non-stars when the star scientist is female compared to male. Consistent with the view that women's path to stars' networks is more indirect than men's, these findings indicate that the gap between female and male non-star scientists is smaller when non-star scientists have third-party ties in common with the star scientist than when they have no third-party ties.

### 2.5.1. Limitations

Certain limitations of our study should be considered when interpreting our results. First, a drawback of using large-scale observational data, as we do, is that it is impossible to tease out the details of the decision-making process guiding stars' choice of whom to collaborate with.

This leaves open potential different micro-level mechanisms. For example, we find evidence consistent with the "cogs in the machine" argument. However, we have no direct evidence of the motivations driving female (or male) star scientists' collaboration choices. Second, we focus on stars' decision-making problem assuming that star scientists have full discretion in choosing their collaborators and considering that non-stars always prefer to collaborate with star scientists. Although this is a plausible assumption, we cannot check its validity in the context of our study. Consequently, we are unable to rule out the possibility that some of our results may be driven by the behaviors and choices of non-star scientists. Future work considering non-star scientists' perspective would be necessary to provide a more comprehensive understanding of how male and female non-star scientists gain access to the collaboration network of star scientists. Third, we have no information on the formal positions of scientists within our data set. Collecting such data in a longitudinal, large-scale project like ours is difficult because (a) it would require access to companies archival HR records and (b) it is hard to compare job titles across firms. For that reason, we are unable to examine whether and how scientists' formal positions affect their collaboration opportunities and choices.

### 2.5.2. Contributions

It is becoming increasingly clear that men's and women's differential access to social capital represents a key reason for the persistent gender gap in career outcomes within contemporary, knowledge-based organizations (Burt, 1998; O'Neill & Gidengil, 2013; Singh et al., 2010). Despite wide recognition that access to social capital is often gendered (Kay & Wallace, 2009; Lutter, 2015), few studies provide detailed theoretical accounts or empirical evidence of the mechanisms affecting this important driver of gender disparity. To advance our understanding of the phenomenon, we examined whether and how gender may influence access to a crucial source

of social capital – high-status colleagues – in knowledge-based organizations where the human capital of women has met, if not surpassed, that of men. Specifically, we focused on the pharmaceutical sector and examined the American R&D laboratories of the forty largest pharmaceutical companies globally. This context is ideally suited to our study because it features an unambiguous case of high-status actors who control a disproportional amount of social capital within the organization – star scientists – and entering the collaboration network of those high-status actors has been shown to matter greatly for one's legitimacy, performance and career progress (Azoulay, Ding, & Stuart, 2009; Oettl, 2012; Tzabbar & Kehoe, 2014; Waldinger, 2012; Zucker & Darby, 1998).

Our study offers several important contributions. First, prior research on social networks has shown that women and men follow different strategies in order to pursue similar career outcomes, e.g., early promotions. In particular, Burt (1998) argued that whereas men achieve higher career outcomes than women by building their own social capital, women need to borrow social capital from a strategic partner to succeed. We complement this view by examining under which conditions women are more likely to access social capital from high-status colleagues. Our results show that female and male scientists follow different paths when it comes to forming collaborations with high-status colleagues. Whereas both men and women are more likely to form high-status collaboration ties in the presence of common third parties, such indirect connections are far more important for women than for men. That is, to access the social capital of high-status colleagues, women depend on third-party ties more than men do.

Second, extant research has examined whether having large shares of women in the high-status strata of organizations favors workplace gender equality (Cohen & Huffman, 2007; Kurtulus & Tomaskovic-Devey, 2012; Srivastava & Sherman, 2015). Most of this discussion

builds on two opposite lines of argument. One line posits that woman in high-status organizational positions may serve as *"agents of change"* who favor their lower-status counterparts and, therefore, reduce the gender gap (Huffman et al., 2010; Kurtulus & Tomaskovic-Devey, 2012; Stainback et al., 2011). The second line of argument, so called *"cogs in the machine"* (Derks et al., 2011; Maume, 2011), suggests that women at the top act in certain ways that may exacerbate the gender gap (Ellemers et al., 2004; Paustian-Underdahl et al., 2017; Stroebe et al., 2009). In this paper, we contribute to this debate by showing that female star scientists are more likely to initiate collaborative relations with male non-star scientists rather than with female non-stars. This finding challenges the *"agents of change"* line on argument and supports the *"cogs in the machine"* view. Most importantly, we shed light on the conditions under which female star scientists are more likely to start collaborations with female non-stars. In particular, our results indicate that female star scientists are more likely to include female non-stars in their collaboration networks when they have third-party ties in common. Therefore, our results show that having women at the top of the status hierarchy results in women having greater access to social capital only when there are third-party connections between the high- and low-status women.

Our research also contributes to the intra-organizational network literature. Prior research has shown that becoming part of the collaboration network of high-status colleagues is hugely important for the career advancement of their low-status counterparts (Oettl, 2012). Even if this is a well-established fact, few studies (e.g., Kleinbaum, 2012) have examined under which conditions low-status actors are more likely to become part of the intra-organizational network of their high-status colleagues. We contribute to this line of inquiry by looking at the antecedents of tie formation between star scientists and non-stars. Our results show that having indirect

connections, i.e., third-party ties, make it more likely that a star scientist initiates collaborating with a non-star. Common ties between stars and non-star scientists increase the chances that a star chooses a specific non-star over others for which no such common ties exist.

Relatedly, our findings also contribute to a better understanding on the role of status and gender homophily and social network position in tie formation. With few exceptions (e.g., Castellucci & Ertug, 2010; Shipilov, Li, & Greve, 2011), prior research focused predominantly on understanding homophily and network structure as the key drivers for new connections (e.g., Singh, Lee, & Chung, 2000; McPherson, Smith-Lovin, & Cook, 2001). This work suggests that actors form social connections based on similar gender and status (McPherson, Smith-Lovin, & Cook, 2001) and common contacts (Burt, 2009). These two phenomena tend to co-occur and mutually reinforce each other (Kossinets & Watts, 2006), resulting in clearly-segregated communities based on gender and status. However, less is known about how such interactions are initiated when actors have different levels of status. We extend this line of inquiry by considering the role of gender in understanding how low-status scientists connect with high-status ones. Our results indicate that gender-based homophily plays a marginal role in the absence of a third-party: in fact, female stars are more likely to collaborate with male non-stars than with female non-star scientists (see Figure 2-3). Yet, these effects reverse when ties are formed through a common connection ('triadic closure'): this seems to foster homophilous collaborations of male stars with male non-star scientists and female stars with female non-star scientists. These insights suggest that homophily, based on individual characteristics, and network positions, based on social characteristics, jointly influence forming connections with status differences.

To the extent that the presence of third-party ties is more valuable for female non-star scientists, rather than male non-stars, our findings suggest that organizations need to implement concrete ways to increase women's chances of connecting to third-parties. Recently, organizations have developed programs to promote women's opportunities for collaborating with colleagues from different areas and hierarchical levels (Kalev, 2009; Kalev, Dobbin, & Kelly, 2006). For instance, self-directed work teams and cross-training programs bring together employees from different areas and hierarchical positions to develop collaborative ideas and to share knowledge (Kalev, 2009). This may be particularly beneficial for women because these programs foster collaborative ties between female employees and their colleagues. In turn, such colleagues can serve as bridges to connect female employees with other high-status colleagues. Therefore, female non-star scientists have higher chances of being chosen by a star scientist because they have gained access to a larger intra-organizational network, which may, in turn, result in connections with other star scientists. These dynamics maximize employees' likelihood of forming third-party connections as a potentially effective approach toward equalizing women's and men's access to social capital.

## FIGURES

**Figure 2-1.** Star scientists within the firm, share of the female star scientists

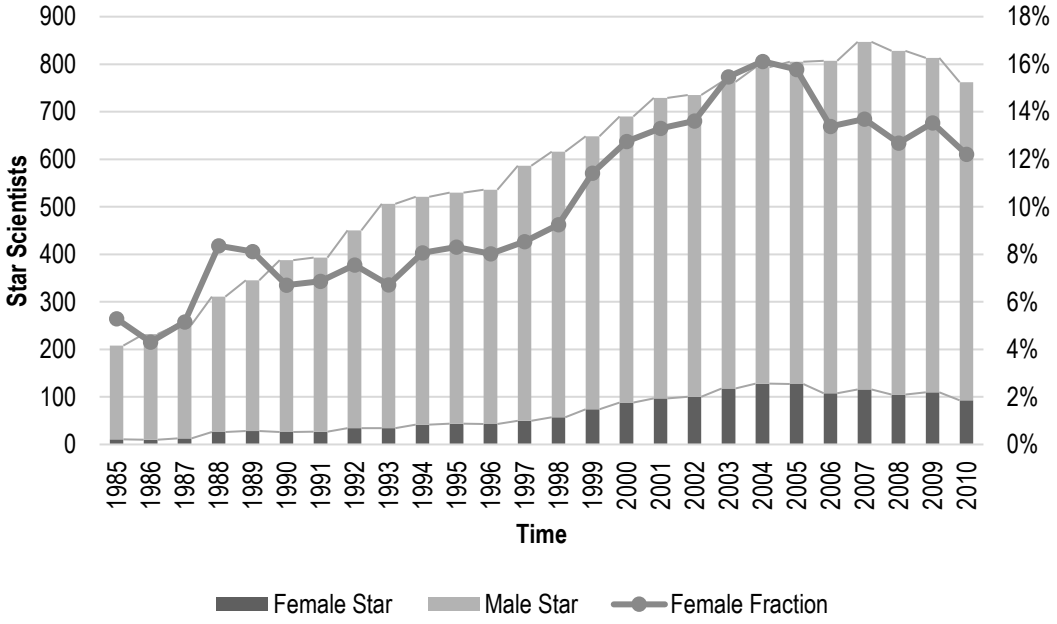



**Figure 2-2.** Predicted first-time collaboration between star scientist and non-star scientist, by non-star scientists' gender, splitting star scientists' gender

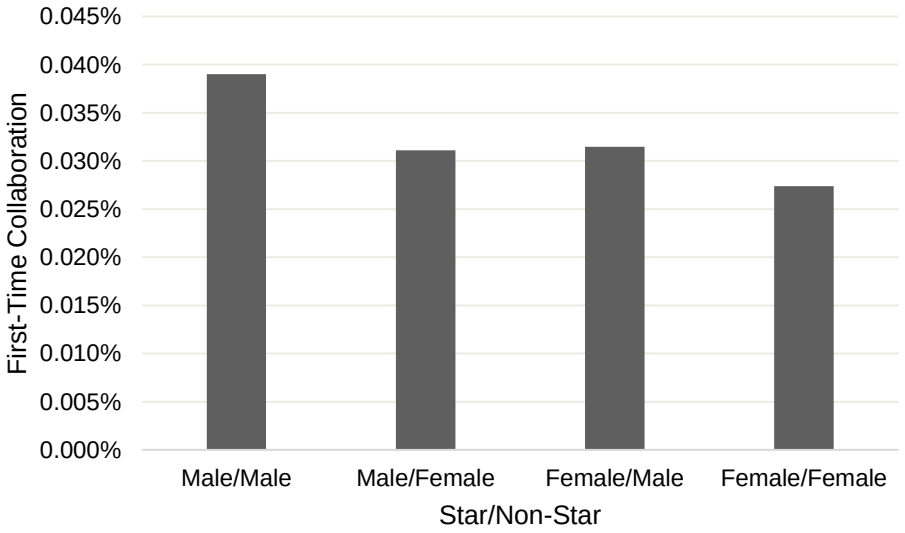
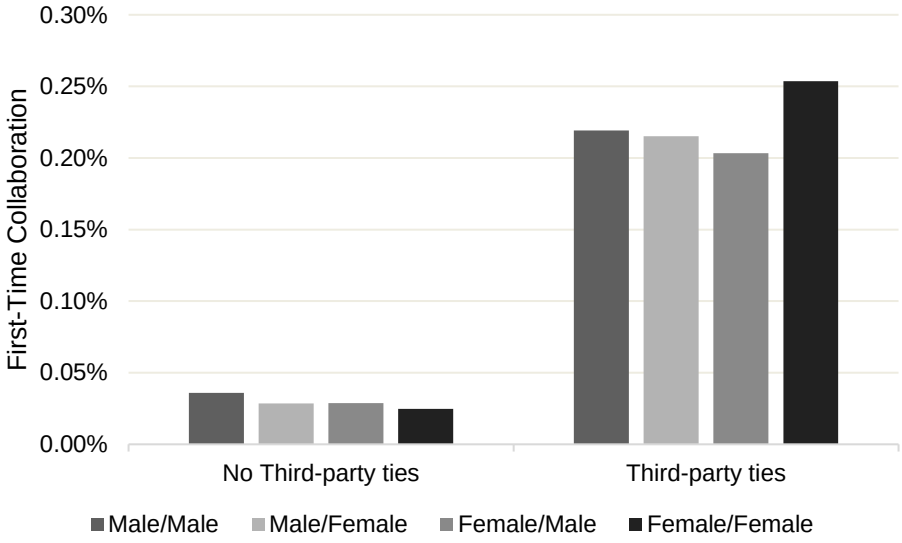


**Figure 2-3.** Predicted initial collaboration between star scientist and non-star scientist, by non-star scientists' gender splitting star scientists' gender, and sharing non-star third-party ties



## TABLES

**Table 2-1** Descriptive Statistic and Pairwise Correlations

| | **Mean** | **S.D.** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** | **(13)** | **(14)** | **(15)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1.** First-time collaboration | 0.001 | 0.037 | 1 | | | | | | | | | | | | | | |
| **2.**Female non-star | 0.217 | 0.412 | 0 | 1 | | | | | | | | | | | | | |
| **3.**Female-star/Female-non-star | 0.024 | 0.152 | 0.001 | 0.295 | 1 | | | | | | | | | | | | |
| **4.**Female-star/Male-non-star | 0.082 | 0.274 | -0.002 | -0.157 | -0.046 | 1 | | | | | | | | | | | |
| **5.**Male-star/Female-non-star | 0.194 | 0.395 | -0.001 | 0.93 | -0.076 | -0.146 | 1 | | | | | | | | | | |
| **6.**Male-star/Male-non-star | 0.701 | 0.458 | 0.001 | -0.807 | -0.238 | -0.456 | -0.751 | 1 | | | | | | | | | |
| **7.**Third-party ties | 0.044 | 0.206 | 0.085 | 0.014 | 0.01 | -0.001 | 0.011 | -0.013 | 1 | | | | | | | | |
| **8.**Star tenure | 9.379 | 5.553 | 0.002 | 0.025 | -0.047 | -0.103 | 0.044 | 0.04 | 0.037 | 1 | | | | | | | |
| **9.**Star prior productivity | 17.962 | 13.106 | 0.005 | 0.03 | 0.002 | -0.007 | 0.031 | -0.023 | 0.058 | 0.094 | 1 | | | | | | |
| **10.**Star current projects | 3.63 | 4.602 | 0.019 | 0.01 | -0.016 | -0.028 | 0.017 | 0.007 | 0.017 | -0.023 | 0.387 | 1 | | | | | |
| **11**.Non-star tenure | 5.334 | 4.589 | 0.003 | -0.088 | -0.026 | 0.019 | -0.082 | 0.068 | 0.045 | 0.047 | 0.023 | -0.003 | 1 | | | | |
| **12.**Non-star prior productivity | 2.354 | 2.101 | 0.025 | -0.04 | -0.012 | 0.01 | -0.037 | 0.03 | 0.134 | 0.034 | 0.068 | 0.025 | 0.237 | 1 | | | |
| **13.**Technological distance | 0.724 | 0.353 | -0.045 | -0.03 | -0.015 | 0.009 | -0.025 | 0.021 | -0.239 | -0.071 | -0.013 | 0.004 | -0.059 | -0.128 | 1 | | |
| **14.**Spatial distance (ln) | 5.148 | 2.465 | -0.032 | -0.027 | -0.012 | 0.003 | -0.023 | 0.023 | -0.15 | -0.147 | -0.005 | 0.023 | -0.116 | -0.064 | 0.175 | 1 | |
| **15.**Collaboration opportunity | 72.338 | 37.077 | -0.016 | 0.038 | 0.011 | 0.01 | 0.035 | -0.04 | -0.068 | 0.064 | 0.117 | 0.052 | 0.036 | 0.084 | 0.046 | 0.201 | 1 |

N=10,185,024. All correlations larger than |0.0014| are significant at the 0.01 level.

**Table 2-2.** Logistic Regression Predicting First-Time Collaboration

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | 0.093** | 0.083* | 0.083* | 0.083* | 0.076* | 0.077* |
| | (0.036) | (0.033) | (0.033) | (0.033) | (0.034) | (0.034) |
| Star prior productivity (ln) | -0.221*** | -0.399*** | -0.398*** | -0.398*** | -0.401*** | -0.400*** |
| | (0.049) | (0.047) | (0.047) | (0.047) | (0.047) | (0.047) |
| Star current projects (ln) | 0.783*** | 0.797*** | 0.796*** | 0.797*** | 0.794*** | 0.795*** |
| | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) |
| Non-star tenure (ln) | -0.241*** | -0.215*** | -0.220*** | -0.220*** | -0.220*** | -0.220*** |
| | (0.028) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Non-star prior productivity (ln) | 0.830*** | 0.546*** | 0.541*** | 0.542*** | 0.541*** | 0.542*** |
| | (0.027) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| Technological distance | -2.751*** | -2.054*** | -2.055*** | -2.054*** | -2.053*** | -2.052*** |
| | (0.052) | (0.054) | (0.054) | (0.054) | (0.054) | (0.054) |
| Spatial distance (ln) | -0.373*** | -0.307*** | -0.307*** | -0.308*** | -0.308*** | -0.308*** |
| | (0.012) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Collaboration opportunity | -0.006*** | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Third-party ties | | 1.869*** | 1.871*** | 1.872*** | 1.871*** | 1.808*** |
| | | (0.041) | (0.041) | (0.041) | (0.041) | (0.043) |
| Female non-star | | | -0.098** | -0.220*** | | |
| | | | (0.032) | (0.042) | | |
| Female non-star x Third-party ties | | | | 0.242*** | | |
| | | | | (0.055) | | |
| Male-star/Female-non-star | | | | | -0.120*** | -0.227*** |
| | | | | | (0.033) | (0.043) |
| Female-star/Male-non-star | | | | | -0.147* | -0.215** |
| | | | | | (0.059) | (0.080) |
| Female-star/Female-non-star | | | | | -0.060 | -0.354** |
| | | | | | (0.079) | (0.110) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.218*** |
| | | | | | | (0.056) |
| Female-star/Male-non-star x Third-party ties | | | | | | 0.147 |
| | | | | | | (0.109) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.524*** |
| | | | | | | (0.148) |
| Constant | -4.644*** | -4.645*** | -4.641*** | -4.652*** | -4.588*** | -4.568*** |
| | (0.265) | (0.255) | (0.254) | (0.254) | (0.255) | (0.254) |
| Observations | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 |

Standard errors, clustered by star, non-star, and dyad, in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

## Appendix: Robustness checks

**Table 2-A3.** Logistic Regression Predicting First-Time Collaboration (Unknown gender categorized as Female)

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | 0.093** | 0.083* | 0.083* | 0.083* | 0.077* | 0.078* |
| | (0.036) | (0.033) | (0.033) | (0.033) | (0.033) | (0.033) |
| Star prior productivity (ln) | -0.220*** | -0.396*** | -0.396*** | -0.396*** | -0.398*** | -0.397*** |
| | (0.049) | (0.047) | (0.047) | (0.047) | (0.047) | (0.047) |
| Star current projects (ln) | 0.783*** | 0.797*** | 0.796*** | 0.797*** | 0.795*** | 0.795*** |
| | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) |
| Non-star tenure (ln) | -0.241*** | -0.214*** | -0.219*** | -0.219*** | -0.219*** | -0.219*** |
| | (0.028) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Non-star prior productivity (ln) | 0.830*** | 0.546*** | 0.544*** | 0.544*** | 0.544*** | 0.544*** |
| | (0.027) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| Technological distance | -2.750*** | -2.054*** | -2.055*** | -2.055*** | -2.053*** | -2.054*** |
| | (0.052) | (0.054) | (0.054) | (0.054) | (0.054) | (0.054) |
| Spatial distance (ln) | -0.374*** | -0.307*** | -0.307*** | -0.308*** | -0.308*** | -0.308*** |
| | (0.012) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Collaboration opportunity | -0.006*** | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Third-party ties | | 1.869*** | 1.871*** | 1.869*** | 1.871*** | 1.800*** |
| | | (0.041) | (0.041) | (0.041) | (0.041) | (0.045) |
| Female non-star | | | -0.063* | -0.161*** | | |
| | | | (0.029) | (0.038) | | |
| Female non-star x Third-party ties | | | | 0.198*** | | |
| | | | | (0.052) | | |
| Male-star/Female-non-star | | | | | -0.070* | -0.158*** |
| | | | | | (0.031) | (0.039) |
| Female-star/Male-non-star | | | | | -0.075 | -0.139* |
| | | | | | (0.048) | (0.065) |
| Female-star/Female-non-star | | | | | -0.095 | -0.307*** |
| | | | | | (0.064) | (0.086) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.184*** |
| | | | | | | (0.053) |
| Female-star/Male-non-star x Third-party ties | | | | | | 0.139 |
| | | | | | | (0.090) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.388*** |
| | | | | | | (0.115) |
| Constant | -4.635*** | -4.627*** | -4.625*** | -4.633*** | -4.589*** | -4.566*** |

| **Dependent Variable:** **First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| | (0.265) | (0.254) | (0.254) | (0.254) | (0.254) | (0.254) |
| Observations | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 |

Standard errors, clustered by star, non-star, and dyad, in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 2-A4.** Logistic Regression Predicting First-Time Collaboration –Star Scientists Limited to Top-2%

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | 0.155** | 0.118* | 0.118* | 0.118* | 0.109* | 0.109* |
| | (0.051) | (0.047) | (0.047) | (0.047) | (0.047) | (0.048) |
| Star prior productivity (ln) | -0.152* | -0.352*** | -0.351*** | -0.351*** | -0.350*** | -0.351*** |
| | (0.076) | (0.074) | (0.074) | (0.074) | (0.074) | (0.074) |
| Star current projects (ln) | 0.774*** | 0.784*** | 0.783*** | 0.783*** | 0.779*** | 0.779*** |
| | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) |
| Non-star tenure (ln) | -0.220*** | -0.197*** | -0.204*** | -0.204*** | -0.205*** | -0.204*** |
| | (0.035) | (0.033) | (0.033) | (0.033) | (0.033) | (0.033) |
| Non-star prior productivity (ln) | 0.783*** | 0.512*** | 0.507*** | 0.507*** | 0.506*** | 0.507*** |
| | (0.033) | (0.034) | (0.034) | (0.034) | (0.034) | (0.034) |
| Technological distance | -2.741*** | -2.028*** | -2.029*** | -2.028*** | -2.027*** | -2.026*** |
| | (0.069) | (0.071) | (0.072) | (0.072) | (0.072) | (0.072) |
| Spatial distance (ln) | -0.378*** | -0.311*** | -0.311*** | -0.311*** | -0.312*** | -0.312*** |
| | (0.016) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| Collaboration opportunity | -0.028*** | -0.013*** | -0.013*** | -0.013*** | -0.013*** | -0.013*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Third-party ties | | 1.832*** | 1.834*** | 1.838*** | 1.835*** | 1.789*** |
| | | (0.056) | (0.056) | (0.056) | (0.056) | (0.058) |
| Female non-star | | | -0.126** | -0.238*** | | |
| | | | (0.041) | (0.055) | | |
| Female non-star x Third-party ties | | | | 0.218** | | |
| | | | | (0.073) | | |
| Male-star/Female-non-star | | | | | -0.136** | -0.240*** |
| | | | | | (0.042) | (0.057) |
| Female-star/Male-non-star | | | | | -0.242* | -0.255* |
| | | | | | (0.098) | (0.119) |
| Female-star/Female-non-star | | | | | -0.220+ | -0.456** |
| | | | | | (0.122) | (0.162) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.203** |
| | | | | | | (0.074) |
| Female-star/Male-non-star x Third-party ties | | | | | | 0.030 |
| | | | | | | (0.181) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.432+ |
| | | | | | | (0.225) |
| Constant | -5.028*** | -4.936*** | -4.932*** | -4.943*** | -4.870*** | -4.854*** |
| | (0.399) | (0.393) | (0.392) | (0.392) | (0.392) | (0.392) |
| Observations | 4,717,444 | 4,717,444 | 4,717,444 | 4,717,444 | 4,717,444 | 4,717,444 |

Standard errors, clustered by star, non-star, and dyad, in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 2-A5.** Logistic Regression Predicting First-Time Collaboration –Star Scientists Extended to Top 10%

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | 0.078** | 0.069** | 0.069** | 0.069** | 0.068** | 0.068** |
| | (0.026) | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) |
| Star prior productivity (ln) | -0.254*** | -0.413*** | -0.412*** | -0.412*** | -0.413*** | -0.413*** |
| | (0.036) | (0.034) | (0.034) | (0.034) | (0.034) | (0.034) |
| Star current projects (ln) | 0.788*** | 0.796*** | 0.796*** | 0.796*** | 0.795*** | 0.795*** |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) |
| Non-star tenure (ln) | -0.227*** | -0.203*** | -0.209*** | -0.209*** | -0.209*** | -0.209*** |
| | (0.023) | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) |
| Non-star prior productivity (ln) | 0.862*** | 0.572*** | 0.568*** | 0.568*** | 0.569*** | 0.568*** |
| | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) |
| Technological distance | -2.731*** | -2.072*** | -2.073*** | -2.073*** | -2.072*** | -2.072*** |
| | (0.042) | (0.043) | (0.043) | (0.043) | (0.043) | (0.043) |
| Spatial distance (ln) | -0.382*** | -0.316*** | -0.317*** | -0.317*** | -0.317*** | -0.317*** |
| | (0.009) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| Collaboration opportunity | -0.003*** | -0.001* | -0.001* | -0.001* | -0.001* | -0.001* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Third-party ties | | 1.894*** | 1.896*** | 1.895*** | 1.896*** | 1.844*** |
| | | (0.033) | (0.033) | (0.033) | (0.033) | (0.035) |
| Female non-star | | | -0.105*** | -0.201*** | | |
| | | | (0.028) | (0.036) | | |
| Female non-star x Third-party ties | | | | 0.201*** | | |
| | | | | (0.048) | | |
| Male-star/Female-non-star | | | | | -0.127*** | -0.220*** |
| | | | | | (0.029) | (0.037) |
| Female-star/Male-non-star | | | | | -0.070+ | -0.102+ |
| | | | | | (0.041) | (0.055) |
| Female-star/Female-non-star | | | | | -0.021 | -0.152+ |
| | | | | | (0.062) | (0.083) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.199*** |
| | | | | | | (0.049) |
| Female-star/Male-non-star x Third-party ties | | | | | | 0.077 |
| | | | | | | (0.077) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.260* |
| | | | | | | (0.108) |
| Constant | -4.330*** | -4.402*** | -4.399*** | -4.407*** | -4.366*** | -4.351*** |
| | (0.205) | (0.195) | (0.195) | (0.195) | (0.196) | (0.196) |
| Observations | 17,257,734 | 17,257,734 | 17,257,734 | 17,257,734 | 17,257,734 | 17,257,734 |

Standard errors, clustered by star, non-star, and dyad, in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 2-A6.** Random-Effects Logit Regression Predicting First-Time Collaboration

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | 0.143*** | 0.122*** | 0.122*** | 0.122*** | 0.114*** | 0.114*** |
| | (0.035) | (0.032) | (0.032) | (0.032) | (0.033) | (0.033) |
| Star prior productivity (ln) | -0.177*** | -0.393*** | -0.391*** | -0.392*** | -0.391*** | -0.390*** |
| | (0.033) | (0.032) | (0.032) | (0.032) | (0.032) | (0.032) |
| Star current projects (ln) | 0.860*** | 0.854*** | 0.854*** | 0.854*** | 0.853*** | 0.854*** |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) |
| Non-star tenure (ln) | -0.234*** | -0.211*** | -0.217*** | -0.217*** | -0.217*** | -0.217*** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| Non-star prior productivity (ln) | 0.806*** | 0.550*** | 0.546*** | 0.547*** | 0.546*** | 0.546*** |
| | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) |
| Technological distance | -2.887*** | -2.204*** | -2.206*** | -2.205*** | -2.205*** | -2.204*** |
| | (0.030) | (0.032) | (0.032) | (0.032) | (0.032) | (0.032) |
| Spatial distance (ln) | -0.436*** | -0.354*** | -0.354*** | -0.355*** | -0.355*** | -0.355*** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Collaboration opportunity | -0.009*** | -0.003** | -0.003** | -0.003** | -0.003** | -0.003** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Third-party ties | | 1.771*** | 1.773*** | 1.774*** | 1.773*** | 1.706*** |
| | | (0.021) | (0.021) | (0.021) | (0.021) | (0.024) |
| Female non-star | | | -0.097*** | -0.219*** | | |
| | | | (0.022) | (0.031) | | |
| Female non-star x Third-party ties | | | | 0.246*** | | |
| | | | | (0.043) | | |
| Male-star/Female-non-star | | | | | -0.119*** | -0.227*** |
| | | | | | (0.023) | (0.032) |
| Female-star/Male-non-star | | | | | -0.171** | -0.246*** |
| | | | | | (0.064) | (0.072) |
| Female-star/Female-non-star | | | | | -0.086 | -0.378*** |
| | | | | | (0.078) | (0.106) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.223*** |
| | | | | | | (0.046) |
| Female-star/Male-non-star x Third-party ties | | | | | | 0.181* |
| | | | | | | (0.073) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.543*** |
| | | | | | | (0.119) |
| Constant | -5.376*** | -4.841*** | -4.841*** | -4.852*** | -4.791*** | -4.773*** |

| **Dependent Variable:** **First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| | (0.247) | (0.239) | (0.239) | (0.239) | (0.240) | (0.240) |
| Observations | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 | 10,185,024 |
| Number of dyads | 2,821 | 2,821 | 2,821 | 2,821 | 2,821 | 2,821 |

Standard errors, clustered by dyad, in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 2-A7.** Logistic Regression Predicting First-Time Collaboration - Matched Sample

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | 0.160* | 0.137+ | 0.137+ | 0.136+ | 0.131+ | 0.131+ |
| | (0.071) | (0.070) | (0.071) | (0.070) | (0.070) | (0.070) |
| Star prior productivity (ln) | -0.169+ | -0.380*** | -0.380*** | -0.380*** | -0.382*** | -0.382*** |
| | (0.099) | (0.101) | (0.101) | (0.101) | (0.101) | (0.101) |
| Star current projects (ln) | 0.682*** | 0.687*** | 0.687*** | 0.687*** | 0.685*** | 0.685*** |
| | (0.063) | (0.063) | (0.063) | (0.063) | (0.063) | (0.063) |
| Non-star tenure (ln) | -0.557*** | -0.511*** | -0.511*** | -0.511*** | -0.511*** | -0.511*** |
| | (0.087) | (0.086) | (0.086) | (0.086) | (0.086) | (0.085) |
| Non-star prior productivity (ln) | 1.055*** | 0.697*** | 0.698*** | 0.696*** | 0.699*** | 0.696*** |
| | (0.092) | (0.093) | (0.092) | (0.092) | (0.092) | (0.092) |
| Technological distance | -2.943*** | -2.082*** | -2.080*** | -2.081*** | -2.079*** | -2.081*** |
| | (0.118) | (0.131) | (0.131) | (0.131) | (0.131) | (0.131) |
| Spatial distance (ln) | -0.450*** | -0.350*** | -0.350*** | -0.350*** | -0.351*** | -0.350*** |
| | (0.034) | (0.031) | (0.031) | (0.031) | (0.032) | (0.032) |
| Collaboration opportunity | -0.007* | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Third-party ties | | 2.362*** | 2.366*** | 2.378*** | 2.367*** | 2.198*** |
| | | (0.107) | (0.107) | (0.106) | (0.107) | (0.132) |
| Female non-star | | | -0.183* | -0.349*** | | |
| | | | (0.078) | (0.100) | | |
| Female non-star x Third-party ties | | | | 0.373** | | |
| | | | | (0.138) | | |
| Male-star/Female-non-star | | | | | -0.202* | -0.351*** |
| | | | | | (0.080) | (0.103) |
| Female-star/Male-non-star | | | | | -0.171 | -0.144 |
| | | | | | (0.170) | (0.226) |
| Female-star/Female-non-star | | | | | -0.174 | -0.478+ |
| | | | | | (0.182) | (0.248) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.340* |
| | | | | | | (0.141) |
| Female-star/Male-non-star x Third-party ties | | | | | | -0.048 |
| | | | | | | (0.335) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.597+ |
| | | | | | | (0.331) |

| **Dependent Variable:**<br>**First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Constant | -4.757***<br>(1.209) | -5.137***<br>(1.231) | -5.143***<br>(1.232) | -5.152***<br>(1.232) | -5.019***<br>(1.232) | -4.951***<br>(1.231) |
| Observations | 2,489,048 | 2,489,048 | 2,489,048 | 2,489,048 | 2,489,048 | 2,489,048 |

Standard errors, clustered by star, non-star, and dyad, in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 2-A8.** Rare-Events Logit Predicting First-Time Collaboration

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | 0.085*** | 0.073** | 0.073** | 0.073** | 0.061* | 0.061* |
| | (0.024) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| Star prior productivity (ln) | -0.211*** | -0.398*** | -0.400*** | -0.399*** | -0.405*** | -0.403*** |
| | (0.033) | (0.039) | (0.039) | (0.039) | (0.039) | (0.039) |
| Star current projects (ln) | 0.772*** | 0.766*** | 0.767*** | 0.766*** | 0.764*** | 0.763*** |
| | (0.020) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) |
| Non-star tenure (ln) | -0.244*** | -0.220*** | -0.227*** | -0.227*** | -0.228*** | -0.227*** |
| | (0.021) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) |
| Non-star prior productivity (ln) | 0.836*** | 0.590*** | 0.585*** | 0.585*** | 0.587*** | 0.587*** |
| | (0.024) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| Technological distance | -2.731*** | -2.048*** | -2.049*** | -2.049*** | -2.044*** | -2.044*** |
| | (0.033) | (0.038) | (0.038) | (0.038) | (0.038) | (0.038) |
| Spatial distance (ln) | -0.381*** | -0.315*** | -0.315*** | -0.315*** | -0.316*** | -0.316*** |
| | (0.006) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Collaboration opportunity | -0.006*** | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Third-party ties | | 1.897*** | 1.899*** | 1.848*** | 1.901*** | 1.848*** |
| | | (0.031) | (0.031) | (0.035) | (0.031) | (0.036) |
| Female non-star | | | -0.102** | -0.230*** | | |
| | | | (0.035) | (0.036) | | |
| Female non-star x Third-party ties | | | | 0.235*** | | |
| | | | | (0.067) | | |
| Male-star/Female-non-star | | | | | -0.129*** | -0.237*** |
| | | | | | (0.036) | (0.038) |
| Female-star/Male-non-star | | | | | -0.214*** | -0.229*** |
| | | | | | (0.058) | (0.057) |
| Female-star/Female-non-star | | | | | -0.084 | -0.376*** |
| | | | | | (0.105) | (0.107) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.202** |
| | | | | | | (0.070) |
| Female-star/Male-non-star x Third-party ties | | | | | | 0.033 |
| | | | | | | (0.111) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.480* |
| | | | | | | (0.196) |

| **Dependent Variable:**<br>**First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Constant | -4.722*** | -4.718*** | -4.687*** | -4.667*** | -4.661*** | -4.635*** |
| | (0.264) | (0.284) | (0.285) | (0.283) | (0.286) | (0.284) |
| Observations | 136,810 | 136,810 | 136,810 | 136,810 | 136,810 | 136,810 |

Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 2-A9.** Logistic Regression Predicting First-Time Collaboration -Star Scientists/Non-Star Collaborators Living within a Hundred Kilometers Radius-

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | 0.062+ | 0.056 | 0.056 | 0.056 | 0.049 | 0.049 |
| | (0.037) | (0.034) | (0.034) | (0.034) | (0.035) | (0.035) |
| Star prior productivity (ln) | -0.231*** | -0.417*** | -0.416*** | -0.416*** | -0.419*** | -0.418*** |
| | (0.052) | (0.049) | (0.049) | (0.049) | (0.049) | (0.049) |
| Star current projects (ln) | 0.819*** | 0.824*** | 0.823*** | 0.824*** | 0.821*** | 0.821*** |
| | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) |
| Non-star tenure (ln) | -0.222*** | -0.195*** | -0.202*** | -0.203*** | -0.202*** | -0.202*** |
| | (0.028) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Non-star prior productivity (ln) | 0.802*** | 0.526*** | 0.521*** | 0.521*** | 0.521*** | 0.521*** |
| | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) |
| Technological distance | -2.603*** | -1.909*** | -1.911*** | -1.910*** | -1.909*** | -1.908*** |
| | (0.054) | (0.057) | (0.057) | (0.057) | (0.057) | (0.057) |
| Spatial distance (ln) | -0.133*** | -0.112*** | -0.112*** | -0.112*** | -0.112*** | -0.112*** |
| | (0.016) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| Collaboration opportunity | -0.005*** | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Third-party ties | | 1.713*** | 1.715*** | 1.721*** | 1.716*** | 1.650*** |
| | | (0.040) | (0.040) | (0.040) | (0.040) | (0.043) |
| Female non-star | | | -0.123*** | -0.243*** | | |
| | | | (0.034) | (0.043) | | |
| Female non-star x Third-party ties | | | | 0.251*** | | |
| | | | | (0.059) | | |
| Male-star/Female-non-star | | | | | -0.143*** | -0.252*** |
| | | | | | (0.035) | (0.044) |
| Female-star/Male-non-star | | | | | -0.141* | -0.203* |
| | | | | | (0.061) | (0.082) |
| Female-star/Female-non-star | | | | | -0.100 | -0.353** |
| | | | | | (0.076) | (0.109) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.234*** |
| | | | | | | (0.060) |
| Female-star/Male-non-star x Third-party ties | | | | | | 0.143 |
| | | | | | | (0.113) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.485** |
| | | | | | | (0.149) |
| Constant | -5.364*** | -5.084*** | -5.082*** | -5.096*** | -5.023*** | -5.006*** |
| | (0.267) | (0.250) | (0.250) | (0.250) | (0.250) | (0.250) |

| **Dependent Variable:**<br>**First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Observations | 4,251,356 | 4,251,356 | 4,251,356 | 4,251,356 | 4,251,356 | 4,251,356 |

Standard errors, clustered by star, non-star, and dyad, in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 2-A10.** Logistic Regression Predicting First-Time Collaboration - Cox Proportional Hazard Analysis

| **Dependent Variable: First-time collaboration** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** |
|---|---|---|---|---|---|---|
| Year dummies | YES | YES | YES | YES | YES | YES |
| Star tenure (ln) | -0.513*** | -0.523*** | -0.522*** | -0.522*** | -0.523*** | -0.522*** |
| | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) |
| Star prior productivity (ln) | -0.559*** | -0.719*** | -0.719*** | -0.719*** | -0.720*** | -0.718*** |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) |
| Star current projects (ln) | 0.790*** | 0.783*** | 0.783*** | 0.784*** | 0.783*** | 0.784*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| Non-star tenure (ln) | -0.808*** | -0.765*** | -0.763*** | -0.763*** | -0.763*** | -0.763*** |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) |
| Non-star prior productivity (ln) | -0.151*** | -0.379*** | -0.377*** | -0.376*** | -0.377*** | -0.376*** |
| | (0.017) | (0.017) | (0.018) | (0.018) | (0.018) | (0.018) |
| Technological distance | -2.449*** | -1.764*** | -1.763*** | -1.763*** | -1.763*** | -1.763*** |
| | (0.028) | (0.030) | (0.030) | (0.030) | (0.030) | (0.030) |
| Spatial distance (ln) | -0.303*** | -0.235*** | -0.234*** | -0.235*** | -0.234*** | -0.234*** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Collaboration opportunity | -0.001 | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Third-party ties | | 1.719*** | 1.718*** | 1.714*** | 1.718*** | 1.648*** |
| | | (0.020) | (0.020) | (0.020) | (0.020) | (0.023) |
| Female non-star | | | 0.034 | -0.060* | | |
| | | | (0.021) | (0.030) | | |
| Female non-star x Third-party ties | | | | 0.194*** | | |
| | | | | (0.042) | | |
| Male-star/Female-non-star | | | | | 0.019 | -0.060+ |
| | | | | | (0.022) | (0.031) |
| Female-star/Male-non-star | | | | | -0.041 | -0.182*** |
| | | | | | (0.035) | (0.048) |
| Female-star/Female-non-star | | | | | 0.113* | -0.211* |
| | | | | | (0.055) | (0.089) |
| Male-star/Female-non-star x Third-party ties | | | | | | 0.171*** |
| | | | | | | (0.045) |
| Female-star/Male-non-star x Third-party ties | | | | | | 0.325*** |
| | | | | | | (0.069) |
| Female-star/Female-non-star x Third-party ties | | | | | | 0.609*** |
| | | | | | | (0.116) |
| Observations | 1,789,777 | 1,789,777 | 1,789,777 | 1,789,777 | 1,789,777 | 1,789,777 |

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

## 3. WHO BENEFITS FROM GENDER DIVERSITY? UNPACKING THE DIFFERENTIAL EFFECT OF GENDER DIVERSITY ON INDIVIDUALS' INNOVATIVE PERFORMANCE[6]


### Abstract

Extant research has shown that gender-diverse organizations tend to be more innovative than gender homogenous ones but has left unaddressed the question of who, among an organization's knowledge workers, becomes more innovative as gender diversity increases. We address this question by examining how gender diversity affects individual-level innovative performance, measured through patent-based indicators, within the R&D labs of the 40 largest pharmaceutical companies over the period 1985-2010. We argue that higher levels of gender diversity increase the performance of three categories of knowledge workers – women, rookies, and brokers – whereas men, long-tenured employees, and employees embedded in constrained networks experience limited or no performance benefits. By demonstrating that gender diversity has a heterogeneous effect across different segments of an organization's knowledge workers, these results both deepen and qualify current understandings of how gender diversity affects innovation within organizations. A key implication of our proposed argument is that gender diversity does not only affect the overall performance of the organization; it also affects how performance (and hence the material and symbolic resources associated with it) are distributed within the organization.



**Keywords:** Gender, Gender Diversity, Performance, R&D labs, Pharmaceutical Firms, Patents.


[6] Paper co-authored with Gianluca Carnabuci

## 3.1. INTRODUCTION

A sizeable body of research concurs that more gender-diverse organizations – organizations featuring a more balanced composition of male and female workers – tend to be more innovative than gender-homogeneous ones because gender diversity leads to superior creativity and improved problem-solving among knowledge workers (Herring, 2009; Joshi et al., 2006; Lyngsie & Foss, 2017; Richard et al., 2004). The association between gender diversity and organization-level innovation has been established across a wide variety of industries (Boone & Hendriks, 2009; Campbell & Vera, 2009; Dezsö & Ross, 2012; Joecks, Pull, & Vetter, 2013). Despite broad recognition of the relevance of this finding, however, much remains to be understood concerning how gender diversity affects innovation within organizations (Boone & Hendriks, 2009; Kaplan, 2017b, 2017a). Notably, extant theoretical accounts are moot concerning *who* benefits from gender diversity, that is, whose innovative performance is more likely to improve because of gender diversity.

Drawing from extant organizational research, we argue that certain knowledge workers' characteristics moderate the effect of organizational gender diversity on knowledge workers' innovative performance. Accordingly, we suggest that rather than assuming a homogeneous effect of gender diversity throughout the organization, it is important to explore how gender diversity may affect different categories of knowledge workers in different ways. We focus on three commonly-investigated characteristics of knowledge workers - gender, tenure, and network structure – and theorize that each moderates the effect of gender diversity on innovative performance (Kish-Gephart, Jennifer & Campbell, 2013; Lewis, Walls, & Dowell, 2014). Specifically, we hypothesize that higher levels of gender diversity increase the innovative performance of women, freshly-tenured knowledge workers, and knowledge workers with networks rich in structural holes; by contrast, men, long-tenured knowledge workers, and

knowledge workers embedded in constrained networks are less likely to experience improvements in their innovative performance.

As we articulate in the remainder of the paper, our arguments deliver testable implications regarding why gender diversity unequally affects these categories of knowledge workers. In particular, we examine a longitudinal data set describing a large population of R&D scientists employed by the forty largest pharmaceutical firms worldwide between 1985 and 2010. To examine whether gender diversity affects the innovative performance of different categories of R&D scientists in different ways, we traced each firm's R&D scientist longitudinally using patent data (e.g., Carnabuci & Operti, 2013). Based on a set of panel negative binomial models, our empirical analyses provide support to our argument and hypotheses. Specifically, we find that whereas gender diversity enhances the innovative performance of freshly-tenured scientists and scientists in brokerage positions, long-tenured scientists and scientists embedded in a constrained network are less likely to improve their innovative performance in a gender-diverse organization. Furthermore, contrary to our expectation, we find that the effect of gender diversity is equally positive for both women' and men's innovative performance. By demonstrating that gender diversity has a heterogeneous effect across different segments of an organization's workforce, our findings both deepen and qualify current understandings of how gender diversity affects innovation within organizations.

Our study extends current knowledge on the performance effect of gender diversity within knowledge-based organizations. Examining the effects of gender diversity among R&D scientists is important for two main reasons. First, exploring the uneven distribution of performance benefits through gender diversity aides in understanding which organizations benefit more from gender-diverse workforces. This can reconcile the inconsistent and conflicting

findings of prior research (e.g., Cox & Blake, 1991; Cumming et al., 2015; Herring, 2009; Joshi et al., 2006) that have shown effects varying in their magnitude and significance. Identifying which knowledge workers are (more) affected by gender diversity can, therefore, clarify which organizations benefit (more) from increased diversity. Second, recognizing that organizational-level gender diversity differently affects knowledge workers may reveal potential barriers to the representation of women within organizations. That is, if certain groups of knowledge workers benefit less than, not at all, or are even negatively affected by gender diversity, organizations may, in turn, become less inclined to support gender diversity within organizations. In this paper, our goal is to unpack the differential benefits of gender diversity for different types of knowledge workers. In particular, we seek to improve our understanding of how widely knowledge workers within organizations benefit from increased gender diversity and *who* exactly benefits from it. We provide novel theory and evidence to show how organizational-level gender diversity affects both the overall performance of the organization and the distribution of performance among knowledge workers. Considering this heterogeneous nature of performance effects is relevant to understand how the relative standing among knowledge workers emerges, which in turn is consequential for their access to valued material and symbolic resources.

## 3.2. THEORETICAL DEVELOPMENT

A considerable body of theoretical and empirical research suggests that women should benefit from organizational gender diversity more than men do. Since women represent a minority group within most organizations, their legitimacy when engaging in organizational initiatives is limited (Correll & Ridgeway, 2003; Ely, Ibarra, & Kolb, 2011; Fiske & Stevens, 1993; Ibarra, 1997; Kanter, 1977; Ridgeway & Smith-Lovin, 1999). This is especially true for innovative and knowledge-based activities, as these are characteristically more uncertain and, therefore, lend

themselves to more subjective interpretations and evaluations on the part of organizational decision-makers (Gorman, 2005, 2006; Grams & Schwab, 1985; Joshi, Neely, Emrich, Griffiths, & George, 2015; Kanter, 1977). Because most of the valued jobs and competences are male-typed (Ding, Murray, & Stuart, 2012; Tsui, Egan, & O'Reilly III, 1992; Westphal & Milton, 2000), women tend to be systematically undervalued and face a disadvantage when competing for the material and symbolic resources that may help them perform their task (W. Ding et al., 2012; Tsui et al., 1992; Westphal & Milton, 2000). In a similar vein, a sizeable body of evidence indicates that R&D and innovation-related activities are strongly male-typed and that female knowledge workers face more challenging conditions than male knowledge workers do when attempting to have their innovative ideas recognized and valued within the organization (Cardador, 2017; DiTomaso, Post, Smith, & Farris, 2007; Eagly & Karau, 1991; Handley, Brown, Moss-Racusin, & Smith, 2015; Joshi, 2014; Moss-Racusin, Dovidio, Brescoll, Graham, & Handelsman, 2012). For example, Tsui, Egan, and Reilly (1992) found that female workers in male-typed jobs report suffering from a hostile environment from their male colleagues. Similarly, experimental evidence has shown that women receive lower performance evaluations because they are incorrectly perceived as being less qualified than men (Heilman, Wallen, Fuchs, & Tamkins, 2004). Furthermore, prior research has shown that within male-dominated workplaces, female knowledge workers face harsher conditions than male knowledge workers, including higher standards in terms of both ability and warmth expectations, exclusion from informal and professional networks and dismissal of women's contributions and achievements (Bernal et al., 2019; Faulkner, 2013; Heilman & Okimoto, 2007; Heilman et al., 2004; Kanter, 1977b; Ridgeway & Smith-Lovin, 1999).

In male-typed jobs, a larger presence of female workers within the organization may result in reduced gender-related disadvantages. Ely (1995), for instance, found that gender-based roles and stereotypes are less salient in organizations with a relatively high proportion of women. As the share of women within an organization increases, negative stereotypes about women's qualities may decrease, which in turn may enhance women's credibility and legitimacy within the organization (Hillman, Shropshire, & Cannella, 2007). Furthermore, as the gender composition of an organization becomes more balanced, gender may become a less salient category among organizational decision-makers (Chatman, Polzer, Barsade, & Neale, 1998; Ely, 1995; Reskin, 2000). Consistent with these arguments, research has shown that organizational-level gender diversity is positively associated with women's likelihood of being hired and promoted (Cohen et al., 1998). Furthermore, organizational gender diversity enables women to access work-related networks that would otherwise be inaccessible and gives women more leeway in shaping their network (Blair-Loy, 2001; Davies-Netzley, 1998; Ibarra, 1992). Accordingly, female knowledge workers' effectiveness when pushing forward their innovative ideas and projects increases with the gender diversity of an organization, as does female knowledge workers' ability to secure resources that are instrumental to making those ideas a success (Ridgeway & Smith-Lovin, 1999). These arguments suggest that organizational gender diversity should be especially beneficial for female knowledge workers, leading to our first hypothesis:

*Hypothesis 1: Organizational-level gender diversity increases the innovative performance of female knowledge workers more than the innovative performance of male knowledge workers.*

In addition to gender, we theorize that organizational tenure – the length of service of an individual within his or her current organization – should moderate the effect of gender diversity on individual innovation. Specifically, two interrelated reasons suggest that knowledge workers

with longer tenure should benefit less from gender diversity than freshly tenured ones. First, organizational gender diversity has been steadily increasing over the past decades (Catalyst, 2018a). Consequently, the further back in time a knowledge worker was hired (i.e., the longer his or her organizational tenure), the more male-dominated was the organization at the time of his or her hiring. Following Stinchcombe's (1965) seminal work on “imprinting,” a considerable body of research shows that organizational socialization processes lead employees to internalize the cultural schemas prevailing within the organization at the time of hiring. Imprinting processes help new hires adapt to, and develop a shared understanding of the organizational culture (Dobrev & Merluzzi, 2018; Hannan, Burton, & Baron, 1996; Marquis & Tilcsik, 2013). Prior research found that during their early years within the organization, employees are particularly receptive to the influence of the environment (Higgins, 2005). One reason is that newly hired employees aim to fit into the organization in order to overcome the uncertainty related to being new. Liu (2003), for example, shows that freshly-tenured employees are more flexible and receptive to organizational changes than long-tenured employees. Generally speaking, evidence suggests that freshly-tenured knowledge workers are more likely than long-tenured ones to adapt to new norms, behaviors and cognitive models (Azoulay, Zivin, & Manso, 2011; North, 2019; Tilcsik, 2010). Hence, the latter should be better equipped to adapt to demographic transformations within the organizations, such as an increasingly balanced gender composition.

The imprinting process also generates inertia and resistance to change insofar as knowledge workers tend to remain anchored to the schemas with which they were imprinted. Consistent with this view, prior work has shown that initial organizational features based on founders’ mental models tend to remain within the organization over time (Baron, Hannan, & Burton, 1999; Johnson, 2007). In the same vein, Azoulay *et al.* (2011) found that mentors’ orientation of

early-career scientists affects their patenting behavior in their long-standing careers. Similarly, Kacperczyk (2009) shows that managers make future entrepreneurial decisions based on the characteristics of early-career colleagues. Furthermore, Dokko, Wilk, and Rothbard (2009) found that schemas and norms learned by knowledge workers in one organization affect their performance once they move to another organization. This is particularly so when organizations experience demographic transformations, such as an increasingly balanced gender composition, which require significant cultural adjustments (Carroll & Hannan, 2004). For example, Sørensen (2004) found that changes in racial group composition after workers' time of entry affects their organizational attachment and turnover. These arguments suggest that because of the steady increase of women in the workforce in the last decades, knowledge workers joining organizations earlier (i.e., longer-tenure knowledge workers) will be less able to adjust to and leverage the opportunities provided by gender diversity.

Second, prior studies on the psychological effects of organizational tenure provide further theoretical support about how tenure negatively moderates the effect of gender diversity on innovative performance. Research in this area examines how organizational tenure affects knowledge workers' cognition and information processing dynamics. A common finding is that, as a worker's length of service increases, his or her cognitive structures become more rigid and increase resistance to change (Oreg, 2003). For instance, prior work showed that CEOs who spend more time in organizations are less likely to deviate from earlier courses of actions (Boeker, 1997; Goodstein & Boeker, 1991). As a result, long-tenured knowledge workers tend to forego or even actively resist change opportunities that may arise within their work environment. Furthermore, research shows that organizational tenure is associated with a stronger commitment to maintaining established policies and practices (Katz, 1982) and a tendency to stick to well-

tried routines for solving problems and dealing with coworkers (D. Miller & Friesen, 1984). For example, prior studies found that, relative to managers who joined the organization recently, long-tenured managers are more reluctant to question the *status quo* or envision ways to pursue change opportunities (Finkelstein & Hambrick, 1990; Grimm & Smith, 1991).

Since leveraging the benefits of gender diversity requires knowledge workers to adjust their problem-solving and collaboration routines and to adapt to different perspectives and work styles (Ruiz-Jiménez & Fuentes-Fuentes, 2016), we expect that knowledge workers with longer organizational tenure will generally be less able to benefit from increasing gender diversity within the workplace. On the contrary, long-tenured knowledge workers might see their performance erode as they fail to adjust to the new cultural and cognitive demands of an increasing gender-diverse workplace. By contrast, more recently hired knowledge workers incur fewer adjustment costs because they have been socialized into a (relatively more) gender-diverse environment from the outset. Consequently, they should be culturally and cognitively better equipped to reap the creative potential inherent in gender-diverse organizations. We, therefore, advance the following hypothesis.

*Hypothesis 2: The longer a knowledge worker's organizational tenure is, the less will organizational-level gender diversity increase his/her innovative performance.*

Lastly, we submit that the effect of gender diversity may vary depending on the position knowledge workers occupy within the organization's internal collaboration network. Over the past few decades, a large stream of literature has examined how collaboration networks affect knowledge workers' innovative performance (Fleming, Mingo, & Chen, 2014; Reagans & Zuckerman, 2001; Rodan & Galunic, 2004; Rost, 2011; Schiffauerova & Beaudry, 2011). This research found that knowledge workers whose collaboration network bridges across "structural holes" – that is, network gaps between mutually unconnected colleagues – tend to be

systematically more innovative relative to otherwise-similar knowledge workers embedded in constrained networks. For instance, prior work has found that brokers are more creative (Burt, 2004), tend to be more innovative (Hargadon, 2002) and have a higher capacity for knowledge sharing (Reagans & McEvily, 2003). Consistent with this view, extant theory posits that networks rich in structural holes are conducive to enhanced innovation because they expose individuals to more diverse information flows. For example, Fleming, Mingo, and Chen (2007) found that scientists in brokerage positions tend to identify novel combinations of ideas. Similarly, Tortoriello (2015) found that knowledge workers who occupy brokerage positions are better positioned to absorb external knowledge and are more innovative. Furthermore, Lingo and Mahony (2010) show that brokers act as relational experts integrating others' contributions to foster collective creativity and innovations. In sum, increasing evidence suggests that people in brokerage positions become "more familiar with alternative ways of thinking and behaving" (Burt, 2004, pp. 349–350), which expands their minds and prepares them to deal with a diverse range of individuals, perspectives and situations (Burt, 2010).

Conversely, knowledge workers embedded in constrained networks spend most of their time with people who are mutually and tightly interconnected and, accordingly, tend to view things similarly (Ahuja, 2000; Burt, 1992; Gulati, 1999; Rowley, Behrens, & Krackhardt, 2000). Whereas this kind of networks is conducive to the development of highly efficient work and collaborative routines among insiders (Obstfeld, 2005), it also isolates people from alternative ways of doing things and solving problems. Consistent with this argument, research suggests that knowledge workers in constrained networks develop strong ties characterized by a large number of resource exchanges and interactions (Granovetter, 1973; Reagans & McEvily, 2003; Uzzi, 1999). The cost of maintaining strong ties is not trivial (Burt, 1992) and knowledge workers who

engage in cohesive relationships are expected to contribute reciprocally among them. However, closed networks also generate cognitive lock-ins that close off individuals to potential collaborators outside of their existing network (Quintane & Carnabuci, 2016). Consistent with this view, Gargiulo, and Benassi (2000) show that managers in cohesive networks are less likely to adapt their network composition to changes in their task environment. In short, knowledge workers embedded in constrained networks tend to develop rigid cognitive and cultural boundaries that impede them from adapting to changes in their environment.

As we mentioned above, however, leveraging the benefits of gender diversity requires knowledge workers to adjust to a changing work environment and adapt to different perspectives and work styles (Cox & Blake, 1991; Jehn et al., 1999; Thomas & Ely, 1996). Whereas knowledge workers who have bridging ties should find it relatively easy to envision the opportunities inherent in gender-diverse environments, knowledge workers embedded in a constrained network will find it hard to do so. Due to the thick structural boundaries that isolate knowledge workers in constrained networks, changes occurring outside the clique of interconnected contacts tend to remain unknown and, consequently, most opportunities triggered by those changes are likely to be forgone. Furthermore, knowledge workers in constrained networks tend to develop relatively rigid cultural and cognitive schemas that limit those knowledge workers' ability to adjust to others and/or changing situations. These arguments lead to our third and final hypothesis.

*Hypothesis 3: The more constrained a knowledge worker's collaboration network is, the less will organizational-level gender diversity increase his/her innovative performance.*

## 3.3. METHODOLOGY

### 3.3.1. Setting and data

We test our theoretical arguments in the context of American R&D laboratories of the forty largest pharmaceutical companies. This setting is ideal for testing our hypotheses because the association between gender diversity and innovative performance has shown to be especially strong in knowledge-intensive, innovation-driven organizations, of which pharmaceutical R&D laboratories are an archetypal example (Dezsö & Ross, 2012; Hoogendoorn, Oosterbeek, & Praag, 2013). Although the gender composition of pharmaceutical R&D labs is, on average, male-dominated, and the prototypical R&D scientist job is characteristically male-typed (Eccles, 2007), there is significant variance in gender composition across firms. Furthermore, in pharmaceutical R&D, the supply of academically qualified labor has evolved to become well balanced across genders; the continuing prevalence of gender-homogenous R&D labs, therefore, represents both an intensely debated puzzle and an opportunity for corrective interventions (Hill et al., 2010). Finally, R&D scientist's innovative history is visible in this industry through patent-based measures that are both contextually meaningful and objectively quantifiable (Brouwer & Kleinknecht, 1999).

Our research setting consists of the forty-eight members of the Pharmaceutical Research and Manufacturing Association (PhRMA) in 1985. These are the largest pharmaceutical companies worldwide. Because scientist gender is based on demographic data from the U.S. Social Security Administration (SSA) and these data are only available for the US, we focus on those firms whose R&D laboratories are located within the United States. We collected financial, operational, and patent data for these firms from 1975 until 2010. The financial and operational data was obtained from Mergent WebReports. We used patent data from the European Patent

Office to observe firms' R&D activities. EPO patent data are a reliable source of information because it includes both patent grant and patent applications (including the 50 percent of rejected applications), thereby reducing concerns of sample selection (Ferguson & Carnabuci, 2017). Finally, as the pharmaceutical industry is genuinely globalized, pharmaceutical firms tend to protect their invention in each possible region (Criscuolo, 2005). This, in turn, reduces concerns about possible geographic selection biases.

Our sample is composed of all scientists working for the sample firms, as observed through these firms' patent applications in the past three years. We traced a firm's R&D scientists by examining the names appearing on that firm's patent application (similar to Mcfadyen & Cannella, 2004; Nerkar & Paruchuri, 2005). While not all R&D scientists appear in patents, those who are involved in the creative part of the process are mentioned in patent applications as inventors (Haeussler & Sauermann, 2013). We inferred scientists' gender-based upon the demographic data provided by the U.S. Social Security Administration (SSA). SAA offers annual overviews of all first names, by gender, for American newborns. We identified all female names provided by the SAA and used these to identify women scientists in our sample.

### 3.3.2. Measures

#### 3.3.2.1. Dependent variables

To test our theory, we estimated two equations with different dependent variables that capture R&D scientists' innovative performance. Our first dependent variable is Productivity, and it represents the number of patent applications an R&D scientist has in the current year. The second dependent variable is Citations-weighted productivity, which measures the annual number of patent applications made by a scientist, weighted by the citations that each of those patents received in the subsequent five years from the patent's application (Yayavaram & Ahuja,

2008). A citation-weighted patent count is a standard way of operationalizing innovation impact, and it is also associated with the economic and social value of a patent (Jaffe & Trajtenberg, 2002; Trajtenberg, 1987).

#### 3.3.2.2. Explanatory and moderating variables

*Gender diversity.* This is measured as the share of female R&D scientists within each firm in the last three-year time window. That is, we used at all R&D scientists filing a patent application in the last three years and inferred their gender based on the demographic data provided by the U.S. Social Security Administration (SSA). This data provides an annual overview of all American newborns' first name by gender. We compared each scientist's first name to the name register in the U.S. Social Security Administration and assigned the dominant gender to classify female and male scientists using population statistics. From the complete sample of scientists (57,848 inventors), we could not classify the gender for a small percentage of the first names (4.1 percent). These inventors are often immigrants. To be as conservative as possible in our estimates of gender effects, and given that our sample is composed mainly by male scientists, we deliberately classified these unidentified scientists as male.

*Male.* We used each scientist's gender, setting the variable to one for male scientists. The reference category is female scientists.

*Tenure.* Scientists' organizational tenure was calculated based on the first patent in which a scientist appears within a firm. For each R&D scientist, we tracked its prior activities using earlier patent applications. Given the sample size and longitudinal nature of the study, we are unable to have precise employee records and therefore use the scientist's first patent application as the time of first employment within the firm.

*Constraint.* To observe the embeddedness of a scientist in the social network, we build the intra-organizational collaboration using data from the prior three years[7]. This network consists of all scientists appearing as inventors on patent applications during that period, as nodes, and their collaboration on projects resulting in these patent applications, as ties (similar to Nerkar & Paruchuri, 2005). This network was created in a dichotomous and non-directional manner. To capture R&D scientists' network brokerage, we calculated each R&D scientists' network *Constraint* (Burt, 1992, p. 55):

$$C_i = \left( p_{ij} + \sum_q p_{iq}\, p_{qj} \right)^2, q \neq j, i$$

where $C_i$ is the network constraint of scientist $i$ and $p_{ij}$ represents the proportional strength of ties between R&D scientist $i$ and R&D scientist $j$. The total value for all contacts $j$ returned each R&D scientist's aggregate network constraint. Lower values of *Constraint* imply that R&D scientists occupy a brokerage position within the intra-organizational network structure.

#### 3.3.2.3. Control variables

We included several control variables that can drive systematic differences in R&D scientists' innovative performance. Past productivity reflects R&D scientist's inherent ability, which is measured as R&D scientists' cumulative stock of prior inventions during the three years before the focal year. A scientist with higher cumulative stock in the past is more likely to have higher innovative performance in the present (Felin & Hesterly, 2007). We measured R&D scientists' Technological diversity using the additive inverse of the Blau concentration index (1977). The index captures the main technological subclass(es) in which a scientist patent, and it ranges from 0 to 1. The index takes on the value of 0 when a scientist is specialized in the same main

[7] Results based on two-year windows and four-year windows are reported in the robustness checks section.

technological sub-classes, and it approaches 1 when a scientist patent in many different sub-classes. R&D scientists' mobility increases their visibility and therefore, the impact of their innovative performance (Song, Almeida, & Wu, 2003). Hence, we include scientists' Mobility, measured as the count of prior employers an R&D scientist has had before each focal year. Collaborative ties within the firm have been found to facilitate innovation; accordingly, we control for Network size[8]. R&D scientists tend to be more innovative when they have collaborative ties outside the firm (Tushman & Katz, 1980). Hence, we control for R&D scientists' External ties, which is a dummy variable that takes on the value of one when a scientist has at least one collaborative tie outside the firm. The heterogeneity in team member skills can lead to differences in the innovative performance of R&D scientists. For this reason, we control for the scientists' average team size in the three-year window (Team size) (Reagans & Zuckerman, 2001). Because R&D scientists with a small network size cannot have a brokerage position, we insert a dummy (Network size dummy). This variable takes on the value 1 when an R&D scientist's network size equals to 1.

At the organizational level, we control for firm size because it may change as firm gender composition increases. Following Conti, Gambardella, and Mariani (2014), we created three dummies to classify firms as large (i.e., more than 250 scientists), medium (between 100 and 250 scientists), or small firms (less than 100 scientists). We labeled those dummies as follows: *Large firm dummy*, *Medium firm dummy*, and *Small firm dummy*, respectively. To control for the effect of time on innovation, we include *Year dummies*. Finally, we include fixed-effects at the firm level to account for the fact that firm-specific heterogeneity can affect R&D scientists' innovative performance.

[8] We used a normalized measured of *Network size*, in additional analyses.

### 3.3.3. Estimation Method

Because both dependent variables – i.e., *Productivity* and *Citation-weighted productivity* – are positive integers, the use of linear regression models lead to biased coefficient estimates. In addition, our data is over-dispersed, which violates an underlying assumption of the Poisson estimator (Hausman, Hall, & Griliches, 1984). For those reasons, we use a negative-binomial panel specification, which allows for over-dispersion by including an individual unobserved effect into the conditional mean. Since one of our key variables (i.e., scientist gender) does not vary over time, we included R&D scientist random effects and firm and year fixed effects (Ahuja, 2000). This approach resolves potential bias because the estimated models represent the change in innovative performance with the change in the level of independent variables within the same firm. Furthermore, it also solves the non-independence of observations problem for individual scientists (Allison & Waterman, 2002).

All network measures are built based on the three-year time window (Carnabuci & Operti, 2013). Independent variables are lagged by one year to provide stronger evidence of causality and avoid simultaneity problems. For example, if an R&D scientist's internal network is based in co-patenting ties formed between 1997 and 1999, the *Citations weighted productivity* measure counts the number of patent applications filed by an R&D scientist in 2000, weighted by the number of citations that those patents received until 2005. R&D scientists' organizational tenure is measured in the current year. We mean-centered the main predictors to reduce multicollinearity (Aiken, West, & Reno, 1991). Since some of our control variables are highly skewed, we log-transformed them before entering in the models.

## 3.4. RESULTS

Table 3-1 provides the descriptive statistics for the main variables and the pairwise correlations among the variables. In the period 1985 – 2010, the share of female R&D scientists in our sample firms increased by 15.9 percent, growing from 8.4 percent in 1985 to 24.3 percent in 2010. Between 1985 and 2010, 20 percent of the scientists working on R&D labs were women. R&D scientists have spent, on average, five years within the firm (*Tenure* mean five years). The average *Constraint* of an R&D scientist is 0.61, suggesting that R&D scientists in our sample tend to have network structures with few structural holes. Moving to scientists' attributes, a scientist's *Past productivity* in the prior three years is on average, two patents leading on average to five unique collaborators. On average, two percent of R&D scientists in the sample have *External ties*, and scientists have had around 1.2 employers in the past. Our firm-level dummies suggest that, on average, our sample consists of large firms: small and medium-sized firms represent only 10 percent of the firms in our sample.

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Insert Table 3-1 about here

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Table 3-2 and Table 3-3 provide the results for our two dependent variables measuring innovative performance *Productivity* and *Citation-weighted productivity*, respectively. We estimated the effect of our control variables in Model 1. In line with the view that R&D scientists who are more technological diverse tend to generate more impactful innovations, the effect of scientists' *Technological diversity* on scientists' innovative performance is positive and significant ($p < 0.001$). As expected, the effect of scientists' *Past productivity* on their future innovative performance is positive and significant ($p < 0.001$), which is in line with prior work that has shown systematic differences in the inherent innovative abilities of individuals (Felin & Hesterly, 2007). Corroborating the view that scientists' mobility raises scientists' visibility and

therefore, increases the impact of a scientist's innovations, the effect of *Mobility* on innovative performance is positive and significant ($p < 0.001$). Turning to our network controls, we found that *Network size* has a positive and strong significant effect on innovative performance ($p < 0.001$), suggesting that R&D scientists who have larger networks are more innovative than scientists with smaller networks. Opposing previous findings (Fleming, King, & Juda, 2007), maintaining *External ties* reduces R&D scientists' innovative performance ($p < 0.001$). This result may suggest that collaborations beyond a firm's boundaries may require for R&D scientists to develop new and maybe costly collaboration routines.

Regarding our key explanatory variable, in Model 2 we included *Gender diversity*. In line with prior work, the effect of *Gender diversity* is positive and significant ($p < 0.001$ for *Productivity* and $p < 0.1$ for *Citations weighted* p*roductivity*), suggesting that R&D scientists in gender-diverse organizations tend to be more innovative than R&D scientists in gender-homogeneous organizations. This result corroborates prior findings that show a positive association between gender diversity and overall organizational performance (Boone & Hendriks, 2009; Campbell & Vera, 2009; Dezsö & Ross, 2012; Hoogendoorn et al., 2013; Joecks et al., 2013). We introduced our moderating variables, *Tenure*, *Constraint*, and *Male*, in Model 2. *Male* is positive and significant ($p < 0.001$), suggesting that male R&D scientists are more innovative than female R&D scientists. *Tenure* is negative but non-significant ($p<0.001$) for *Productivity*, but positive and significant for *Citations weighted productivity*. This indicates that R&D scientists' innovative performance increases as a function of their length of service within a firm only when scientists' innovative performance is related to *Citations weighted productivity*. Corroborating prior research, the effect of *Constraint* is negative and significant ($p < 0.001$),

suggesting that R&D scientists whose networks are rich on structural holes tend to be more innovative.

To explore our moderation hypotheses, we included the multiplicative terms of *Gender diversity* and *Male* (Model 4), *Gender diversity* and *Tenure* (Model 5), *Gender diversity* and *Constraint* (Model 6). In Model 4, we introduced the interaction term between *Gender diversity* and *Male*. While the interaction term is negative but non-significant for *Productivity* (Table 3-2), this interaction is negative and marginally significant for *Citations weighted Productivity* (Table 3-3) ($\beta$= -0.430; p < 0.1). These results do not provide support for H1. To test H2, we included the multiplicative term of *Gender diversity* and *Tenure*, in Model 5. The coefficient of this interaction is negative and significant ($\beta$= -0.169; p < 0.001 for *Productivity* and $\beta$= -0.192; p < 0.001 for *Citations weighted productivity*) supporting H2. This indicates that gender-diverse firms are less likely to improve the innovative performance of R&D scientists with longer organizational tenure than the innovative performance of freshly-tenured R&D scientists. In Model 6, we inserted the multiplicative term of *Gender diversity* and *Constraint*. In line with H3, the coefficient of the interaction is negative and strongly significant ($\beta$= -1.100; p < 0.001 for *Productivity* and $\beta$= -1.220; p < 0.001 for *Citations weighted productivity*), demonstrating that R&D scientists who have a more constrained collaboration network are less likely to increase their innovative performance from working in a gender-diverse environment. To further check our moderation hypotheses, we added in the full model (Model 7) the multiplicative terms of *Gender diversity* and *Male*, *Gender diversity* and *Tenure*, and *Gender diversity* and *Constraint*. Similarly to Model 5, the interaction term between *Gender diversity* and *Tenure* is negative and strongly significant ($\beta$= -0.192; p < 0.001 for *Productivity* and $\beta$= -0.214; p < 0.001 for *Citations weighted productivity*), verifying H2. Validating H3, the interaction between *Gender diversity*

and *Constraint* is negative and significant ($\beta$= -1.675; p < 0.001 for *Productivity* and $\beta$= -1.848; p < 0.001 for *Citations weighted productivity*). Lastly, the interaction term between *Gender diversity* and *Male* is negative but not significant for both dependent variables, which again does not support H1.

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Insert Tables 3-2 and 3-3
about here
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Figure 3-1 to Figure 3-6 illustrate the significant findings and show the marginal effects of our multiplicative terms on innovative performance. Figure 3-1 and Figure 3-2 show that both female and male R&D scientists benefit from working in gender-diverse organizations. Although this result does not corroborate H1, it indicates that gender-diverse firms increase the innovative performance of both female and male scientist. Whereas female scientists produce over 23 percent more patents in gender-diverse firms compared with gender-homogeneous ones, male scientists produce 15 percent more patents in gender-diverse firms than in gender-homogeneous firms (Figure 3-1). Likewise, Figure 3-2 shows that compared to gender-homogeneous firms; female scientists have about 27 percent more citations-weighted patent counts in gender-diverse firms. Correspondingly, male scientists have around 11 percent more citations-weighted patent counts in gender-diverse firms than in gender-homogeneous ones.

Figure 3-3 and Figure 3-4 indicate that R&D scientists with longer organizational tenure are less likely to benefit from working in a gender-diverse organization. While freshly-tenured scientists have over 57 percent more patents in gender-diverse firms than in gender-homogeneous ones, scientists who have spent longer time within a firm tend to produce about 69 percent fewer patents in gender-diverse firms compared to gender-homogeneous firms (Figure 3-3). Similarly, Figure 3-4 displays that in comparison to gender-homogeneous firms, freshly-

tenured scientists receive around 43 percent more citation-weighted patent counts in gender-diverse firms. Conversely, long-tenured R&D scientists tend to see their number of citation-weighted patent counts erode about 77 percent in gender-diverse R&D firms compared to gender-homogeneous ones. These results corroborate H2.

Finally, Figure 3-5 and Figure 3-6 show that gender-diverse firms are more likely to increase the innovative performance of R&D scientists who have networks rich in structural holes. Figure 3-5 shows that R&D scientists who have brokering networks produce 53 percent more patents in a gender-diverse firm than in a gender-homogeneous firm. On the contrary, scientists with more cohesive network structures produce 10 percent fewer patents in gender-diverse firms in comparison to gender-homogeneous ones. Likewise, scientists in brokerage networks have 40 percent more citation-weighted patents in gender-diverse firms than in gender homogenous firms. Conversely, scientists in cohesive networks exhibit 3 percent less citation-weighted patents in gender-diverse firms compared to gender-homogeneous ones. These results support H3.

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Insert Figures 3-1 to 3-6
about here

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**Robustness checks**

Since we reported estimates based on random-effects models, we also estimated our models using a fixed-effect estimation approach. The results using this estimation approach and presented in Table 3-A4 remained similar to our main results. We also used a random-effects panel ordinary least squares model specification, using the log of our dependent variables. The results remain qualitatively identical to our earlier findings (Table 3-A5). Because it is impossible to rebuild the exact day in which collaboration between scientists started from patent

data, in our main analyses, we used three-year moving windows. To test if our results remain stable using other specifications, we also used two-year and four-year moving windows. Results based on the four-year window (Paruchuri & Eisenman, 2012), presented in Table 3-A6, provide strong support for our hypotheses. Results based on the two-year window are in line with the ones presented in the paper, but significant levels decrease slightly (Table 3-A7).

Because from patent data, it is impossible to identify the exact day in which a scientist is hired, we created a subsample taking all R&D scientists whose tenure is higher than 15 years. For those scientists, we tacked back their careers through their LinkedIn profiles. This allows us to build a new panel with R&D scientists who have spent the most prolonged period within a firm, and test how accurate is our tenure measure compared to the information that scientists report in their LinkedIn profiles. The number of R&D scientists in our subsample represents the 2,3 percent (1,326 inventors) of the total number of scientists in our sample (57,848 inventors). For these scientists, we identified the exact year in which each of them joined the firm. This allows us to create a more accurate measure of Tenure. We replicated our analyses using the LinkedIn tenure, results presented in Table 3-A8, and Table 3-A9 remain similar to those presented before.

### 3.5. DISCUSSION

Extant research concurs that more gender-diverse organizations – organizations featuring a more balanced composition of male and female workers – tend to be more innovative than gender-homogeneous ones (Herring, 2009; Joshi et al., 2006; Lyngsie & Foss, 2017; Richard et al., 2004). This association has been found in a wide variety of industries and along multiple dimensions of organizational performance (Boone & Hendriks, 2009; Campbell & Vera, 2009; Dezsö & Ross, 2012; Hoogendoorn et al., 2013; Joecks et al., 2013). This paper pushes this line

of argument forward by examining *whose* innovative performance is more likely to improve as a function of increased gender diversity. In particular, we proposed that gender diversity can affect different categories of knowledge workers, in different ways. First, we showed that gender-diverse firms increase the innovative performance of freshly-tenured R&D scientists more than they increase the innovative performance of long-tenured R&D scientists. Second, we explored whether R&D scientists' network structure moderates the effect of gender diversity on innovative performance. We found that higher levels of gender diversity increase the innovative performance of scientists with networks rich in structural holes; conversely, scientist embedded in constrained networks are less likely to benefit from working in gender-diverse firms. Finally, contrary to our expectation, we find that gender diversity is equally positive for both female and male R&D scientists' innovative performance.

### 3.5.1. Limitations

We wish to highlight some of the main limitations of our study. First, consistent with our focus on innovation, we defined the hiring time of an R&D scientist as the first time that scientist appears in a given patent application. However, we are aware that identifying the exact day in which the organization hired each scientist would require a more accurate measure for our analysis. To alleviate concerns about the accuracy of our measure, we collected additional data from LinkedIn. We tracked back the career of R&D scientists with longer tenure and tested how accurate our tenure measure was when compared to the information that scientists report in their LinkedIn profiles. We found that our measure is reasonably accurate. Yet, LinkedIn data is only available for a subset of our sample. Furthermore, arguably, LinkedIn data is not as accurate as HR records of the starting day of each scientist, in the organization. Second, as we used large-scale observational data, we built scientists' intra-organizational networks based on their co-

patenting ties. Nevertheless, co-patenting networks are an imperfect measure of collaboration networks, particularly because they do not trace collaborations that did not result in a patent. Validating our results based on more fine-grained (albeit likely smaller-scale) collaboration data would increase confidence in our findings. Finally, we derived our hypotheses from mechanisms that we are unable to observe empirically. For example, we argued that gender bias and rigidity in cognitive schemas tend to be associated with longer-tenured employees and employees embedded in constraint networks; however, we do not directly observe these micro-level mechanisms. Future work using experimental methods may be necessary to test our proposed mechanisms directly.

### 3.5.2. Contributions

It is becoming increasingly clear that gender diversity provides organizations with a source of intangible assets that create competitive advantage (Barney, 1986), particularly in knowledge-based organizations, where the ability to integrate diverse views and to address complex problems is crucial (Jehn et al., 1999; Penrose, 2009; Schumpeter, 1934). Despite broad recognition of the relevance of gender diversity for innovation, we still know relatively little about *how* gender diversity affects innovation within organizations (Boone & Hendriks, 2009; Kaplan, 2017b, 2017a). Notably, extant theoretical accounts have tended to assume that because the gender composition of an organization influences its culture and organizational climate (Gonzalez & Denisi, 2009; Joshi, Liao, & Jackson, 2006), gender diversity would also have a beneficial effect on the innovative performance of all knowledge workers. By demonstrating that gender diversity has a heterogeneous effect across different segments of an organization's workforce, our results both deepen and qualify current understandings of how gender diversity affects innovation within organizations. Building on existing organization theory, we argued and

showed that the performance benefits of gender diversity are concentrated among selected segments of an organization's knowledge workers, rather than diffused across the whole organization. This is particularly true when it comes to the potential role of knowledge workers' characteristics as a moderator of innovative performance. Our results indicated an interaction between gender diversity and different categories of scientists affecting scientists' innovative performance. Although gender diversity may itself positively affect knowledge workers' innovative performance, certain workers may improve their performance more than others in gender-diverse organizations. We found complete support for the moderating role of tenure and network structure, but we found no support for the role of gender. This finding adds realism and nuance to our theoretical understanding of the relationship between gender diversity and innovation, and it warrants us against portraying such a relationship in over-simplistic terms.

Our study offers several important contributions. First, extant theory posits that gender diversity provides organizations with heterogeneous perspectives and approaches; such diversity, in turn, is theorized to enhance employees' creativity and innovative performance of knowledge workers in general (Joshi et al., 2006; Richard et al., 2004). We complemented this line of inquiry by demonstrating that although gender diversity improves the average innovative performance of an organization's workforce, such performance benefits are distributed highly heterogeneously across knowledge workers. Our results, for example, suggest that long-tenured R&D scientists, as well as R&D scientists embedded in cohesive cliques of collaborators, are less likely to improve their innovative performance in organizations with increasing levels of gender diversity. Similarly, knowledge workers whose collaboration network is constrained tend to benefit significantly less from gender diversity than do knowledge workers embedded in a brokering network. In addition to adding clarity to how gender diversity affects organization's

innovative performance, these findings are important because they highlight how increasing the gender diversity of an organization might affect the relative performance, and hence the relative standing, of different segments of the organization's workforce.

Second, an unexpected and consequential finding of our study is that both men and women benefit equally from gender diversity. Following extant theories on diversity as a legitimizing factor for the minority group, we expected gender diversity to have an especially positive effect on women (Correll & Ridgeway, 2003; Ridgeway, 2001). Yet, our results indicate that both women's and men's innovative performance tend to improve as gender diversity increases. One possible reason for this finding is that the legitimization mechanism associated with increasing gender diversity be offset by a structural opportunity mechanism (Blau, 1964) operating in the opposite direction. Specifically, given that the R&D labs we examined are male-dominated increasing a lab's gender diversity effectively means increasing the share of women in the lab. Consequently, gender diversity will increase men's opportunities for collaboration with other-gender colleagues, and hence may ignite their creativity, *more* than is the case for women. Hence, paradoxically, in the context we studied increasing gender diversity implies that chances of collaborating with colleagues of the opposite gender increase steeply for men, but not for women. While having a more balanced gender composition certainly has a legitimizing effect for women, as demonstrated by much prior research, this structural opportunity mechanism may offset such beneficial effect. Whatever the underlying reason for our finding, that increasing gender diversity benefits *both* women and men is a finding of huge significance for both theory and practice.

Our research also contributes to the intra-organizational network literature. Extant research on social networks has provided extensive evidence on how and why brokers tend to be more

innovative than knowledge workers embedded in cohesive networks (R. S. Burt, 2004; Hargadon, 2002; Obstfeld, 2005). We add to this research by showing that, compared to knowledge workers in constrained networks, brokers are better able to exploit the opportunities that gender diversity provides to organizations. This finding suggests that R&D scientists' ability to use their position in the intra-organizational network structure is strengthened by working in a gender-diverse environment. Furthermore, it adds novel insight into the burgeoning body of literature on the role of network brokers in knowledge-based, innovative contexts (Obstfeld, 2005; Tortoriello, 2015).

Besides confirming the importance of gender diversity for organizations' innovative performance, our findings bear practical implications for how to manage gender diversity within organizations. We showed that some categories of knowledge workers benefit more from gender diversity than do others. Based on this finding, we speculate that these different categories of knowledge workers may develop different attitudes towards gender diversity itself. For example, we found that freshly-tenured employees and brokers benefit from gender diversity more than do long-tenured employees and employees with a constrained collaboration network. This suggests that the latter may be more reluctant to accept gender diversity as a positive development and, hence, they are less likely to endorse such development. While speculative, this argument suggests that an organization's workforce may need to be managed differently in the face of increasing gender diversity. Diversity training, culture audit policies, or two-way socialization process (Chang et al., 2019; Cox, 1994; Cox & Blake, 1991) are helpful approaches to integrate women's perspectives in organizational norms and values and to help the organization's workforce appreciate and manage gender diversity. We believe that these trainings may be

particularly important for those segments of an organization's workforce who, left on their own, would find it hard to understand and leverage the potential of gender diversity.

## FIGURES

**Figure 3-1.** Marginal Effects from the Negative Binomial Regression Predicting Innovative Performance (Productivity)

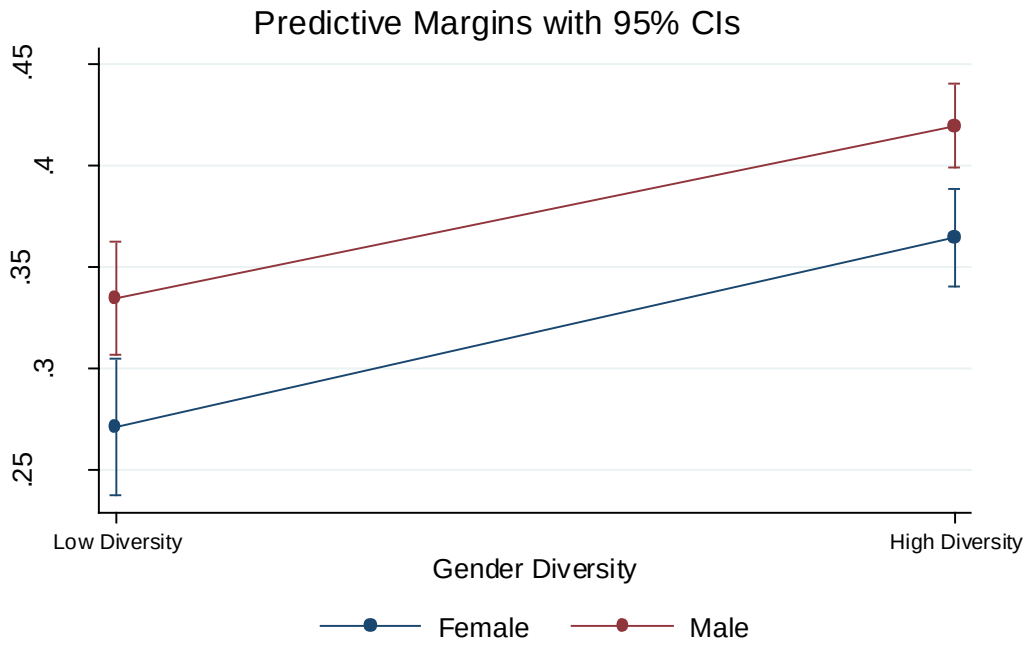



**Figure 3-2.** Marginal Effects from the Negative Binomial Regression Predicting Innovative Performance (Citations Weighted Productivity)

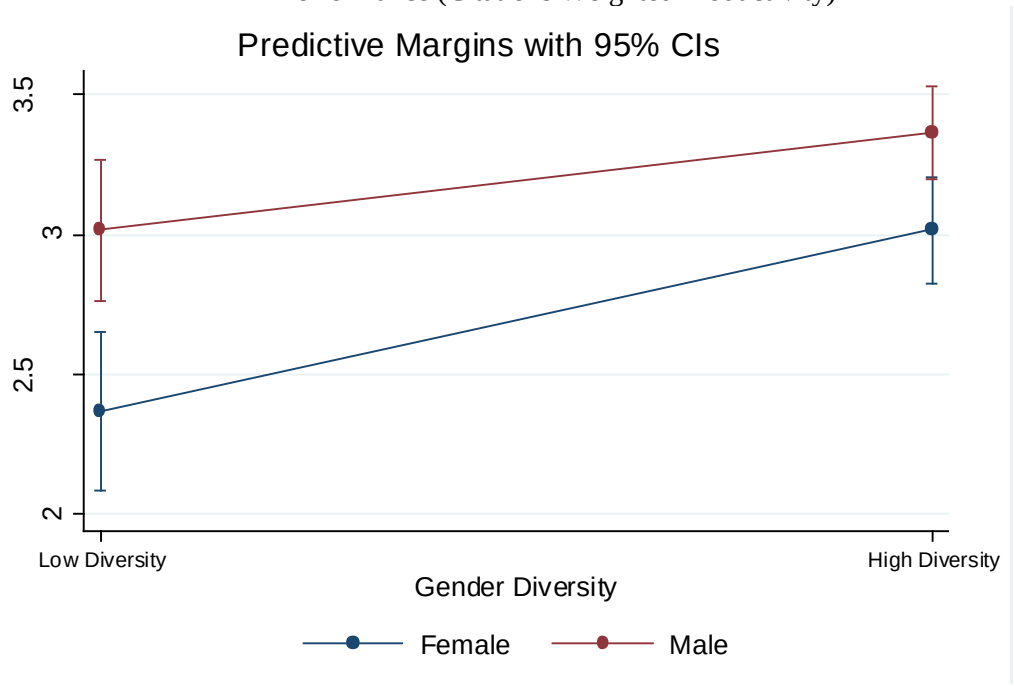


**Figure 3-3.** Marginal Effects from the Negative Binomial Regression Predicting Innovative Performance (Productivity)

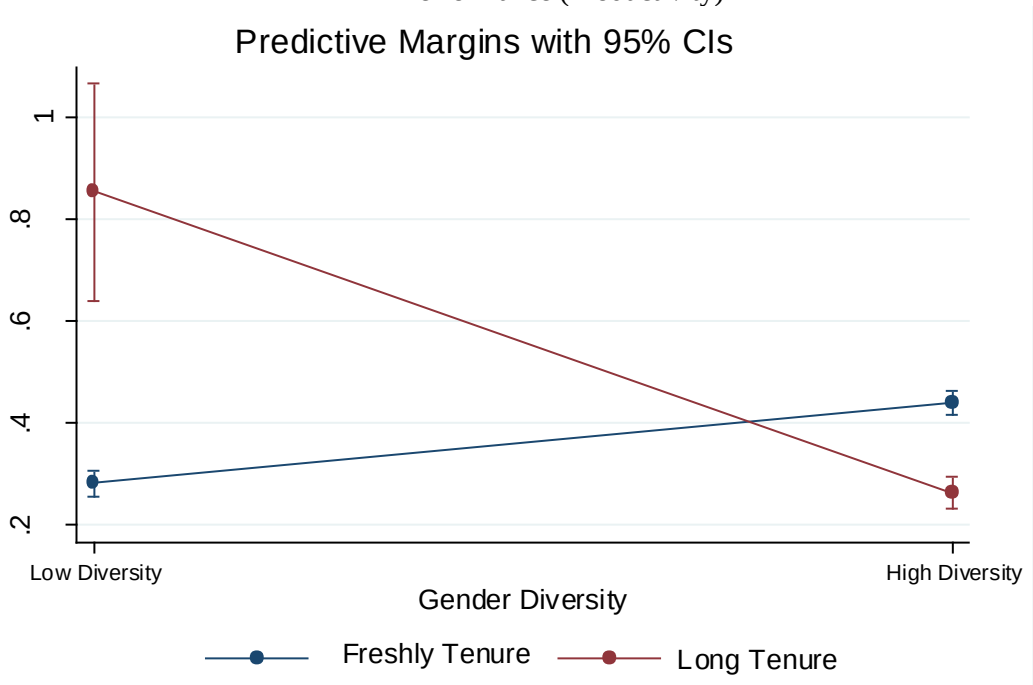



**Figure 3-4.** Marginal Effects from the Negative Binomial Regression Predicting Innovative Performance (Citations Weighted Productivity)

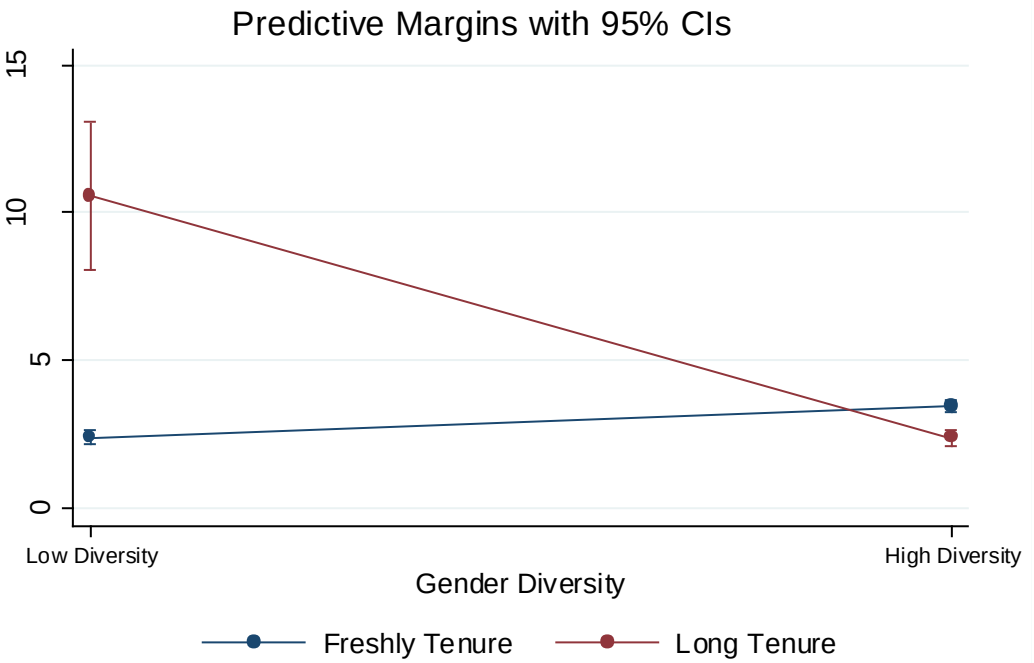


**Figure 3-5.** Marginal Effects from the Negative Binomial Regression Predicting Innovative Performance (Productivity)

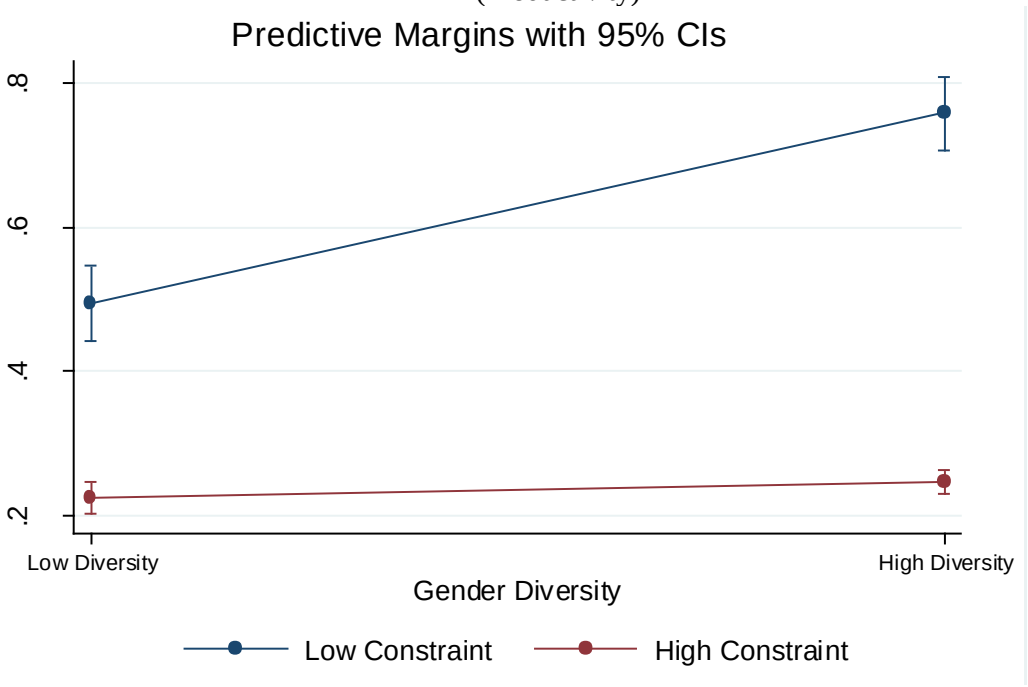
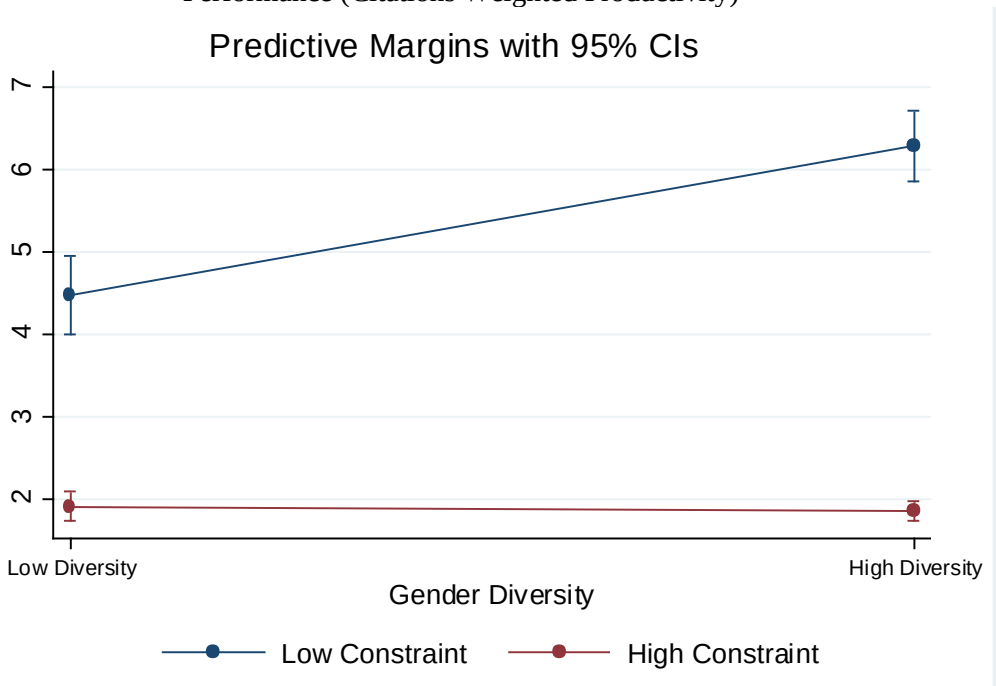



**Figure 3-6.** Marginal Effects from the Negative Binomial Regression Predicting Innovative Performance (Citations Weighted Productivity)



## TABLES

**Table 3-1.** Descriptive Statistic and Pairwise Correlations

| | Mean | S.D. | Min | Max | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1.** Citations weighted productivity | 3.704 | 16.326 | 0 | 995 | 1 | | | | | | | | | | | | | | |
| **2.** Productivity | 0.474 | 1.422 | 0 | 82 | 0.687 | 1 | | | | | | | | | | | | | |
| **3.** Technological diversity | 0.363 | 0.275 | 0 | 0.923 | 0.072 | 0.108 | 1 | | | | | | | | | | | | |
| **4.** Past productivity | 2.330 | 3.098 | 1 | 182 | 0.237 | 0.393 | 0.222 | 1 | | | | | | | | | | | |
| **5.** Network size | 5.578 | 6.264 | 0 | 119 | 0.156 | 0.239 | 0.266 | 0.514 | 1 | | | | | | | | | | |
| **6.** Team size | 4.672 | 3.343 | 1 | 33 | 0.039 | 0.047 | 0.143 | 0.080 | 0.729 | 1 | | | | | | | | | |
| **7.** External ties | 0.021 | 0.143 | 0 | 1 | 0.012 | 0.019 | 0.051 | 0.051 | 0.049 | 0.023 | 1 | | | | | | | | |
| **8.** Mobility | 0.308 | 0.601 | 0 | 6 | 0.030 | 0.036 | 0.108 | 0.063 | 0.114 | 0.079 | 0.131 | 1 | | | | | | | |
| **9.** Network size dummy | 0.049 | 0.216 | 0 | 1 | -0.023 | -0.033 | -0.092 | -0.077 | -0.202 | -0.249 | -0.033 | -0.030 | 1 | | | | | | |
| **10.** Medium firm dummy | 0.076 | 0.266 | 0 | 1 | -0.008 | -0.017 | 0.008 | -0.033 | -0.085 | -0.087 | -0.014 | 0.033 | 0.043 | 1 | | | | | |
| **11.** Small firm dummy | 0.020 | 0.139 | 0 | 1 | -0.008 | -0.016 | 0.005 | -0.027 | -0.062 | -0.060 | 0.001 | 0.027 | 0.031 | -0.041 | 1 | | | | |
| **12.** Gender diversity | 0.195 | 0.055 | 0 | 0.311 | 0.015 | 0.061 | 0.099 | 0.108 | 0.291 | 0.312 | 0.049 | 0.023 | -0.173 | -0.231 | -0.203 | 1 | | | |
| **13.** Male | 0.805 | 0.396 | 0 | 1 | 0.028 | 0.033 | -0.023 | 0.034 | -0.026 | -0.073 | 0.000 | 0.030 | 0.048 | 0.032 | 0.028 | -0.139 | 1 | | |
| **14.** Tenure | 4.616 | 4.431 | 1 | 32 | 0.061 | 0.101 | 0.119 | 0.194 | 0.190 | 0.034 | 0.003 | 0.149 | -0.032 | -0.076 | -0.049 | 0.125 | 0.088 | 1 | |
| **15.** Constraint | 0.608 | 0.305 | 0.025 | 1 | -0.131 | -0.198 | -0.313 | -0.393 | -0.734 | -0.645 | -0.114 | -0.103 | 0.292 | 0.107 | 0.084 | -0.367 | 0.046 | -0.197 | 1 |

N = 290,214. All correlations larger than |0.0055| are significant at the 0.01 level.

**Table 3-2.** Random-Effects Negative Binomial Regression Predicting Innovative Performance
- Productivity -

| **Dependent Variable: Productivity** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** | **(model 7)** |
|---|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES | YES |
| | | | | | | | |
| Technological diversity | 0.417*** | 0.417*** | 0.298*** | 0.298*** | 0.296*** | 0.299*** | 0.297*** |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) |
| Past productivity (ln) | 0.610*** | 0.608*** | 0.457*** | 0.457*** | 0.454*** | 0.457*** | 0.453*** |
| | (0.011) | (0.011) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Network size | 0.003*** | 0.003*** | 0.001 | 0.001 | 0.002+ | 0.000 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Team size | 0.007*** | 0.007*** | -0.029*** | -0.029*** | -0.030*** | -0.030*** | -0.031*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| External ties | -0.093*** | -0.092*** | -0.109*** | -0.109*** | -0.106*** | -0.109*** | -0.107*** |
| | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Mobility | 0.080*** | 0.080*** | 0.081*** | 0.081*** | 0.083*** | 0.082*** | 0.084*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| Network size dummy | -0.024 | -0.024 | 0.140*** | 0.140*** | 0.140*** | 0.127*** | 0.121*** |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) |
| Medium firm dummy | 0.088*** | 0.106*** | 0.099*** | 0.099*** | 0.098*** | 0.102*** | 0.101*** |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) |
| Small firm dummy | 0.080+ | 0.110* | 0.116* | 0.115* | 0.116* | 0.113* | 0.112* |
| | (0.048) | (0.049) | (0.048) | (0.048) | (0.048) | (0.048) | (0.048) |
| Gender diversity | | 0.878*** | 0.758*** | 0.950** | 1.622*** | 0.698*** | 1.652*** |
| | | (0.211) | (0.210) | (0.297) | (0.233) | (0.210) | (0.309) |
| Tenure | | | -0.001 | -0.001 | 0.003** | -0.001 | 0.003** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constraint | | | -1.017*** | -1.017*** | -1.008*** | -1.027*** | -1.023*** |
| | | | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) |
| Male | | | 0.163*** | 0.166*** | 0.163*** | 0.163*** | 0.164*** |
| | | | (0.012) | (0.013) | (0.012) | (0.012) | (0.013) |
| Gender diversity x Male | | | | -0.220 | | | -0.009 |
| | | | | (0.243) | | | (0.244) |
| Gender diversity x Tenure | | | | | -0.169*** | | -0.192*** |
| | | | | | (0.020) | | (0.020) |
| Gender diversity x Constraint | | | | | | -1.100*** | -1.675*** |
| | | | | | | (0.297) | (0.304) |
| | | | | | | | |
| Constant | -1.835*** | -1.776*** | -1.497*** | -1.502*** | -1.464*** | -1.522*** | -1.497*** |
| | (0.050) | (0.052) | (0.053) | (0.053) | (0.053) | (0.054) | (0.054) |
| | | | | | | | |
| Observations | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 |
| Number of scientists | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 |

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 3-3.** Random-Effects Negative Binomial Regression Predicting Innovative Performance - Citations Weighted Productivity –

| **Dependent Variable: Citations weighted productivity** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** | **(model 7)** |
|---|---|---|---|---|---|---|---|
| Firm dummies | YES | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES | YES |
| | | | | | | | |
| Technological diversity | 0.452*** | 0.452*** | 0.308*** | 0.308*** | 0.306*** | 0.309*** | 0.306*** |
| | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) |
| Past productivity (ln) | 0.834*** | 0.834*** | 0.617*** | 0.617*** | 0.612*** | 0.616*** | 0.610*** |
| | (0.009) | (0.009) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Network size | 0.007*** | 0.007*** | 0.003*** | 0.003*** | 0.004*** | 0.002** | 0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Team size | 0.001 | 0.001 | -0.036*** | -0.036*** | -0.036*** | -0.037*** | -0.038*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| External ties | -0.095*** | -0.094*** | -0.108*** | -0.108*** | -0.104*** | -0.109*** | -0.105*** |
| | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Mobility | 0.096*** | 0.096*** | 0.084*** | 0.085*** | 0.086*** | 0.085*** | 0.087*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Network size dummy | -0.023 | -0.022 | 0.161*** | 0.161*** | 0.160*** | 0.147*** | 0.138*** |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.024) | (0.024) |
| Medium firm dummy | 0.103*** | 0.112*** | 0.100*** | 0.100*** | 0.098*** | 0.102*** | 0.102*** |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) |
| Small firm dummy | 0.121* | 0.137** | 0.128** | 0.127** | 0.129** | 0.126** | 0.125** |
| | (0.047) | (0.048) | (0.048) | (0.048) | (0.048) | (0.048) | (0.048) |
| Gender diversity | | 0.401+ | 0.409* | 0.783** | 1.360*** | 0.352+ | 1.541*** |
| | | (0.207) | (0.208) | (0.288) | (0.228) | (0.208) | (0.298) |
| Tenure | | | 0.006*** | 0.006*** | 0.010*** | 0.006*** | 0.011*** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constraint | | | -1.104*** | -1.104*** | -1.094*** | -1.115*** | -1.109*** |
| | | | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) |
| Male | | | 0.152*** | 0.160*** | 0.153*** | 0.152*** | 0.157*** |
| | | | (0.011) | (0.012) | (0.011) | (0.011) | (0.012) |
| Gender diversity x Male | | | | -0.430+ | | | -0.185 |
| | | | | (0.229) | | | (0.230) |
| Gender diversity x Tenure | | | | | -0.192*** | | -0.214*** |
| | | | | | (0.019) | | (0.019) |
| Gender diversity x Constraint | | | | | | -1.220*** | -1.848*** |
| | | | | | | (0.291) | (0.296) |
| | | | | | | | |
| Constant | -3.870*** | -3.845*** | -3.394*** | -3.402*** | -3.357*** | -3.418*** | -3.393*** |
| | (0.045) | (0.047) | (0.050) | (0.050) | (0.050) | (0.050) | (0.050) |
| | | | | | | | |
| Observations | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 |
| Number of scientists | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 |

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

## Appendix: robustness checks

**Table 3-A4.** Fixed-Effects Panel Negative Binomial Regression Predicting Innovative Performance

| | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** | **(model 7)** | **(model 8)** | **(model 9)** | **(model 10)** | **(model 11)** | **(model 12)** | **(model 13)** | **(model 14)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Variables** | Productivity | | | | | | | Citations weighted productivity | | | | | | |
| Year dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Technological diversity | -0.018 | -0.017 | -0.049* | -0.049* | -0.050* | -0.050* | -0.049* | 0.080*** | 0.078*** | 0.038+ | 0.039+ | 0.038+ | 0.038+ | 0.037+ |
| | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| Past productivity (ln) | -0.048*** | -0.051*** | -0.106*** | -0.105*** | -0.104*** | -0.107*** | -0.105*** | 0.233*** | 0.229*** | 0.162*** | 0.162*** | 0.158*** | 0.161*** | 0.156*** |
| | (0.011) | (0.011) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.011) | (0.011) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Network size | 0.015*** | 0.015*** | 0.015*** | 0.015*** | 0.014*** | 0.014*** | 0.014*** | 0.014*** | 0.014*** | 0.013*** | 0.013*** | 0.014*** | 0.013*** | 0.013*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Team size | -0.016*** | -0.016*** | -0.025*** | -0.025*** | -0.025*** | -0.026*** | -0.026*** | -0.017*** | -0.018*** | -0.029*** | -0.029*** | -0.030*** | -0.029*** | -0.030*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| External ties | -0.119*** | -0.112*** | -0.115*** | -0.116*** | -0.115*** | -0.115*** | -0.115*** | -0.070* | -0.064* | -0.068* | -0.068* | -0.069* | -0.068* | -0.070* |
| | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| Mobility | -0.212*** | -0.212*** | -0.209*** | -0.210*** | -0.210*** | -0.209*** | -0.210*** | -0.132*** | -0.129*** | -0.126*** | -0.126*** | -0.124*** | -0.126*** | -0.123*** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| Network size dummy | -0.024 | -0.023 | 0.016 | 0.017 | 0.014 | 0.003 | 0.004 | 0.000 | 0.008 | 0.064* | 0.065* | 0.064* | 0.054* | 0.051+ |
| | (0.026) | (0.026) | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Gender diversity | | 1.298*** | 1.279*** | -0.117 | 0.919*** | 1.186*** | -0.458 | | 1.511*** | 1.470*** | 0.795** | 2.374*** | 1.407*** | 1.497*** |
| | | (0.178) | (0.178) | (0.353) | (0.217) | (0.180) | (0.368) | | (0.151) | (0.151) | (0.283) | (0.194) | (0.152) | (0.302) |
| Constraint | | | -0.266*** | -0.266*** | -0.266*** | -0.278*** | -0.278*** | | | -0.338*** | -0.338*** | -0.339*** | -0.347*** | -0.351*** |
| | | | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) | | | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Gender diversity x Male | | | | 1.611*** | | | 1.601*** | | | | 0.790** | | | 1.026*** |
| | | | | (0.352) | | | (0.352) | | | | (0.280) | | | (0.282) |
| Gender diversity x Tenure | | | | | 0.064** | | 0.046* | | | | | -0.150*** | | -0.165*** |
| | | | | | (0.022) | | (0.022) | | | | | (0.020) | | (0.020) |
| Gender diversity x Constraint | | | | | | -1.186*** | -1.135*** | | | | | | -0.919** | -1.251*** |
| | | | | | | (0.331) | (0.335) | | | | | | (0.320) | (0.323) |
| Constant | 0.215*** | 0.343*** | 0.487*** | 0.499*** | 0.467*** | 0.459*** | 0.458*** | -2.009*** | -1.854*** | -1.682*** | -1.676*** | -1.623*** | -1.701*** | -1.637*** |
| | (0.042) | (0.045) | (0.048) | (0.048) | (0.048) | (0.048) | (0.049) | (0.041) | (0.044) | (0.046) | (0.046) | (0.047) | (0.047) | (0.047) |
| Observations | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 | 178,979 |
| Number of scientists | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 | 22,568 |

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 3-A5.** Random-Effects Ordinary Least Squares Predicting Innovative Performance

| | (model 1) | (model 2) | (model 3) | (model 4) | (model 5) | (model 6) | (model 7) | (model 8) | (model 9) | (model 10) | (model 11) | (model 12) | (model 13) | (model 14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Variables** | Productivity (ln) | | | | | | | Citations weighted productivity (ln) | | | | | | |
| Firm dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Technological diversity | 0.041*** | 0.040*** | 0.029*** | 0.029*** | 0.029*** | 0.029*** | 0.029*** | 0.107*** | 0.106*** | 0.078*** | 0.078*** | 0.077*** | 0.078*** | 0.077*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| Past productivity (ln) | 0.257*** | 0.257*** | 0.227*** | 0.227*** | 0.226*** | 0.227*** | 0.226*** | 0.521*** | 0.521*** | 0.445*** | 0.445*** | 0.443*** | 0.445*** | 0.443*** |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.004) | (0.005) | (0.004) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| Network size | 0.011*** | 0.011*** | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.019*** | 0.019*** | 0.016*** | 0.016*** | 0.017*** | 0.016*** | 0.017*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Team size | -0.012*** | -0.012*** | -0.016*** | -0.016*** | -0.016*** | -0.016*** | -0.016*** | -0.014*** | -0.014*** | -0.025*** | -0.025*** | -0.025*** | -0.025*** | -0.025*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| External ties | -0.025*** | -0.025*** | -0.024*** | -0.024*** | -0.024*** | -0.024*** | -0.024*** | -0.050** | -0.049** | -0.049** | -0.049** | -0.049** | -0.049** | -0.049** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) |
| Mobility | 0.019*** | 0.019*** | 0.016*** | 0.016*** | 0.016*** | 0.016*** | 0.016*** | 0.049*** | 0.049*** | 0.044*** | 0.044*** | 0.044*** | 0.044*** | 0.044*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Network size dummy | 0.009** | 0.010** | 0.020*** | 0.020*** | 0.020*** | 0.018*** | 0.017*** | 0.019* | 0.019* | 0.047*** | 0.047*** | 0.047*** | 0.049*** | 0.047*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| Medium firm dummy | 0.017*** | 0.021*** | 0.019*** | 0.019*** | 0.019*** | 0.020*** | 0.020*** | 0.040*** | 0.045*** | 0.041*** | 0.041*** | 0.041*** | 0.040*** | 0.041*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Small firm dummy | 0.018* | 0.024** | 0.021** | 0.021** | 0.021** | 0.021** | 0.021** | 0.051* | 0.060** | 0.053* | 0.053* | 0.053* | 0.053* | 0.053* |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) |
| Gender diversity | | 0.158*** | 0.172*** | 0.112* | 0.245*** | 0.193*** | 0.204*** | | 0.209+ | 0.225* | 0.253+ | 0.484*** | 0.217* | 0.468*** |
| | | (0.042) | (0.042) | (0.051) | (0.045) | (0.043) | (0.054) | | (0.107) | (0.107) | (0.131) | (0.114) | (0.109) | (0.137) |
| Tenure | | | 0.002*** | 0.002*** | 0.003*** | 0.002*** | 0.003*** | | | 0.004*** | 0.004*** | 0.005*** | 0.004*** | 0.005*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constraint | | | -0.121*** | -0.121*** | -0.120*** | -0.122*** | -0.122*** | | | -0.311*** | -0.311*** | -0.310*** | -0.311*** | -0.310*** |
| | | | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | | | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Male | | | 0.031*** | 0.030*** | 0.031*** | 0.031*** | 0.030*** | | | 0.068*** | 0.068*** | 0.068*** | 0.068*** | 0.068*** |
| | | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | | | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Gender diversity x Male | | | | 0.072+ | | | 0.095* | | | | -0.033 | | | 0.020 |
| | | | | (0.037) | | | (0.037) | | | | (0.094) | | | (0.093) |
| Gender diversity x Tenure | | | | | -0.017*** | | -0.021*** | | | | | -0.061*** | | -0.061*** |
| | | | | | (0.005) | | (0.005) | | | | | (0.011) | | (0.011) |
| Gender diversity x Constraint | | | | | | -0.286*** | -0.331*** | | | | | | 0.124 | 0.001 |
| | | | | | | (0.067) | (0.067) | | | | | | (0.159) | (0.159) |

| | (model 1) | (model 2) | (model 3) | (model 4) | (model 5) | (model 6) | (model 7) | (model 8) | (model 9) | (model 10) | (model 11) | (model 12) | (model 13) | (model 14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Variables** | Productivity (ln) | | | | | | | | Citations weighted productivity (ln) | | | | | |
| Constant | -0.075*** | -0.065*** | -0.021* | -0.020* | -0.019+ | -0.026** | -0.022* | -0.155*** | -0.142*** | -0.018 | -0.019 | -0.008 | -0.016 | -0.008 |
| | (0.008) | (0.009) | (0.009) | (0.010) | (0.010) | (0.010) | (0.010) | (0.019) | (0.020) | (0.022) | (0.022) | (0.022) | (0.022) | (0.023) |
| Observations | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 | 290,214 |
| Number of scientists | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 | 57,848 |

Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 3-A6.** Random-Effects Negative Binomial Regression Predicting Innovative Performance (4 years window)

| | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** | **(model 7)** | **(model 8)** | **(model 9)** | **(model 10)** | **(model 11)** | **(model 12)** | **(model 13)** | **(model 14)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Variables** | | | | Productivity | | | | | | Citations weighted productivity | | | | |
| Firm dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Technological diversity | 0.432*** | 0.433*** | 0.310*** | 0.310*** | 0.309*** | 0.311*** | 0.310*** | 0.456*** | 0.456*** | 0.309*** | 0.309*** | 0.308*** | 0.310*** | 0.308*** |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.016) | (0.016) | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) |
| Past productivity (ln) | 0.581*** | 0.577*** | 0.411*** | 0.411*** | 0.411*** | 0.411*** | 0.410*** | 0.846*** | 0.845*** | 0.623*** | 0.623*** | 0.620*** | 0.621*** | 0.616*** |
| | (0.011) | (0.011) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.008) | (0.008) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Network size | 0.002** | 0.002** | 0.002** | 0.002** | 0.002** | 0.002* | 0.002* | 0.005*** | 0.005*** | 0.004*** | 0.004*** | 0.004*** | 0.003*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Team size | 0.011*** | 0.011*** | -0.032*** | -0.032*** | -0.032*** | -0.033*** | -0.034*** | 0.004** | 0.004* | -0.039*** | -0.039*** | -0.039*** | -0.040*** | -0.040*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| External ties | 0.044*** | 0.045*** | 0.022+ | 0.022+ | 0.024* | 0.020+ | 0.022+ | 0.051*** | 0.052*** | 0.034** | 0.034** | 0.036** | 0.031** | 0.033** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Mobility | 0.041*** | 0.041*** | 0.060*** | 0.060*** | 0.061*** | 0.062*** | 0.063*** | 0.064*** | 0.065*** | 0.066*** | 0.066*** | 0.067*** | 0.068*** | 0.069*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Network size dummy | -0.041+ | -0.040+ | 0.153*** | 0.153*** | 0.153*** | 0.137*** | 0.133*** | -0.039+ | -0.039+ | 0.180*** | 0.180*** | 0.179*** | 0.161*** | 0.154*** |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.025) | (0.025) | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.024) | (0.024) |
| Medium firm dummy | 0.110*** | 0.136*** | 0.145*** | 0.145*** | 0.145*** | 0.144*** | 0.144*** | 0.106*** | 0.120*** | 0.126*** | 0.126*** | 0.127*** | 0.126*** | 0.126*** |
| | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.024) | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) |
| Small firm dummy | 0.070 | 0.102+ | 0.135* | 0.135* | 0.139* | 0.133* | 0.137* | 0.080 | 0.097+ | 0.125* | 0.125* | 0.131* | 0.122* | 0.128* |
| | (0.060) | (0.060) | (0.060) | (0.060) | (0.060) | (0.060) | (0.060) | (0.058) | (0.059) | (0.059) | (0.059) | (0.059) | (0.059) | (0.059) |
| Gender diversity | | 1.188*** | 0.879*** | 0.828** | 1.336*** | 0.786*** | 1.211*** | | 0.585** | 0.441* | 0.620* | 1.101*** | 0.346 | 1.156*** |
| | | (0.218) | (0.218) | (0.300) | (0.243) | (0.218) | (0.314) | | (0.212) | (0.212) | (0.285) | (0.234) | (0.213) | (0.297) |
| Tenure | | | -0.020*** | -0.020*** | -0.018*** | -0.020*** | -0.018*** | | | -0.009*** | -0.009*** | -0.006*** | -0.010*** | -0.006*** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constraint | | | -1.099*** | -1.099*** | -1.094*** | -1.114*** | -1.112*** | | | -1.180*** | -1.180*** | -1.172*** | -1.197*** | -1.193*** |
| | | | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | | | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) |
| Male | | | 0.174*** | 0.173*** | 0.174*** | 0.174*** | 0.171*** | | | 0.159*** | 0.162*** | 0.160*** | 0.159*** | 0.160*** |
| | | | (0.012) | (0.013) | (0.012) | (0.012) | (0.013) | | | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Gender diversity x Male | | | | 0.059 | | | 0.174 | | | | -0.206 | | | -0.042 |
| | | | | (0.238) | | | (0.238) | | | | (0.218) | | | (0.219) |
| Gender diversity x Tenure | | | | | -0.086*** | | -0.113*** | | | | | -0.128*** | | -0.156*** |
| | | | | | (0.020) | | (0.021) | | | | | (0.019) | | (0.019) |
| Gender diversity x Constraint | | | | | | -1.334*** | -1.692*** | | | | | | -1.492*** | -1.972*** |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | (0.290) | (0.298) | | | | | | (0.278) | (0.285) |
| Constant | -1.838*** | -1.744*** | -1.418*** | -1.416*** | -1.403*** | -1.448*** | -1.433*** | -3.979*** | -3.935*** | -3.442*** | -3.446*** | -3.420*** | -3.471*** | -3.454*** |
| | (0.048) | (0.051) | (0.052) | (0.053) | (0.052) | (0.053) | (0.053) | (0.043) | (0.046) | (0.048) | (0.048) | (0.048) | (0.048) | (0.049) |
| Observations | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 | 349,090 |
| Number of scientists | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 | 58,399 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 3-A7.** Random-Effects Negative Binomial Regression Predicting Innovative Performance (2-years window)

| | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** | **(model 7)** | **(model 8)** | **(model 9)** | **(model 10)** | **(model 11)** | **(model 12)** | **(model 13)** | **(model 14)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Variables** | | | | Productivity | | | | | | | Citations weighted productivity | | | |
| Firm dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Technological diversity | 0.374*** | 0.374*** | 0.272*** | 0.273*** | 0.270*** | 0.273*** | 0.270*** | 0.431*** | 0.430*** | 0.298*** | 0.299*** | 0.294*** | 0.299*** | 0.296*** |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.017) | (0.017) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) |
| Past productivity (ln) | 0.592*** | 0.591*** | 0.463*** | 0.463*** | 0.458*** | 0.463*** | 0.457*** | 0.798*** | 0.798*** | 0.593*** | 0.594*** | 0.586*** | 0.595*** | 0.587*** |
| | (0.012) | (0.012) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.010) | (0.010) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Network size | 0.007*** | 0.007*** | 0.002+ | 0.002+ | 0.003** | 0.002 | 0.002* | 0.011*** | 0.011*** | 0.004*** | 0.004*** | 0.005*** | 0.004*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Team size | -0.001 | -0.001 | -0.030*** | -0.030*** | -0.030*** | -0.030*** | -0.031*** | -0.007*** | -0.007*** | -0.038*** | -0.038*** | -0.039*** | -0.038*** | -0.040*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| External ties | -0.045** | -0.045** | -0.046*** | -0.046*** | -0.041** | -0.046*** | -0.042** | -0.039** | -0.039** | -0.042** | -0.033* | -0.037** | -0.034* | -0.029* |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| Mobility | 0.117*** | 0.117*** | 0.101*** | 0.102*** | 0.104*** | 0.101*** | 0.105*** | 0.130*** | 0.129*** | 0.206*** | 0.103*** | 0.209*** | 0.103*** | 0.106*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.007) | (0.007) | (0.013) | (0.007) | (0.013) | (0.007) | (0.007) |
| Network size dummy | -0.007 | -0.006 | 0.111*** | 0.110*** | 0.110*** | 0.109*** | 0.101*** | -0.012 | -0.012 | 0.123*** | 0.122*** | 0.121*** | 0.118*** | 0.108*** |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.023) | (0.023) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) |
| Medium firm dummy | 0.077*** | 0.084*** | 0.076*** | 0.076*** | 0.071*** | 0.076*** | 0.072*** | 0.102*** | 0.106*** | 0.089*** | 0.089*** | 0.084*** | 0.089*** | 0.086*** |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) |
| Small firm dummy | 0.135** | 0.157*** | 0.151*** | 0.150*** | 0.145** | 0.151*** | 0.145** | 0.173*** | 0.183*** | 0.162*** | 0.161*** | 0.159*** | 0.162*** | 0.158*** |
| | (0.045) | (0.045) | (0.045) | (0.045) | (0.045) | (0.045) | (0.045) | (0.044) | (0.045) | (0.045) | (0.045) | (0.045) | (0.045) | (0.045) |
| Gender diversity | | 0.582** | 0.619** | 1.245*** | 1.820*** | 0.608** | 2.187*** | | 0.262 | 0.401* | 1.182*** | 1.601*** | 0.382+ | 2.098*** |
| | | (0.199) | (0.198) | (0.300) | (0.223) | (0.199) | (0.311) | | (0.198) | (0.199) | (0.293) | (0.219) | (0.199) | (0.302) |
| Tenure | | | 0.015*** | 0.015*** | 0.020*** | 0.015*** | 0.020*** | | | 0.020*** | 0.020*** | 0.025*** | 0.020*** | 0.025*** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constraint | | | -0.893*** | -0.893*** | -0.883*** | -0.894*** | -0.888*** | | | -1.005*** | -1.003*** | -0.995*** | -1.007*** | -1.000*** |
| | | | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) | | | (0.026) | (0.026) | (0.026) | (0.026) | (0.026) |
| Male | | | 0.155*** | 0.166*** | 0.156*** | 0.155*** | 0.163*** | | | 0.147*** | 0.163*** | 0.149*** | 0.148*** | 0.160*** |
| | | | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | | | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Gender diversity x Male | | | | -0.721** | | | -0.431+ | | | | -0.901*** | | | -0.583* |
| | | | | (0.259) | | | (0.260) | | | | (0.248) | | | (0.249) |
| Gender diversity x Tenure | | | | | -0.243*** | | -0.250*** | | | | | -0.251*** | | -0.258*** |
| | | | | | (0.020) | | (0.021) | | | | | (0.019) | | (0.020) |
| Gender diversity x Constraint | | | | | | -0.238 | -0.905** | | | | | | -0.476 | -1.156*** |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | (0.315) | (0.320) | | | | | | (0.313) | (0.318) |
| Constant | -1.672*** | -1.636*** | -1.434*** | -1.450*** | -1.377*** | -1.440*** | -1.405*** | -3.678*** | -3.663*** | -3.265*** | -3.289*** | -3.210*** | -3.280*** | -3.249*** |
| | (0.053) | (0.054) | (0.056) | (0.056) | (0.056) | (0.057) | (0.057) | (0.050) | (0.051) | (0.053) | (0.054) | (0.054) | (0.054) | (0.054) |
| Observations | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 | 220,947 |
| Number of scientists | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 | 57,254 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 3-A8.** Random-Effects Ordinary Least Squares Predicting Innovative Performance -Subsample-

| | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** | **(model 7)** | **(model 8)** | **(model 9)** | **(model 10)** | **(model 11)** | **(model 12)** | **(model 13)** | **(model 14)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Variables** | Productivity (ln) | | | | | | | Citations weighted productivity (ln) | | | | | | |
| Firm dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Technological diversity | 0.031 | 0.032 | 0.034 | 0.034 | 0.033 | 0.033 | 0.032 | 0.115* | 0.113* | 0.104* | 0.104* | 0.102* | 0.104* | 0.101* |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.048) | (0.048) | (0.049) | (0.049) | (0.049) | (0.049) | (0.049) |
| Past productivity (ln) | 0.321*** | 0.321*** | 0.313*** | 0.313*** | 0.312*** | 0.313*** | 0.311*** | 0.678*** | 0.679*** | 0.637*** | 0.636*** | 0.634*** | 0.637*** | 0.633*** |
| | (0.016) | (0.016) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.034) | (0.034) | (0.038) | (0.038) | (0.038) | (0.038) | (0.038) |
| Network size | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.009*** | 0.009*** | 0.012*** | 0.012*** | 0.012*** | 0.012*** | 0.012*** | 0.011*** | 0.012*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Team size | -0.011*** | -0.011*** | -0.012*** | -0.012*** | -0.012*** | -0.013*** | -0.013*** | -0.002 | -0.002 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 |
| | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| External ties | -0.073+ | -0.072+ | -0.086* | -0.086* | -0.086* | -0.086* | -0.087* | -0.119 | -0.120 | -0.153+ | -0.152+ | -0.154+ | -0.153+ | -0.154+ |
| | (0.037) | (0.037) | (0.037) | (0.037) | (0.037) | (0.037) | (0.037) | (0.087) | (0.087) | (0.085) | (0.085) | (0.085) | (0.085) | (0.085) |
| Mobility | 0.001 | -0.000 | -0.008 | -0.008 | -0.008 | -0.007 | -0.007 | 0.010 | 0.013 | -0.005 | -0.005 | -0.006 | -0.005 | -0.005 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.035) | (0.035) | (0.034) | (0.034) | (0.034) | (0.034) | (0.034) |
| Network size dummy | 0.012 | 0.012 | 0.018 | 0.018 | 0.017 | 0.011 | 0.009 | 0.033 | 0.031 | 0.063 | 0.063 | 0.062 | 0.060 | 0.057 |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.053) | (0.053) | (0.053) | (0.053) | (0.054) | (0.054) | (0.054) |
| Medium firm dummy | 0.009 | 0.012 | 0.015 | 0.014 | 0.016 | 0.014 | 0.016 | 0.031 | 0.020 | 0.026 | 0.026 | 0.030 | 0.026 | 0.030 |
| | (0.023) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.059) | (0.061) | (0.061) | (0.061) | (0.061) | (0.061) | (0.061) |
| Small firm dummy | -0.106* | -0.101+ | -0.091+ | -0.092+ | -0.087 | -0.094+ | -0.090+ | -0.271* | -0.289* | -0.258* | -0.260* | -0.248* | -0.260* | -0.251* |
| | (0.051) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.121) | (0.125) | (0.125) | (0.125) | (0.125) | (0.125) | (0.126) |
| Gender diversity | | 0.147 | 0.201 | 0.301 | 0.585* | 0.257 | 0.727* | | -0.511 | -0.431 | -0.029 | 0.459 | -0.405 | 0.810 |
| | | (0.207) | (0.207) | (0.317) | (0.274) | (0.213) | (0.365) | | (0.514) | (0.514) | (0.858) | (0.692) | (0.529) | (0.966) |
| Tenure | | | -0.005*** | -0.005*** | -0.005*** | -0.005*** | -0.004*** | | | -0.013*** | -0.013*** | -0.013*** | -0.013*** | -0.013*** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Constraint | | | -0.025 | -0.025 | -0.025 | -0.030 | -0.031 | | | -0.171* | -0.171* | -0.170* | -0.173* | -0.174* |
| | | | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) | | | (0.068) | (0.068) | (0.068) | (0.068) | (0.068) |
| Male | | | 0.048** | 0.049*** | 0.049*** | 0.048** | 0.049*** | | | 0.063 | 0.068 | 0.065 | 0.063 | 0.068 |
| | | | (0.015) | (0.015) | (0.015) | (0.015) | (0.014) | | | (0.041) | (0.042) | (0.041) | (0.041) | (0.042) |
| Gender diversity x Male | | | | -0.109 | | | -0.055 | | | | -0.437 | | | -0.329 |
| | | | | (0.264) | | | (0.264) | | | | (0.749) | | | (0.754) |
| Gender diversity x Tenure | | | | | -0.032* | | -0.035* | | | | | -0.074* | | -0.075* |
| | | | | | (0.015) | | (0.015) | | | | | (0.038) | | (0.038) |
| Gender diversity x Constraint | | | | | | -0.598+ | -0.669+ | | | | | | -0.273 | -0.424 |
| | | | | | | (0.347) | (0.347) | | | | | | (0.853) | (0.855) |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Constant | -0.012 | -0.003 | -0.002 | -0.003 | 0.006 | -0.010 | -0.004 | -0.061 | -0.093 | 0.045 | 0.040 | 0.064 | 0.041 | 0.054 |
| | (0.049) | (0.050) | (0.056) | (0.056) | (0.056) | (0.056) | (0.056) | (0.117) | (0.121) | (0.135) | (0.135) | (0.135) | (0.135) | (0.136) |
| Observations | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 |
| Number of scientists | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 |

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 3-A9.** Random-Effects Negative Binomial Regression Predicting Innovative Performance - Subsample-

| | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** | **(model 6)** | **(model 7)** | **(model 8)** | **(model 9)** | **(model 10)** | **(model 11)** | **(model 12)** | **(model 13)** | **(model 14)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dependent Variables** | Productivity | | | | | | | Citations weighted productivity | | | | | | |
| Firm dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Technological diversity | 0.218*** | 0.221*** | 0.169** | 0.169** | 0.168** | 0.167** | 0.165** | 0.247*** | 0.247*** | 0.192*** | 0.192*** | 0.190*** | 0.189*** | 0.186*** |
| | (0.057) | (0.057) | (0.058) | (0.058) | (0.058) | (0.058) | (0.058) | (0.052) | (0.052) | (0.052) | (0.052) | (0.052) | (0.052) | (0.052) |
| Past productivity (ln) | 0.482*** | 0.478*** | 0.403*** | 0.403*** | 0.400*** | 0.401*** | 0.397*** | 0.594*** | 0.595*** | 0.510*** | 0.509*** | 0.507*** | 0.508*** | 0.505*** |
| | (0.028) | (0.028) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.025) | (0.025) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| Network size | 0.005* | 0.005* | 0.005* | 0.005* | 0.005** | 0.004* | 0.004* | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Team size | -0.000 | -0.000 | -0.016** | -0.016** | -0.016** | -0.017** | -0.018** | 0.010* | 0.010* | -0.007 | -0.008 | -0.008 | -0.008 | -0.009 |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| External ties | -0.218** | -0.216** | -0.231** | -0.230** | -0.231** | -0.231** | -0.231** | -0.145* | -0.145* | -0.171* | -0.170* | -0.171* | -0.172* | -0.172* |
| | (0.075) | (0.075) | (0.075) | (0.075) | (0.075) | (0.075) | (0.075) | (0.071) | (0.071) | (0.071) | (0.071) | (0.071) | (0.071) | (0.070) |
| Mobility | 0.013 | 0.007 | -0.012 | -0.012 | -0.014 | -0.010 | -0.012 | 0.008 | 0.009 | -0.012 | -0.012 | -0.013 | -0.010 | -0.011 |
| | (0.035) | (0.035) | (0.035) | (0.035) | (0.035) | (0.035) | (0.035) | (0.029) | (0.029) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| Network size dummy | -0.044 | -0.042 | 0.055 | 0.055 | 0.055 | 0.026 | 0.022 | -0.033 | -0.033 | 0.076 | 0.075 | 0.075 | 0.044 | 0.038 |
| | (0.078) | (0.078) | (0.080) | (0.080) | (0.080) | (0.081) | (0.082) | (0.074) | (0.074) | (0.076) | (0.076) | (0.076) | (0.077) | (0.077) |
| Medium firm dummy | 0.038 | 0.057 | 0.063 | 0.063 | 0.063 | 0.063 | 0.064 | 0.027 | 0.024 | 0.035 | 0.035 | 0.036 | 0.036 | 0.036 |
| | (0.066) | (0.067) | (0.067) | (0.067) | (0.067) | (0.067) | (0.067) | (0.063) | (0.064) | (0.064) | (0.064) | (0.064) | (0.064) | (0.064) |
| Small firm dummy | -0.331+ | -0.305+ | -0.280 | -0.280 | -0.274 | -0.295+ | -0.289+ | -0.363* | -0.366* | -0.331* | -0.332* | -0.322+ | -0.346* | -0.338* |
| | (0.174) | (0.175) | (0.175) | (0.175) | (0.175) | (0.175) | (0.175) | (0.165) | (0.166) | (0.166) | (0.166) | (0.166) | (0.166) | (0.166) |
| Gender diversity | | 0.971+ | 0.934 | 1.033 | 1.816* | 0.935 | 2.002+ | | -0.131 | -0.185 | 0.419 | 0.624 | -0.203 | 1.254 |
| | | (0.572) | (0.573) | (1.065) | (0.775) | (0.573) | (1.168) | | (0.544) | (0.544) | (0.980) | (0.720) | (0.544) | (1.066) |
| Tenure | | | -0.012*** | -0.012*** | -0.011*** | -0.012*** | -0.011*** | | | -0.015*** | -0.015*** | -0.014*** | -0.014*** | -0.014*** |
| | | | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Constraint | | | -0.436*** | -0.436*** | -0.434*** | -0.458*** | -0.460*** | | | -0.483*** | -0.483*** | -0.482*** | -0.509*** | -0.512*** |
| | | | (0.071) | (0.071) | (0.071) | (0.072) | (0.072) | | | (0.067) | (0.067) | (0.067) | (0.068) | (0.068) |
| Male | | | 0.123** | 0.124* | 0.125** | 0.122* | 0.125* | | | 0.093* | 0.104** | 0.095* | 0.092* | 0.103* |
| | | | (0.048) | (0.050) | (0.048) | (0.048) | (0.050) | | | (0.038) | (0.040) | (0.038) | (0.038) | (0.040) |
| Gender diversity x Male | | | | -0.107 | | | -0.020 | | | | -0.648 | | | -0.560 |
| | | | | (0.964) | | | (0.964) | | | | (0.873) | | | (0.872) |
| Gender diversity x Tenure | | | | | -0.073+ | | -0.087* | | | | | -0.069+ | | -0.080* |
| | | | | | (0.043) | | (0.043) | | | | | (0.040) | | (0.040) |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Gender diversity x Constraint | | | | | | -2.052* | -2.326* | | | | | | -2.214* | -2.444** |
| | | | | | | (0.974) | (0.986) | | | | | | (0.917) | (0.925) |
| Constant | -1.192*** | -1.125*** | -0.957*** | -0.958*** | -0.937*** | -0.998*** | -0.980*** | -1.247*** | -1.256*** | -1.005*** | -1.015*** | -0.990*** | -1.052*** | -1.047*** |
| | (0.159) | (0.164) | (0.175) | (0.176) | (0.176) | (0.176) | (0.177) | (0.152) | (0.157) | (0.164) | (0.164) | (0.164) | (0.165) | (0.166) |
| Observations | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 | 17,276 |
| Number of scientists | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 | 1,326 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

# 4. HOW GENDER-EQUITY ATTITUDES AFFECT GENDER PERFORMANCE GAPS


## Abstract

Does the level of gender bias in a broader society affect differences in performance between men and women within organizations in that society? Prior work has found a positive relationship between the level of gender bias and the size of performance gaps by gender in firms. Yet that work has been unable to control for prior selection by men and women into different types of organizations. Thus, prior work has been unable to determine whether the observed gender-performance gaps are a treatment or a selection effect. This paper analyzes the relationship between gender bias within a society and gender-performance gaps by combining data on attitudes and behavior in contemporary US society with information on the background and training of academic scientists at top-ranked universities around the United States. Because this setting includes data on men and women's training and quality before they start work, I can control for the possibility of labor-market sorting by men and women (and thus selection effects) in a way that prior work could not. Like previous work, I find that in regions with a stronger bias against gender equality, gender performance gaps are larger. This effect largely disappears, though, when I control for selection. These findings suggest that gender bias within a society mostly affects performance gaps by influencing where workers of different quality choose to work. Therefore, distinguishing between selection and treatment effects is important for understanding gender gaps.



**Keywords:** Performance gap, Gender, Academic Scientists, Societal Attitudes, Regions

## 4.1. INTRODUCTION

There are significant disparities in men's and women's career attainment, despite decades of fitful progress (Brass, 1985; Fernandez-Mateo, 2009; Fernandez & Sosa, 2005; Forret & Dougherty, 2004; Ibarra, 1992, 1997). Researchers often attribute gaps in the genders' wages, promotions, and managerial representation to gaps in their productivity. But those productivity gaps themselves are harder to explain. Part of the difference in productivity has in turn been attributed to lifestyle choices, areas of specialization, and firms' characteristics (Fox, 1983; Haberfeld & Shenhav, 1990; Keith, Layne, Babchuk, & Johnson, 2002; Ward & Grant, 1996; Xie & Shauman, 1998), but such factors only explain a small part of the observed gaps (Cole & Zuckerman, 1984; Fox, 2001; Reskin & Ross, 1992; Shenhav & Haberfeld, 1992).

More recently, broader social attitudes have been suggested as an explanation for some of the variation in gender-performance gaps within organizations. For example, managers in societies with higher baseline levels of bias against women in the workplace may feel more licensed to discriminate against their female employees, to favor male workers with opportunities they would not provide female workers, and so on. Because gender differences in productivity have not disappeared and because there is considerable variation both between and within societies in the level of bias toward women workers, the effects of broader social attitudes on gender-performance gaps within organizations could be quite important. Indeed, previous studies have concluded that organizations in regions where the population is less disposed toward gender equality have a greater internal disparity in men's and women's output (Charles & Guryan, 2008; Charles et al., 2009; Fortin, 2005; Janssen et al., 2016).

I do not dispute the potential importance of broader discriminatory attitudes for women's performance at work. However, it is not clear how such attitudes translate into performance gaps.

Past work has implicitly assumed a sort of "treatment effect," where the actions of decision-makers in less gender-equal regions somehow lower the productivity of their female workers (or raise male workers'). While this is possible, it could also be that broad social attitudes influence where men and women choose to work in the first place. If, for example, higher-ability women chose to avoid jobs in more biased areas, then we would still see a correlation between attitudes and performance gaps, but this would be a "selection effect." In this case, broader social attitudes widen the gender-performance gap not by making women workers less productive on the job but by influencing, which jobs women of different productivity are willing to take.

This distinction between treatment and selection effects is essential to understand, not least because it matters for how we might try to reduce such performance gaps. If everything is treatment, for example, we should closely focus on decision-makers' actions, because it is at the workplace itself that women's performance is affected. If everything is selection, on the other hand, then the processes of hiring and recruiting are more important than what happens post-hire. In practice, both selection and treatment effects likely exist, but the emphasis we should place on different types of interventions depends on how large these different effects are.

Recent work that has explored this issue relies on multi-site firms where the firms' sites are in different parts of a country that differ in their attitudes toward women in the workplace. For example, Janssen, Sartore, & Backes-Gellner (2016) analyze firms all located in Switzerland, which ensures that they operate under the same national standards and regulations, but with establishments in different cantons that have distinct gender-bias attitudes. This research design resolves several inferential issues that bedeviled earlier research, such as non-overlapping support between firms and regions. However, even these studies do not control for the possibility that regional variance toward gender equality influences how individuals self-select into different

regions. Thus, it remains unclear, for example, whether gender bias attitudes make high-productivity women less productive, or drive high-productivity women away. This, in turn, makes it hard to theorize how greater gender bias within a society translates into gender gaps in less proximate outcomes like wages, promotions, and representation.

To control for selection, we need to know something about men's and women's ability or potential productivity before they sort into workplaces. In this paper, I examine the graduates of and faculty in science, technology, engineering, and mathematics (STEM) departments in top-ranked public universities across the United States. Like previous work (Charles, Guryan, & Pan, 2009; Janssen et al., 2016), I use one country for my analysis because social attitudes vary between regions, but national regulations and technological standards do not. Prior research has used STEM fields to analyze gender differences in individual outcomes (Aksnes, Rorstad, Piro, & Sivertsen, 2011; Ding, Murray, & Stuart, 2006; Fox, 2001; Haberfeld & Shenhav, 1990; Handelsman et al., 2005; Hunt, 2016; Sonnert & Holton, 1996). Most importantly, because information on academics' background and training is publicly available, we can control for men's and women's quality before they start their jobs, and thus control for selection. To do so, I use a matched-pair analysis that pairs female scientists with observationally similar male ones. I create pairs of dyads of female and male scientists that graduated from similarly top-ranked universities and took jobs in similarly ranked universities, where the destination universities are in regions that differ in their broader social attitudes toward gender equality. This design enables a difference-in-difference analysis on the dyads, varying only the broader attitudes in the areas where scientists work.

If I pool the observations in my data, I find a strong relationship between social attitudes towards gender equality and gender-performance gaps between regions. This replicates the

findings from prior research (Janssen et al., 2016). However, once I use the matched-pair analysis to account for differences in selection, I find that the effect of social attitudes against gender equality on gender-performance gaps is only marginally significant. This indicates that most of the variation in the gaps across regions can be explained by selection rather than by treatment effects.

This study provides new insights into how social attitudes influence gender gaps inside organizations. While prior studies have assumed treatment effects (Charles & Guryan, 2008; Charles et al., 2009a; Janssen et al., 2016), I show that such attitudes also influence where women decide to work. As mentioned, this has implications for the type of policy interventions we might choose. Human resources practices like diversity training, and inclusion programs as well as mentorship and sponsorship, may improve the productivity of women if treatment is the issue. Still, they may have little effect if selection is the matter. Another implication is that organizations in more biased regions forego opportunities to hire highly qualified women. Such organizations may be less attractive to women in general and, therefore, less gender diverse. As diversity in the workplace provides functional and intellectual diversity (Antonio et al., 2004; Loyd, Wang, Phillips, & Lount, 2013; Phillips, Northcraft, & Neale, 2006), organizations that forego women hires forego the benefits that diversity brings, which may hurt their performance.

In short, the goal of this study is not to downplay the importance of regional gender bias on the difference between men and women's performance at work. It is to emphasize that importance can take many forms. Most research on career inequality focuses on what happens to people inside organizations; the sorting of people between organizations is too often overlooked (Bidwell & Mollick, 2015; Ferguson & Koning, 2018). This study's focus on selection

emphasizes an additional source of trouble, but it also suggests other channels for reducing inequality over time.

## 4.2. THEORETICAL DEVELOPMENT

The institutional theory recognizes organizations as open systems with interdependent ties to their external environment, from which they obtain resources and legitimacy to conform to societal expectations (DiMaggio & Powell, 1983; Lawrence & Lorsch, 1967; Meyer & Rowan, 1977; Salancik, 1979; Thompson, 1967). Scholars in this tradition have emphasized that the external environment provides organizations with values, beliefs, and expectations that allow them to assess organizational fitness (DiMaggio & Powell, 1983; Suchman, 1995). From this perspective, organizational behavior can be seen as a reaction to the demands that surround the institutional environment (Stainback, Robinson, & Tomaskovic-Devey, 2005). An organization's institutional environment is comprised of institutions that create influence through norms, regulations, and culture. For example, the prevailing social attitudes of the regions in which organizations are embedded can influence organizational behavior (Scott, 2015) because they confer organizations with the legitimacy to perform specific practices (Ashforth & Gibbs, 1990; Meyer & Rowan, 1977). By implication, the predominant social values of a region are likely to permeate the organizational culture and practices of firms operating therein. This, in turn, suggests that societal attitudes toward gender equality may affect the internal dynamics of organizations by influencing the levels of tolerance towards gender bias by decision-makers, managers, colleagues, customers, and employees (Charles & Guryan, 2008; Charles et al., 2009; Janssen et al., 2016).

**Hypotheses**

Prior work has explained the relationship between societal attitudes and gender-performance gaps (Charles & Guryan, 2008; Fortin, 2005). This work suggests that in regions where intrinsic societal gender bias is normalized, women's progress tends to be pushed back (Charles et al., 2009; Janssen et al., 2016). For instance, in regions with higher societal gender bias, female employees can be subjected to higher standards (Foschi, 2000), receive unfair treatment from colleagues (Evans, Hendron, & Oldroyd, 2015; J. Singh et al., 2010), and can see their contributions dismissed (Bihagen & Ohls, 2006; Merluzzi & Dobrev, 2015). In the scientific field, for instance, prior work shows that societal factors are associated with women's disadvantages in the workplace (Leahey, Crockett, & Hunter, 2008; D. Moore & Toren, 1998). For example, stereotypical gender roles in society can shape the perception and judgments of women's abilities and commitment at work. That is, in social contexts where men are expected to be the breadwinner, and women to be the child holder, women's chances of being hired and promoted are lower than men's (Eagly, 1987; Wotschack, 2009). These stereotypical roles of women and men in society can be strengthened in more gender bias regions and, therefore, firms located in such places may exercise a differential treatment of women and men, favoring most of the time men over women.

Prior research suggests two main reasons why social attitudes towards gender equality can affect gender-performance gaps. The first that the gender bias of a region can shape *decision-makers'* behavior by influencing, for example, their likelihood of hiring women (Akerlof & Kranton, 2000; Ridgeway, 1997). Gender biased decision-makers can give different opportunities for men and women, even if both hold similar qualifications (Blau & Kahn, 2007; Elliott & Smith, 2004; Hawkins & Noordenbos, 1991; Lawler, 1999). For instance, in STEM,

prior research shows that because of gender bias, women face higher standards than men when applying for academic jobs (Baron & Kenny, 1986; Moss-Racusin et al., 2012; Sheltzer & Smith, 2014), submit research papers (Petty, Fleming, & Fabrigar, 1999) or requesting for research grants (Bornmann, Mutz, & Daniel, 2007; Oliveira, Ma, Woodruff, & Uzzi, 2019). Similarly, biased decision-makers can also take direct actions to decrease women's potential productivity, such as withholding relevant information about research funds and projects (Reskin, 1978), excluding them from collaborations with relevant colleagues (Daday & Burris, 2002; Kanter, 1977a; Ollilainen & Rothschild, 2001; Sheltzer & Smith, 2014), or giving to them negative evaluations despite their objectively good performance (Baron & Kenny, 1986; Berger, 1977; Elvira & Town, 2001; Williams & O'Reilly III., 1998). Furthermore, decision-makers can also involve women in bureaucratic activities that reduce their time for research (Cardador, 2017), or decide to invest less in women's human capital than in men's (Bender, Donohue, & Heywood, 2005; Blau & Kahn, 2006; Buser, Niederle, & Oosterbeek, 2014; Konrad, Ritchie, Lieb, & Corrigall, 2000).

The second reason asserts that regional gender bias can also shape *colleagues'* behaviors, making them more or less prompt to favor men over women (Ridgeway & Correll, 2004; Stainback et al., 2011). Biased colleagues can provide negative peer evaluations or even prefer to work with male colleagues instead of female ones (Bettencourt, Charlton, Dorr, & Hume, 2001; Chattopadhyay, Tluchowska, & George, 2004; Derks, Van Laar, Ellemers, & De Groot, 2011; Duguid, Loyd, & Tolbert, 2012; Eagly et al., 1992; Eagly & Karau, 1991). In this vein, Joshi (2014) found that male scientists get more opportunities than female scientists to collaborate in ongoing research projects. Similarly, Merluzzi and Dobrev (2015) showed that compared to men, women need to invest more time and effort in maintaining relationships with other colleagues

once relationships are formed. Furthermore, colleagues to a great extent can give men preferential access to scientific goods like resources, mentoring, public visibility, which may lead to significant differences in men's and women's productivity (Eagly, Makhijani, & Klonsky, 1992).

Given these arguments, because in regions with higher gender bias, decision-makers and colleagues tend to hold higher gender bias than in regions with a more equalitarian approach toward women, women working in gender bias regions may receive fewer opportunities and support than men from decision-makers and colleagues at work. As a result, women working in gender bias regions may have lower performance than men - i.e., have a treatment effect. Therefore, regions with a stronger social bias against gender equality may experience larger gender performance gaps. Consequently, I predict:

*Hypothesis 1: Regions with a high tolerance toward gender inequality generate larger gender performance gaps within organizations.*

Although the arguments above posit that gender bias in a region shapes the behavior of decision-makers and colleagues, it is also possible that it influences how women self-select into workplaces. This selection mechanism assumes that women may prefer workplaces, where gender biases are less salient (Jolls, 2001; Schultz, 1990). That is, women who have the option to choose between alternative workplaces will tend to select themselves into regions where societal attitudes are less biased toward women. In such workplaces, women may feel more comfortable because they are treated equally by decision-makers and colleagues (Joshi, Neely, Emrich, Griffiths, & George, 2015). Similarly, in organizations located in less biased regions, men and women can have equal access to information, advice, projects, and collaborations. Importantly, the option to choose between alternative regions is more likely to be available for highly

qualified women. Therefore, this selection mechanism suggests that more gender-equal regions perform better than regions that are more biased towards gender because highly skilled women self-select into the former and eschew the latter. Conversely, less talented women may end up working in less gender-equalitarian regions. Even though these women may be equally interested in finding a job in a more gender-equalitarian region, they may also be less likely to do so, since competition for jobs among more-talented women in these regions is more intense.

By arguing that exposure to more biased decision-makers and colleagues does not directly affect their performance, having less-talented women on average in more biased regions may produce larger gender-performance gaps in observational data. That is, if individual talent affects productivity in some unobservable way, and if higher-quality female employees tend to self-select into less biased regions more often, then the observed gender-performance gap might be explained by a selection mechanism. I, therefore, predict that, after accounting for differences in selection, the gender-performance gaps theorized in Hypothesis 1 will be smaller.

*Hypothesis 2: Accounting for selection will mediate the effect in H1.*

## 4.3. METHODOLOGY

### 4.3.1. Setting and data

I analyze a dataset of academic scientists trained and employed at top-ranked public universities in the United States. I select one country because doing so controls for other country-specific factors, such as national regulations and technological standards. Fortunately, the United States has great variance in culture and traditions, which makes it easier to study attitudinal variations. Within universities, I focus on academic scientists in science, technology, engineering, and mathematics (STEM). I chose this area because there is persistent evidence that gender matters in STEM fields. STEM scientists have backgrounds in sciences and engineering, which are

traditionally male-dominated fields (Eccles, 2007). These gender differences are still reflected in the fields' demographics. Besides, prior research has used STEM fields to analyze gender differences in individual outcomes (Aksnes et al., 2011; Ding et al., 2006; Fox, 2001; Haberfeld & Shenhav, 1990; Handelsman et al., 2005; Hunt, 2016; Sonnert & Holton, 1996), which provides a good starting point to analyze the relationship between societal attitudes and gender differences in productivity. Furthermore, unlike industry settings, academics' backgrounds and training are observable to the researcher. This is important because we cannot control for selection without information on prior quality. By accounting for employees' background and training, I can construct a matched sample, pairing each female scientist with an observationally equivalent male scientist. To do this, I create pairs of dyads who came from similarly top-ranked universities and ended up in similarly top-ranked working places. As an ideal case, imagine four scientists, two males, and two females, all of whom graduated from the same department in the same year. One man and one woman take jobs at a top-ranked university in a US region with little bias against gender equality in the workplace. The other male/female pair take jobs at an equally ranked university in a region with a considerable bias against gender equality. This design allows me to do a difference-in-differences analysis on the dyads, varying only societal attitudes in the area where the scientists work. This helps me to understand whether selection affects the observed gender-productivity gaps across regions.[9]

To select scholars for my analysis, I began with the population of STEM departments[10] that belong to public universities that are top-ranked in R&D expenditures and the number of earned

[9] This research design keeps constant scientists' quality, which ensures the orthogonality of the treatment by keeping it uncorrelated with scientists' assignment to a particular region.

[10] Table 4-1 presents the academic research areas of these departments. These areas represent the most popular scientific disciplines related to STEM fields (Ding et al., 2006). I focus on public universities because data on their R&D expenditure is publicly available.

doctorates (National Science Foundation, 2014, 2015). By selecting top-ranked universities, I control for some resource-based influences on productivity, including economic factors such as research funding and travel expenses and also expectations about the time one should devote to research relative to teaching (Fox, 1992). Also, having similarly ranked universities ensures that the quality and quantity of research is consistent across regions (Xie & Shauman, 1998). Focusing on comparable organizations helps isolate the effect of different societal attitudes on individuals' productivity. In forming the sample, I selected every faculty member in these departments who received their PhD between 1972 and 2010 from a US university. Next, I obtained from the ISI's *Web of Science dataset* scientists' publication records and coauthors. Productivity, measured in terms of publication quantity, has been used by prior research on gender gaps (e.g., Allison & Long, 1990; Fox & Faver, 1985; Fox, 1992; Leahey, 2006; Leahey, 2016; Xie & Shauman, 1998). The number of publications is highly associated with productivity and is perhaps the primary criterion for academic success. Also, in academic research, co-authors represent access to expertise, cross-fertilization across disciplines, and knowledge sharing, which enhance individuals' productivity (Bozeman & Corley, 2004; Van Rijnsoever & Hessels, 2011).

To get variance in societal attitudes towards gender equality, I focused on top-ranked public universities located in different regions of the United States. The United States has great variation in culture and traditions, which makes it a useful setting to understand different societal attitudes' impact on organizational behavior and, therefore, on individuals' productivity. Prior research has measured variation in social attitudes against gender equality in similar contexts, such as Switzerland. I draw on the example of Janssen *et al.* (2016), who use two sources to measure societal attitudes toward gender equality. First, they used the 1981 amendment to the Swiss constitution on equal rights for men and women (Lalive & Stutzer, 2009). Second, they

used the 2001 amendment to the Swiss law, which required a fair representation of women in the confederal administration. In both cases, they used cantonal votes for the amendments. I used data from the General Social Survey (GSS), which provides information on trends, attitudes, and behaviors of contemporary American society. The GSS offers data from 1972. The survey contains gender attitudinal questions divided by region, which lets me measure different levels of social approval of equal rights for women and men across regions. In summary, I chose this setting to observe differences in productivity between men and women in different universities that act under the same country-level regulations and standards, but that under their location are exposed to different social attitudes towards gender equality.

### 4.3.2. Measures

#### 4.3.2.1. Dependent variable

*Research output.* From the *Web of Science*, I computed an annual paper publication count for each scientist. This is the most common measure used in academic productivity literature (Allison & Long, 1990; Leahey, Crockett, & Hunter, 2008; Xie & Shauman, 1998). Alternative measures for research output also account for journal prestige and co-authorship status, but they correlate highly with the raw count of journal articles (Cole & Zuckerman, 1984). I only included peer-reviewed journal articles because, among research universities, prior studies have found a high correlation between publications and total productivity (Leahey, 2007; Reskin, 1978).

#### 4.3.2.2. Explanatory variables

*Female*. Scientists' genders are imputed from their names, using demographic data from the U.S. Social Security Administration (SSA).

*Social bias toward gender equality.* I computed societal attitudes towards gender equality by using GSS data across different regions. There are four main questions rotated through years that are related to women's role in society. Some of them focus on women's work and family roles in society *(work/fam)*. For example, a respondent can agree or disagree with statements like *"mother working doesn't hurt children"; "better for men work, women tend home"* or *"preschool kids suffer if mother works."* Other questions ask about women's participation in American political life *(fepres)*. For example, respondents might be asked whether they would *"vote for women for president."*

I used data from the 1972, 1982, 1990, 1998, 2010, and 2015 waves. I linearly interpolated observations between data points. I decided to interpolate because the survey is not conducted annually, and gender-related questions are not asked in every wave. The best coverage is for the *fepres* questions. I followed responses to these questions for a decade to observe whether there are significant differences between the historical and interpolated trends, and found none. In the case of the *work/fam* group, the first survey that asked about women's work and family roles in society was done in 1977. Thus, I extrapolated missing observations from 1972 to 1976. To check whether extrapolation affects the pattern of results, I run additional analyses removing the extrapolated years from the sample. Doing so does not affect the pattern of results.

I used Cronbach's alpha on responses to these questions to evaluate their internal consistency. The resulting α coefficient provides an overall valuation of the measure's reliability (i.e., the higher α coefficient indicates that items probably measure the same underlying concept). The α coefficient on responses to these questions was 0.7. To facilitate comparisons of the degree of women's work and family constraints across individuals and regions, I combined the GSS

responses into a unidimensional work and family index. Confirmatory factor analysis showed that the first factor explained 80% of the variance across responses.

#### 4.3.2.3. Control variables

To control for life-cycle effects (Levin & Stephan, 1991), I included the number of years since a scientist earned his/her PhD (*Experience*). I measured the quality of a scientist's PhD degree-granting institution as the institution's position on "R&D expenditures" (*University graduate school R&D ranking*) and "number of earned doctorates" *(University graduate school earned doctorates ranking)* rankings from the National Science Foundation. There are several reasons to believe that the quality of a scientist's granting institution influences their performance (Allison & Long, 1990; Cole, 1979; Fox & Faver, 1985; Fox, 1983; Reskin, 1978). For example, individuals who graduated from better-ranked institutions can access more resources and higher-quality co-authors. I assigned universities their original rankings in 1970 and updated them every other year. Because by having more co-authors scientists are more likely to publish (Allison & Long, 1990; Cole & Zuckerman, 1984), I control for the total number of co-authors a scientist has in a given year (*Coauthors*). Finally, because scientists postdoctoral periods can also affect their productivity, I added the number of years that a scientist spent as a postdoc (*Postdoctoral years*).

### 4.3.3. Modeling strategy

I run all the analyses for this study twice. First, I tested the effect of discriminatory social attitudes on performance gaps between men and women across my full dataset. I started with a sample of every faculty member from STEM departments that belong to top-ranked public

universities across regions. I excluded all scientists that graduated before 1972 and after 2010.[11] The final sample comprises 1250 scientists, 417 women, and 833 men. This complete sample allows me to test possible treatment effects (hypothesis 1).

Second, I constructed a matched-pair sample as described above, using an approach similar to coarsened exact matching (Blackwell, Iacus, King, & Porro, 2009). For all potential matches, I selected the best match between a male and female scientist using the control variables from the complete sample as matching criteria, *i.e., year in which a scientist earned his/her Ph.D., years that a scientist spend in a Postdoctoral position, quality of scientists' Ph.D. degree-granting institution, and quality of scientists' first job institution*. The final matched-pair sample includes 316 observations: 176 men and 138 women.[12] This matched sample allows me to test female and male scientists that are similar to critical dimensions that matter for selection.

This empirical strategy is pertinent because it is not otherwise possible to rule out unobserved heterogeneity between female and male scientists. I cannot, for example, include scientists' fixed effects because one of my key variables, gender, does not vary over time. The matched-pair sample lets me rule out most issues related to unobserved individual heterogeneity, such as self-selection based on ability (hypothesis 2). Moreover, by selecting a sample of scientists with identical educations, from similarly ranked institutions and who get their first faculty positions in similarly ranked institutions, I not only minimize variance in human capital but also account for the prior finding that being appointed in a prestigious institution enhances productivity (Allison & Long, 1990). Table 4-2 shows the mean differences between female and male scientists in the matched-pair sample. There are no significant differences in the matching criteria used. I did not

[11] Before 1972 few women graduated from STEM fields. By restricting the graduation year to 2010, I assure that those scientists who have a faculty position had a chance to produce at least one publication.

[12] There are more men than women because I need as many women as possible for statistical power. Thus, men are repeated in 12% of the dyads.

match the number of coauthors because this continues to vary over time after scientists are placed in their jobs. Instead, I control for it in the match-pair analyses.

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Insert Table 2 about here
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### 4.3.4. Estimation method

I used negative-binomial regressions to test my hypotheses because the dependent variable is a count variable, and it is unconditional mean is lower than its unconditional variance, which suggests that the dependent variable is over-dispersed (mean = 4.40; S.D. = 7.71). The likelihood-ratio test indicates that a negative-binomial model fits significantly better than a Poisson model ($\chi^2 = 5.4e + 04, Pr > \chi^2 = 0.000$). I standardized the social bias toward gender equality variables before I include them in the models. All non-binary variables are mean-centered to reduce multicollinearity (Dalal & Zickar, 2012). Finally, to control for unobserved time-specific heterogeneity, I included year dummies in the models.

## 4.4. RESULTS

I began with descriptive statistics. Between 1972 and 2010, the productivity of both female and male scientists increased. In the complete sample (Figure 4-1), male scientist productivity is higher than female scientist productivity, which is consistent with prior research (Bernard, 1964; Fulton, 1973). Figure 4-2 shows the results from the matched-pair sample; here, we observe smaller differences between women's and men's productivity. This makes sense because the matched-pair sample has more similar individuals. Table 4-3 presents descriptive statistics for both the complete and the matched-pair samples, and Table 4-4 shows pairwise correlations among the variables. Whereas 30 percent of the sample is female in the complete sample, in the matched-pair sample, 44 percent are women. While the average *Experience* of a scientist is 14 years in the complete sample, in the matched-pair sample his/her average *Experience* is 12 years.

While in the complete sample, the average number of *Coauthors* a scientist has is 13, in the matched-pair sample, the average number of *Coauthors* equals nine. In both samples, scientists spend, on average, four years in postdoctoral positions.

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Insert Figure 4-1 and 4-2,
and Table 4-3 and 4-4
about here
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Table 4-5 reports the results of the negative binomial regression models that predict Research output in the complete sample. I estimated the effect of my control variables in Model 1. In line with the view that scientists with larger networks tend to publish more, the effect of scientists' Coauthors on Research output is positive and strongly significant (p<.001). As expected, the effect of scientists' *Experience* on his/her number of future publications is positive and strongly significant (p<.001), which suggests that scientists' publications increases as a function of his/her career length. Corroborating the view that scientists with larger postdoctoral periods tend to publish less, the effect of *Postdoctoral years* on *Research output* is negative and significant (p<.001). The effect of *University graduate school R&D ranking* on *Research output* is negative and strongly significant (p<.001), suggesting that the quality of the university from which a scientist graduated affects s/he future productivity.

Turning now to my key explanatory variables, in Model 2, I introduced *Female*. *Female* is negative and strongly significant ($\beta$=-0.120; p<.001), suggesting that female scientists are less productive than male scientists. In Model 3, I included *Social bias toward gender equality.*[13] The effect of *Social bias toward gender equality* is positive but non-significant. In Model 4, I

[13] The variables used to measure discriminatory social attitudes (i.e., *fepres* and *work-fam*) look at the same effect and I found the same patterns of results from both. However, I decide to report results from the *fepres* variable because it has greater coverage through years. In the Appendix A, I report results from the *work-fam* variable.

examined whether female scientists are more productive in regions with more equalitarian attitudes toward gender by introducing the interaction term between *Female* and *Social bias toward gender equality*. The multiplicative term between *Female* and *Social bias toward gender equality* is positive and strongly significant ($\beta$=0.076; p<.001). This suggests that, even though female scientists are overall less productive (Model 3), they are more productive in organizations located in regions with greater support to gender equality, supporting H1. Because the effect of the interaction may also partly reflect nonlinearity in terms of the variation in social attitudes toward gender equality and female scientists' productivity, in Model 5 I included the interaction between *Female* and *Social bias toward gender equality* as well as the squared term of the interaction. The coefficient of the interaction indicates that, independently of nonlinearity, the moderating effect exists (Ganzach, 1997).

**Figure 4-3** presents the significant findings and shows the marginal effects of the multiplicative term between Female and Social bias toward gender equality. This figure indicates that a female scientist is more productive when she works in an organization located in a region with greater support for gender equality. While female scientists are 54% less productive than male scientists in regions with higher gender bias, in regions where gender bias is less salient, female scientists tend to be 1.6% more productive than male scientists. This finding suggests that gender productivity gaps are larger in regions with more salient gender bias. Conversely, in more gender equalitarian regions, productivity differences between female and male scientists are only marginally significant.

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Insert Table 4-5 and Figure 4-3
about here

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**Accounting for Selection**

Table 4-6 reproduces the models from Table 4-5. As in Table 4-5, I began by estimating a baseline model, including only control variables (Model 1). Because all controls included in Model 1 were used as matching criteria in my matched-pair sample analysis - except by the number of coauthors -, there are no significant differences among these control variables. Related to scientists' number of coauthors, consistent with the view that scientists with a larger number of collaborators tend to be more productive, the effect of Coauthors on Research output is positive and strongly significant ($p<.001$).

Turning to my covariates of interest, I introduced Female in Model 2, *Social bias toward gender equality* in Model 3, and their interaction term in Model 4. H2 predicts that once I account for selection, the effect of societal attitudes on gender performance gaps is weakened. In line with this hypothesis, the effect of the interaction between *Female* and *Social bias toward gender equality* is positive but marginally significant ($\beta$=0.053; $p<.1$). This suggests that unlike in the complete sample, there is no evidence here to say that female scientists are more productive when they work in an organization located in a region with higher support to gender equality.

Figure 4-4 displays the marginal effects of Female and Female interaction with Social bias toward gender equality on scientists' publications. This figure shows that there are no significant differences in the productivity of female scientists across regions, once we control for selection using the matched sample. Whereas female scientists are 32% less productive than male scientists in regions with higher gender bias, in regions with lower levels of gender bias, female scientists tend to be 0.82% more productive than male scientists. Comparing the results from the two analyses lets me conclude that there is very little empirical support for treatment effects here.

Despite the assumptions of prior studies, my results suggest that it is also necessary to account for selection to understand gender-productivity gaps.

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Insert Table 6 and Figure 4
about here
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**Robustness checks**

Whereas in STEM fields, the first authorship is assigned to the most junior author - who generally speaking is the one that leads the research -, the principal investigator gets the last authorship. For this reason, I use the order of authorship to compute the number of articles in which the scientist appears in the first or last position (Azoulay et al., 2009). Table 4-A7 andTable ***4-A8*** display the results for the complete and matched-pair sample, respectively. These results are qualitatively identical to my earlier findings. Since I reported estimates based on negative binomial models, I repeated my analysis using other model specifications: (i) Poisson regression with robust standard errors and (ii) Ordinary Least Squares regression, where the dependent variable (Research Output) is log-transformed. The results present in Table 4-A9 remain similar to those presented before.

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Insert Table 4-A7, 4-A8 and 4-A9
about here
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## 4.5. DISCUSSION

Prior research has used broader societal attitudes toward gender equality to explain gender gaps in contemporary organizations (Charles & Guryan, 2008; Charles et al., 2009; Janssen et al., 2016). This research found an association between societal attitudes toward gender equality and the differences between men's and women's career outcomes. For example, compared to more gender equalitarian regions, regions with stronger gender bias tend to have larger gender wage

gaps (Janssen et al., 2016). This paper reproduces findings from prior studies, in particular, the strong and robust relationship between social attitudes toward gender equality and gender gaps when selection is not accounted for. Prior research suggests that workplaces located in less gender equalitarian regions are more likely to tolerate decision-makers and colleagues who provide unfair treatment to women. This unfair treatment, in turn, contributes to the larger gender-performance gap found in the observable data. I do not disagree with this theoretical argument. My research design, however, suggests an alternative explanation for the pattern of results found. If social attitudes toward gender equality influence the location preferences of women, then variance on gender productivity gaps regarding social attitudes toward gender equality will appear smaller when we account for selection. This is indeed what I have found. These results suggest that the use of a research design suitable to account for selection effects can provide alternative explanations of how social attitudes toward gender equality influence gender gaps. Notably, when the effect of interest is driven by female scientists' preference for more gender equalitarian regions, our understanding about whether broader societal attitudes affect gender productivity gaps would be improved by accounting for selection effects.

#### 4.5.1. Limitations

I wish to highlight some limitations of this study. First, this study does not lend itself to a perfect comparison to prior research. While prior work has explored the effect of social attitudes toward gender equality on gender gaps in industrial contexts, I lay out my arguments in the context of science. Therefore, I highlight that a similar approach to the one proposed in this paper, but the industrial context – using industrial employees' backgrounds – could take us closer to the findings of prior work. This, in turn, allows us to layout more general conclusions about the effect of social attitudes toward gender equality on career outcomes. Second, I am also aware of

the fact that clustering individuals by their institutional affiliation do not rule out issues of individual heterogeneity. Indeed, to control for heterogeneity, it would be preferable to have additional information about individuals' quality and talents, such as grades, performance, community service, and involvement, among others. Nevertheless, the argument and results I present here provide a better understanding of how selection effects can affect gender gaps. Finally, another limitation of this study is the lack of detailed information on the actual behavior of decision-makers and colleagues. For example, from large-scale data, I am not able to observe whether the gender-performance gap is the result of the unfair treatment of scientists' decision-makers or colleagues. As a consequence, I am unable to distinguish between the different mechanisms that I theorize about fully. Future work using qualitative as well as experimental methods may be necessary to provide complete evidence of the causal mechanisms driving the treatment effects theorized here.

#### 4.5.2. Contributions

Prior work has emphasized the role of social biases toward gender equality in explaining women's career disadvantages within organizations. I add to this body of work by analyzing whether and how broader social attitudes may affect the gender-performance gap. Prior research argues that social biases increase the gender-performance gap in organizations through treatment, often by decision-makers or colleagues (Charles & Guryan, 2008; Charles et al., 2009a; Janssen et al., 2016). While I do not dispute the feasibility of such mechanisms, I argue that social biases can also affect performance by influencing the placement of different workforces in different types of organizations. Higher qualified women, for example, may exercise the option not to work in biased regions or organizations. Such selection can produce similar gaps. By approaching this data in the same way of earlier studies that do not control for selection, I can

reproduce prior findings of gender gaps that vary along with broad social attitudes. Once I control for selection, though, this difference disappears.

I should also emphasize why selection effects can be so important. In the full sample, I found that the gender-performance gap was larger in universities, in regions with a greater gender bias. An obvious implication of that finding, consistent with existing theory, would be those decision-makers or colleagues in those universities are more tolerant of biases than their colleagues in other regions. That is, however, a strong claim. Another possibility is that the people working in those particular universities are no better or worse than their colleagues elsewhere, but that their organization is instead situated in a broader environment where such attitudes *are* tolerated - and such an environment is undoubtedly one thing that potential colleagues keep in mind when they decide where to work. In this sense, organizations may lose their best when hiring time comes. These are profoundly different explanations, both for the pattern of results and the beliefs and motivations of the people in these organizations. Notice, for example, that the organizational reform I suggest looks very different under those two explanations. In my first explanation, I would want to address sexism, latent, or otherwise, among the organization's staff. In my second explanation, there may be no sexism to address. The truth probably lies somewhere in between, but the very possibility opened up by controlling for selection shows how the relationship between an organization and its broader social environment may be more complicated than prior work has theorized.

Finally, the approach I follow in this paper is useful to determine places where interventions need to be implemented. Evidence from prior research suggests that organizational human resource policies, such as diversity training, and inclusion programs as well as mentorship, sponsorship initiatives can reduce women's disadvantages inside organizations. Mentorship and

training, for example, improve a female employee's chances of career success when it comes to earnings, promotional opportunities, and social integration (Maume, 2011; Wallace, 2001). For example, by having a mentor, female protégés are exposed to advise and information that may help them adapt more smoothly to new work environments without going through the complicated process of exclusively experiential learning. Sponsors, in the meanwhile, may help female mentees gain visibility within the company. They go beyond providing feedback and advice, promoting their protégés, and supporting them throughout their career paths (Ibarra, 1997; Ragins, Townsend, & Mattis, 1998; Ridgeway & Smith-Lovin, 1999). Although these policies may improve women's career attainments, especially when they confront strong biases, my findings suggest that it may be essential to define when and where such policies may be more effective. While mentorship, sponsorship, and diversity training programs can help women who are located in regions with strong societal attitudes toward gender equality, these policies may have little or no effects on women with more choices for potential workplaces. My findings also suggest that organizations in regions where gender biases are more prevalent may forego opportunities to hire highly qualified women. Because these organizations may be less attractive to women in general and in particular to highly skilled women, these organizations tend to be less gender-diverse. Since diversity in the workplace provides functional and intellectual diversity (Antonio et al., 2004; Loyd et al., 2013; Phillips et al., 2006), organizations that are less attractive to women are deprived of the benefits that diversity produces, which in the long run can affect an organization's performance.

## FIGURES

**Figure 4-1.** Productivity by year complete sample

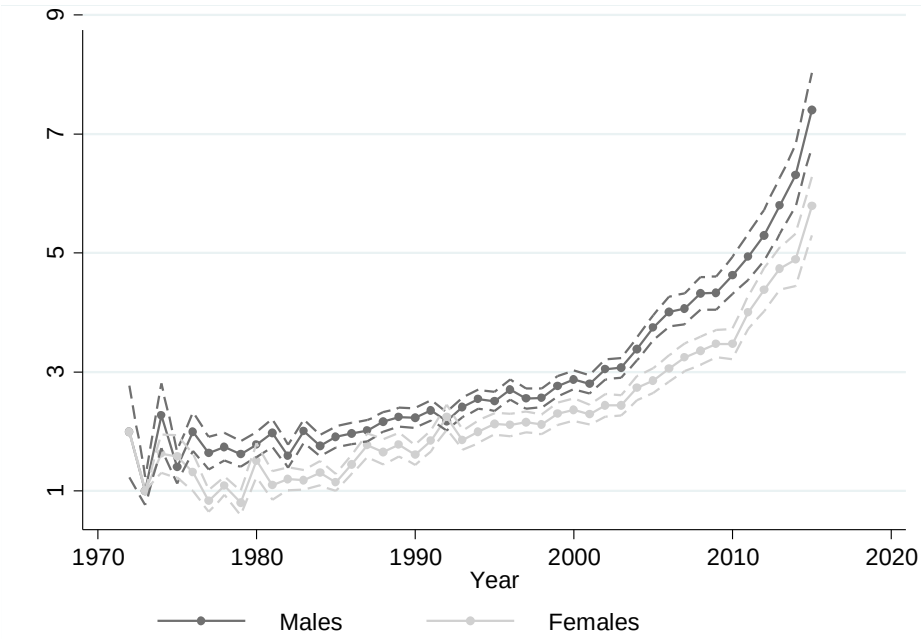



**Figure 4-2.** Productivity by year matched-pair sample

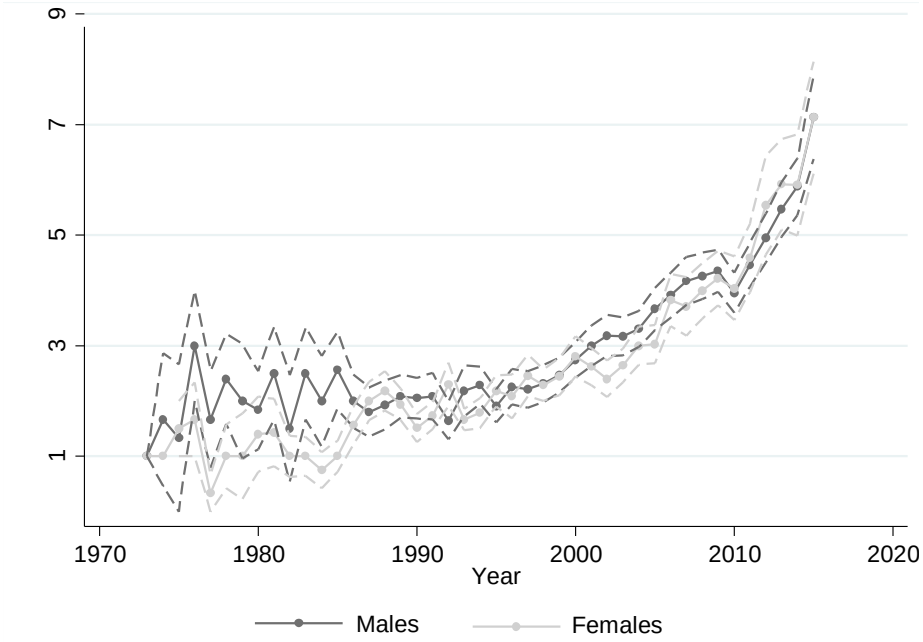


**Figure 4-3.** Predicted number of publications, by gender and social bias toward gender equality. Complete sample.

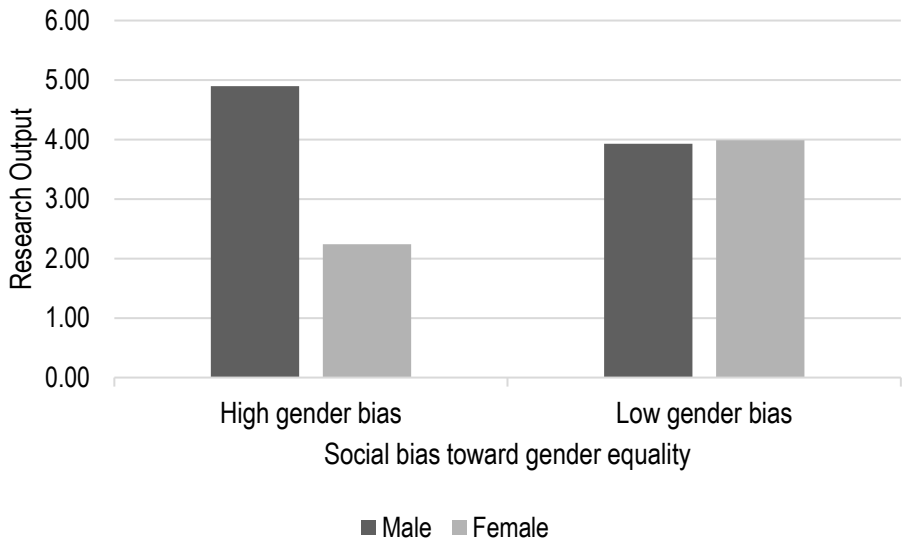
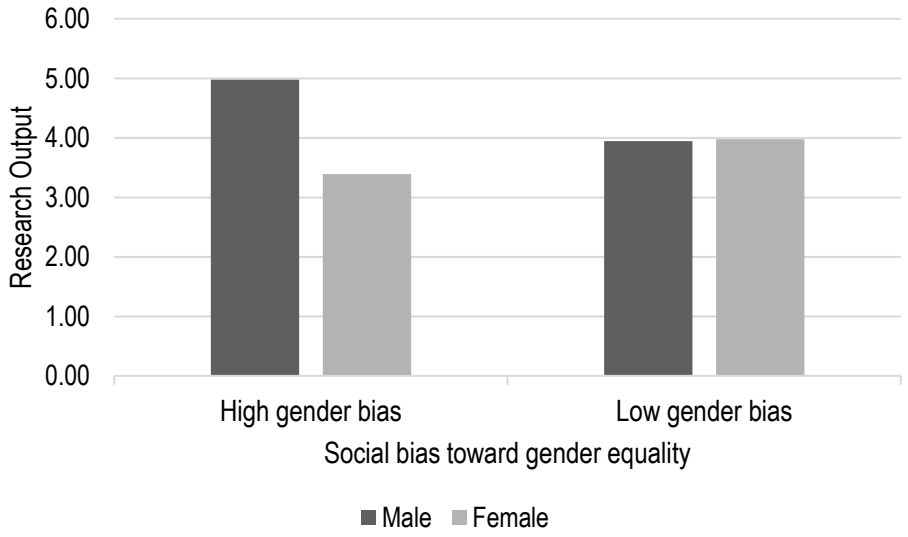



**Figure 4-4.** Predicted number of publications, by gender and social bias toward gender equality. Matched-pair sample.



## TABLES

**Table 4-1.** Scientific Disciplines in the Sample

| Subject Description | | Frequency |
|---|---|---|
| Anatomy and physiology | 0 | (0.0%) |
| Animals | 0 | (0.0%) |
| Biochemistry | 61 | (19.3%) |
| Biology | 74 | (23.4%) |
| Biophysics | 5 | (1.6%) |
| Chemical engineering | 47 | (14.9%) |
| Genetics | 36 | (11.4%) |
| Immunology | 5 | (1.6%) |
| Molecular biology | 46 | (14.6%) |
| Organic chemistry | 30 | (9.5%) |
| Pathology | 0 | (0.0%) |
| Pharmacology | 12 | (3.8%) |

**Table 4-2.** Mean Scientists Differences from the Matched-Pair Sample

| Criteria | Female | Male | p.value |
|---|---|---|---|
| Postdoctoral years | 3.79 | 3.91 | 0.55 |
| Graduation year | 1997 | 1997 | 0.89 |
| University first job R&D ranking | 14.21 | 14.22 | 1.00 |
| University graduate. school R&D ranking | 9.86 | 9.50 | 0.64 |
| University first job earned doctorates ranking | 14.84 | 14.82 | 0.99 |
| University graduate school earned doctorates ranking | 13.04 | 12.73 | 0.79 |

**Table 4-3.** Summary Statistics

| | Count | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|
| **Complete Sample** | | | | | |
| *Number of publications* | 19,179 | 4.41 | 7.71 | 1 | 249 |
| *Coauthors* | 19,179 | 13.66 | 72.73 | 0 | 2895 |
| *Experience* | 19,179 | 14.45 | 9.74 | 0 | 45 |
| *Postdoctoral years* | 19,179 | 4.28 | 3.48 | 0 | 33 |
| *University graduate school R&D ranking* | 19,179 | 34.18 | 37.31 | 1 | 273 |
| *University graduate school earned doctorates ranking* | 19,179 | 43.33 | 56.76 | 1 | 483 |
| *Female* | 19,179 | 0.31 | 0.46 | 0 | 1 |
| *Social bias toward gender equality (Political attitudes - fepres)* | 19,179 | 0.94 | 0.03 | 0.70 | 1.00 |
| *Social bias toward gender equality (Work and family attitudes – work/fam)* | 19,179 | 0.64 | 0.06 | 0.28 | 0.76 |
| **Matched Sample** | | | | | |
| *Number of publications* | 4,307 | 4.45 | 5.63 | 1 | 86 |
| *Coauthors* | 4,307 | 9.17 | 29.29 | 0 | 690 |
| *Experience* | 4,307 | 12.32 | 8.92 | 0 | 43 |
| *Postdoctoral years* | 4,307 | 3.98 | 2.58 | 0 | 14 |
| *University graduate school R&D ranking* | 4,307 | 14.94 | 19.23 | 1 | 123 |
| *University graduate school earned doctorates ranking* | 4,307 | 15.96 | 22.71 | 1 | 195 |
| *Female* | 4,307 | 0.44 | 0.50 | 0 | 1 |
| *Social bias toward gender equality (Political attitudes - fepres)* | 4,307 | 0.94 | 0.02 | 0.78 | 1.00 |
| *Social bias toward gender equality (Work and family attitudes – work/fam)* | 4,307 | 0.65 | 0.06 | 0.29 | 0.76 |

**Table 4-4** Bivariate Correlations

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|---|
| **(1)** | Number of publications | 1 | | | | | | | | |
| **(2)** | Coauthors | 0.429 | 1 | | | | | | | |
| **(3)** | Experience | 0.065 | 0.027 | 1 | | | | | | |
| **(4)** | Postdoctoral years | -0.023 | 0.009 | 0.037 | 1 | | | | | |
| **(5)** | University graduate school R&D ranking | 0.003 | 0.026 | 0.012 | 0.045 | 1 | | | | |
| **(6)** | University graduate school earned doctorates ranking | 0.006 | 0.027 | 0.017 | 0.091 | 0.68 | 1 | | | |
| **(7)** | Female | -0.047 | -0.011 | -0.062 | 0.033 | 0 | -0.037 | 1 | | |
| **(8)** | Social bias toward gender equality (Political attitudes - *fepres*) | 0.131 | 0.088 | 0.356 | 0.019 | -0.007 | -0.012 | 0.028 | 1 | |
| **(9)** | Social bias toward gender equality (Work and family attitudes – *work/fam*) | 0.148 | 0.114 | 0.384 | 0.003 | -0.019 | -0.018 | 0.035 | 0.847 | 1 |

N = 19,179

**Table 4-5.** Negative Binomial Regression Predicting Number of Publications -Complete Sample-

| **Dependent Variable: Research output** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** |
|---|---|---|---|---|---|
| Year dummies | YES | YES | YES | YES | YES |
| *Coauthors* | 0.011*** | 0.010*** | 0.010*** | 0.010*** | 0.010*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Experience* | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Postdoctoral years* | -0.006*** | -0.005** | -0.006** | -0.006** | -0.006** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| *University graduate school R&D ranking* | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *University graduate school earned doctorates ranking* | 0.000+ | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Square social bias toward gender equality (fepres)* | | | | | -0.011** |
| | | | | | (0.003) |
| Female | | -0.120*** | -0.121*** | -0.129*** | -0.129*** |
| | | (0.013) | (0.013) | (0.013) | (0.013) |
| Social bias toward gender equality (*fepres*) | | | 0.021 | 0.000 | -0.023 |
| | | | (0.014) | (0.015) | (0.016) |
| Female x Social bias toward gender equality(*fepres*) | | | | 0.076*** | 0.078*** |
| | | | | (0.015) | (0.015) |
| Constant | 0.341 | 0.384 | 0.487 | 0.550+ | 0.701* |
| | (0.318) | (0.318) | (0.325) | (0.328) | (0.332) |
| Observations | 19,186 | 19,186 | 19,186 | 19,186 | 19,186 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 4-6.** Negative Binomial Regression Predicting Number of Publications -Matched Sample-

| **Dependent Variable: Research output** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** |
|---|---|---|---|---|---|
| Year dummies | YES | YES | YES | YES | YES |
| *Coauthors* | 0.021*** | 0.022*** | 0.022*** | 0.021*** | 0.021*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Experience* | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| *Postdoctoral years* | 0.012* | 0.010* | 0.010* | 0.010* | 0.010* |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| *University graduate school R&D ranking* | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *University graduate school earned doctorates ranking* | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Square Social bias toward gender equality (fepres)* | | | | | -0.042** |
| | | | | | (0.013) |
| Female | | -0.090*** | -0.090*** | -0.092*** | -0.088*** |
| | | (0.025) | (0.025) | (0.025) | (0.025) |
| Social bias toward gender equality (*fepres*) | | | -0.019 | -0.048 | -0.028 |
| | | | (0.033) | (0.037) | (0.037) |
| Female x Social bias toward gender equality (*fepres*) | | | | 0.053+ | 0.042 |
| | | | | (0.027) | (0.027) |
| Constant | 0.206 | 0.236 | 0.117 | 0.041 | 1.832* |
| | (0.687) | (0.687) | (0.719) | (0.722) | (0.918) |
| Observations | 4,307 | 4,307 | 4,307 | 4,307 | 4,307 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

## Appendix: Robustness checks

**Table 4-A7.** Negative Binomial Regression Predicting First and Last Author Number of Publications
-Complete Sample-

| **Dependent Variable: Research output** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** |
|---|---|---|---|---|---|
| Year dummies | YES | YES | YES | YES | YES |
| *Coauthors* | 0.006*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Experience* | 0.013*** | 0.012*** | 0.012*** | 0.012*** | 0.012*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Postdoctoral years* | -0.018*** | -0.017*** | -0.017*** | -0.017*** | -0.017*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| *University graduate school R&D ranking* | -0.001** | -0.001* | -0.001* | -0.001* | -0.001* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *University graduate school earned doctorates ranking* | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Square Social bias toward gender equality (fepres)* | | | | | -0.012** |
| | | | | | (0.004) |
| Female | | -0.144*** | -0.145*** | -0.150*** | -0.149*** |
| | | (0.015) | (0.015) | (0.015) | (0.015) |
| Social bias toward gender equality (*fepres*) | | | 0.024 | 0.009 | -0.018 |
| | | | (0.016) | (0.016) | (0.019) |
| Female x Social bias toward gender equality (*fepres*) | | | | 0.057*** | 0.058*** |
| | | | | (0.016) | (0.017) |
| Constant | 0.807* | 0.842* | 0.976* | 0.979* | 1.213** |
| | (0.383) | (0.383) | (0.392) | (0.394) | (0.402) |
| Observations | 19,186 | 19,186 | 19,186 | 19,186 | 19,186 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 4-A8.** Negative Binomial Regression Predicting First and Last Author Number of Publications
-Matched Sample-

| **Dependent Variable: Research output** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** |
|---|---|---|---|---|---|
| Year dummies | YES | YES | YES | YES | YES |
| *Coauthors* | 0.010*** | 0.011*** | 0.010*** | 0.010*** | 0.010*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Experience* | 0.010*** | 0.009*** | 0.009*** | 0.009*** | 0.009*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| *Postdoctoral years* | 0.010+ | 0.008 | 0.008 | 0.008 | 0.008 |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) |
| *University graduate school R&D ranking* | 0.001 | 0.000 | 0.000 | 0.000 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *University graduate school earned doctorates ranking* | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Square Social bias toward gender equality (fepres)* | | | | | -0.059*** |
| | | | | | (0.015) |
| Female | | -0.185*** | -0.185*** | -0.188*** | -0.182*** |
| | | (0.029) | (0.029) | (0.029) | (0.029) |
| Social bias toward gender equality (*fepres*) | | | -0.007 | -0.026 | 0.003 |
| | | | (0.038) | (0.041) | (0.042) |
| Female x Social bias toward gender equality (*fepres*) | | | | 0.035 | 0.021 |
| | | | | (0.031) | (0.031) |
| Constant | 0.232 | 0.291 | 0.245 | 0.199 | 2.712** |
| | (0.695) | (0.694) | (0.734) | (0.737) | (0.993) |
| Observations | 4,307 | 4,307 | 4,307 | 4,307 | 4,307 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 4-A9.** Different Estimation Methods Predicting Research Output

| **Dependent Variable: Research output** | Complete Sample (Hypothesis 1) | | Matched Sample (Hypothesis 2) | |
|---|---|---|---|---|
| | **Ordinary Least Square** (Log transformed dependent variable) | **Poisson** | **Ordinary Least Square** (Log transformed dependent variable) | **Poisson** |
| Female | -*** | -*** | - | - |
| Social bias toward gender equality (*fepres*) | + | + | -** | + |
| Female x Social bias toward gender equality (*fepres*) | +*** | +*** | ++ | +** |
| Observations | 19,186 | 19,186 | 4,307 | 4,307 |
| Year dummies | YES | YES | YES | YES |
| Robust standard errors | YES | YES | YES | YES |

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 4-A8.** Negative Binomial Regression Predicting Number of Publications -Complete Sample-

| **Dependent Variable: Research output** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** |
|---|---|---|---|---|---|
| Year dummies | YES | YES | YES | YES | YES |
| *Coauthors* | 0.011*** | 0.010*** | 0.010*** | 0.010*** | 0.010*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Experience* | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Postdoctoral Years* | -0.006*** | -0.005** | -0.005** | -0.005** | -0.005** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| *Univ. Grad. School R&D ranking* | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Univ. Grad. School earned doctorates ranking* | 0.000+ | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Square Social bias toward gender equality (work-fam)* | | | | | 0.004 |
| | | | | | (0.009) |
| Female | | -0.120*** | -0.121*** | -0.128*** | -0.128*** |
| | | (0.013) | (0.013) | (0.013) | (0.013) |
| Social bias toward gender equality (*work-fam*) | | | 0.041* | 0.028 | 0.028 |
| | | | (0.020) | (0.020) | (0.020) |
| Female x Social bias toward gender equality (*work-fam*) | | | | 0.052*** | 0.052*** |
| | | | | (0.014) | (0.014) |
| Constant | 0.341 | 0.384 | 0.583+ | 0.629+ | 0.546 |
| | (0.318) | (0.318) | (0.331) | (0.333) | (0.393) |
| Observations | 19,186 | 19,186 | 19,186 | 19,186 | 19,186 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

**Table 4-A9.** Negative Binomial Regression Predicting Number of Publications -Matched Sample-

| **Dependent Variable: Research output** | **(model 1)** | **(model 2)** | **(model 3)** | **(model 4)** | **(model 5)** |
|---|---|---|---|---|---|
| Year dummies | YES | YES | YES | YES | YES |
| *Coauthors* | 0.021*** | 0.022*** | 0.022*** | 0.022*** | 0.022*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Experience* | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| *Postdoctoral Years* | 0.012* | 0.010* | 0.011* | 0.011* | 0.011* |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| *Univ. Grad. School R&D ranking* | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Univ. Grad. School earned doctorates ranking* | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Square Social bias toward gender equality (work-fam)* | | | | | 0.033+ |
| | | | | | (0.019) |
| Female | | -0.090*** | -0.092*** | -0.094*** | -0.094*** |
| | | (0.025) | (0.025) | (0.025) | (0.025) |
| Social bias toward gender equality (*work-fam*) | | | 0.083* | 0.066 | 0.063 |
| | | | (0.039) | (0.040) | (0.041) |
| Female x Social bias toward gender equality (*work-fam*) | | | | 0.038 | 0.035 |
| | | | | (0.027) | (0.027) |
| Constant | 0.206 | 0.236 | 0.713 | 0.685 | -0.447 |
| | (0.687) | (0.687) | (0.722) | (0.723) | (0.984) |
| Observations | 4,307 | 4,307 | 4,307 | 4,307 | 4,307 |

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

# 5. CONCLUSIONS

## 5.1. MAIN FINDINGS

This dissertation examines how intra-organizational networks interact with individual (**Chapter 2** and **Chapter 3**) and macro-level (**Chapter 4**) characteristics to affect employees' innovativeness and access to social capital in knowledge-based organizations. Primarily, my dissertation focuses on how such intra-organizational network dynamics limit or perpetuate gender inequality in the workplace. For example, I demonstrate that to enter the collaboration network of a high-status colleague, men and women need to follow different strategies. I also show that three employees' characteristics, namely gender, tenure, and position in the intra-organizational network, explain why some individuals are more innovative than others in gender-diverse organizations. Besides demonstrating how individuals' networks interact with individuals' characteristics to explain gender disparities in the workplace, I explore how regional-level factors affect differences between men and women in organizations. In particular, I show that the level of gender bias in the region in which an organization is located affects gender performance gaps within organizations in that region. Therefore, I provide new insights into the mechanisms by which gender inequality persists in knowledge-intensive organizations, and it suggests possible avenues to overcome such gender disparities.

A key contribution of this dissertation is to illuminate the importance of employees' networks in explaining gender differences in knowledge-based firms. The forty largest pharmaceutical firms globally serve as the context of study. The main findings of the dissertation are listed as follows: In **Chapter 2**, I found that men and women face different conditions and, therefore, adopt different strategies to gain entry into a star scientists' collaboration network. Specifically, this chapter shows that it is harder for women than for men to initiate high-status collaborations;

that women's path to high-status colleagues is more indirect, and hence more difficult than men's; and that such difficulties are amplified, rather than reduced, when the high-status actor is a woman. **Chapter 3** shows that individuals' characteristics explain why some employees are more innovative than others by working in a gender-diverse organization. In **Chapter 3**, I demonstrate that although organizational-level gender diversity has a positive effect on overall organizational performance, this performance effect is heterogeneously distributed among three categories of scientists. Whereas organizational gender diversity increases the innovativeness of network brokers and freshly-tenured scientists, this is not the case for long-tenured scientists and scientists embedded in constrained networks. Furthermore, contrary to our expectation, we find that both female and male scientists benefit equally from working in a gender diverse workplace.

Finally, in **Chapter 4**, I explore whether and how the level of gender bias in the region a university is located affects gender performance gaps. To do so, I use data on attitudes and behaviors in contemporary US society and information on the background and training of academic scientists at top-ranked US universities. **Chapter 4** shows that in regions characterized by stronger gender bias, gender performance gaps are larger. However, this effect largely disappears when I control for the selection processes occurring before employees joining an organization. That is when I account for the fact that women may choose workplaces based on how stronger gender bias in the regions where the organization is located.

## 5.2. CONTRIBUTIONS

This dissertation primarily contributes to the intra-organizational networks literature. Mainly, the insights and findings of this dissertation advance the discussion on whether and how different network dynamics occurring in the workplace strengthen or weaken gender inequality. Extant research has shown that a major reason for the persistent gender disparity in the workplace lies in

women's reduced access to valuable sources of social capital within the organization (Burt, 1998; Kay & Wallace, 2009; Lutter, 2015; O'Neill & Gidengil, 2013; Singh, Hansen, & Podolny, 2010). Inspired by the view that informal networks are a critical source of social capital and they explain to some extent men's and women's differences in performance and career outcomes (Forret & Dougherty, 2004; Ibarra, 1992, 1997), this dissertation shows, first, that to access the social capital of high-status colleagues, men and women need to follow different strategies (**Chapter 2**). By focusing on how employees' gender may affect the likelihood that s/he enters the collaboration networks of a high-status colleague, this dissertation extends current understandings of the antecedents of gender inequality in knowledge-intensive firms. In particular, **Chapter 2** shows that the strategies non-star scientists follow to connect with stars varies depending on non-star scientists' gender. Whereas male non-star scientists have direct access to stars, female non-stars need to use their network connections to reach the stars. **Chapter 2**, therefore, sheds light on gender differences in network creation by explaining whether and how men and women follow different strategies to the same end. Second, my dissertation shows that the intra-organizational networks that employees build influence to what extent they can benefit from the increase of women within organizations (**Chapter 3**). **Chapter 3** also shows that the longer the tenure of a scientist, the less s/he benefits from gender diversity. This result suggests that when the gender diversity of an organization increases, long-tenured scientists, who had built their collaboration networks in times when the firm was mainly male-dominated, risk being left behind. This finding is important to understand how employees' collaboration networks make employees more or less likely to take advantage of organizational changes like the increase of women in organizations.

My dissertation also contributes to the literature on gender inequality. Extensive research has shown gender differences in employees' career outcomes like wages and promotions (Ely et al., 2011; Hultin & Szulkin, 1999; Joshi, Son, et al., 2015; Lips, 2013; D. Moore & Toren, 1998). This research has explored how individual-level (Fernandez-Mateo, 2009; Joshi, 2014; Leahey, Beckman, & Stanko, 2016; Sterling & Fernandez, 2018), organizational-level (Herring, 2009; Joshi et al., 2006) and regional-level factors (Charles & Guryan, 2008; Charles, Guryan, & Pan, 2009; Janssen et al., 2016) explain gender disparities in the workplace. This dissertation complements this view by exploring, first, how regional gender bias (**Chapter 4**) affect gender differences in performance. To do so, **Chapter 4** demonstrates that, on the one hand, in regions with higher gender bias, the difference between men's and women's performance is larger. On the other hand, **Chapter 4** also shows that regional gender bias also influences where women decided to work in the first place. Second, since another source of gender inequality is women's lack of access to important sources of social capital in the workplace, **Chapter 2** examines what makes women more likely to enter the network of a high-status colleague. In this chapter, I found that using intermediaries - third-party connections - to approach star scientists is a more accepted relational strategy for women than for men. Therefore, female non-star scientists can be better than male non-stars to use their network of relationships to connect with star scientists. This is particularly the case if the star scientists is a woman rather than a man. Taken together, these results enable us to gain further knowledge of how female employees can enhance their career perspectives by improving their performance and accessing essential sources of social capital.

By studying whether and how organizational gender diversity has a heterogeneous effect on individuals' performance, my dissertation also contributes to the organizational literature on innovation. While existing research consistently finds that organizations that are gender diverse

are more innovative (Boone & Hendriks, 2009; Hoogendoorn et al., 2013; Joshi et al., 2006; World Economic Forum, 2019), we do not yet know which employees become more innovative. A critical insight of **Chapter 3** is that increasing gender diversity equally amplifies the innovativeness of both men and women; however, the longer the tenure of a scientist, and the more constraint the networks of the scientists is the less s/he benefits from gender diversity. These novel findings are crucial because of two reasons. First, they provide evidence that, in the setting of pharmaceutical firms, male scientists benefit on average just as much as female scientists from increased levels of gender diversity. Second, they suggest that when the gender diversity of a firm increases, long-tenured scientists, and scientists in more constraint networks who had built their collaboration networks in times when the firm was mainly male-dominated, risk do not be able to adapt to such changes. Both these findings are essential when devising strategies to increase gender diversity within organizations. For example, they suggest that organizations should pay special attention to long-tenured scientists when introducing gender policies and should actively support them in building more inclusive collaboration networks.

Finally, my dissertation offers several insights for organizations that aim to create more gender-balanced workplaces. For instance, findings from **Chapter 2** can help organizations to understand the importance of network connections as a means to improve women's chances to connect to high-status colleagues. Since using third-party connections is the strategy that women need to follow to reach the stars, **Chapter 2** suggests that organizations need to implement concrete ways to increase women's chances of connecting to third-parties. **Chapter 3** highlights the importance of gender diversity in the workplace. This chapter goes beyond the well-established argument that gender diversity enhances the overall performance of the organizations by examining how such performance improvement is distributed among different kinds of

scientists. Understanding this heterogeneous effect of gender diversity is essential because it may help organizations to manage their workforces differently to make everyone able to enjoy the benefits that women bring into organizations. Lastly, **Chapter 4** can help organizations to determine places where interventions need to be implemented. Whereas human resources practices like diversity training, inclusion programs, mentorship, and sponsorship can improve women's productivity if regional gender bias directly affects women's productivity, such interventions may have little effect if regional gender bias affects where women choose to work in the first place. Therefore, understanding how selection works have implications for the type of policy interventions organizations might choose.

## 5.3. SCOPE CONDITIONS

The main findings in this dissertation may hold for different knowledge-intensive firms that are predominantly male-dominated, where women have equalized or even exceeded men in terms of education and experience - the human capital view -. Besides, my arguments hold mostly for organizations where the collaboration networks individuals build are essential for knowledge sharing and innovation.

The arguments in this dissertation gain relevance in organizations where the social capital perspective complements the human capital view on persistent gender disparities (Burt, 1998; Kay & Wallace, 2009; Lutter, 2015; O'Neill & Gidengil, 2013; Singh, Hansen, & Podolny, 2010). The social capital perspective explains, for example, why forming collaboration ties with high-status colleagues is essential to reduce gender gaps in the workplace. Besides, it also describes how the collaboration networks individuals build determine who become more innovative in a gender-diverse organization. This social capital view on gender inequality, therefore, allows us to understand which are the antecedents of gender disparities in the

workplace. What is more, it also enhances our knowledge of the conditions that can help women to overcome difficulties in the workplace and of which interventions organizations can put in place to provide equal opportunities for men and women in organizations. Knowledge-intensive organizations as diverse as universities, law firms, financial companies, high-tech organizations to mention some can be suitable settings for the study of gender inequality through social capital lenses. Accordingly, I would expect my arguments to generalize to this kind of organization and look forward to future research in this direction.

## 5.4. LIMITATIONS AND FUTURE RESEARCH

An important limitation of my dissertation relates to the fact that the theoretical arguments, as well as the empirical analysis of both **Chapter 2** and **Chapter 3**, are conditional on R&D scientists joining the organization. Since I can only observe R&D scientists when they have joined the organization, I am unable to control for the selection process that leads each of those scientists to become part of a firm. To overcome this limitation, data on R&D scientists' career is required. Collecting complete career data for the scientists I studied may help to ascertain whether and how self-selection affects my results. While in **Chapter 4**, I attempt to assuage this concern by controlling for self-selection using academic scientists, future research should develop research designs that leverage individuals' complete careers to better understand the selection processes occurring prior to employees joining an organization.

One of the most significant downsides of using large-scale data like the ones I used throughout this dissertation is the difficulty of teasing out the micro-mechanisms driving individual behavior. Although I was able to understand some of the observed patterns of results through qualitative evidence, future work using experimental research can lead us to a better understanding of the individuals' motivations for the observed pattern of results. For instance,

getting to know what are the intrinsic motivations of star and non-star scientists to form first-time collaborations may enrich the findings of **Chapter 2**.

The limitations described above, as well as the main findings of this dissertation, provide avenues for new projects. In what follows, I give an overview of what I consider the most promising avenues of future work.

### 5.4.1. Network creation and change

The evolution of networks can, to some extent, explain gender differences in organizations. In **Chapter 3**, I explain how organizational-level gender diversity affects employees differently. One question that is still unaddressed from this chapter is whether and how by increasing the number of women within organizations - i.e., the increased levels of gender diversity -, the intra-organizational network of employees can be modified. For instance, having more women in the organization can lead to a higher number of women entering employees' networks, therefore, changing employees' network composition. Besides, more women within the organization may modify employees' network structures by either creating new structural holes or more constraint networks. What is more, these changes in network composition and structure can vary by scientists' gender and can affect their innovative performance. Future research should examine how organizational-level gender diversity modifies the intra-organizational network composition and network structure of employees. This is essential because it can help us to understand how the intra-organizational network of employees changed, creating new organizational network dynamics.

As important as it is to understand which factors affect tie formation, understanding what leads to the maintenance of network ties is essential. Few studies have explored what influences tie repetition (e.g., Dahlander and McFarland (2013)). Future work should explore, for instance,

how having third-party ties in common affects the tie repetition between star and non-star scientists. Besides, this work should also examine to what extent scientists' gender matters. This line of work can provide new insights to this social capital perspective on gender inequality that I aim to contribute to with my dissertation. This can give a better understanding of other network dynamics in the workplace and how such dynamics explain gender disparities.

Extant research has shown that individuals' network composition and structure affect gender differences in individuals' career outcomes (Burt, 1998; Ibarra, 1992; Lutter, 2015). In my dissertation, I aim to complement this line of work by showing how successful strategies to enter the collaboration network of a high-status colleague vary by gender. Notably, in **Chapter 2**, I showed how female and male non-star scientists follow different strategies to enter the collaboration network of a high-status colleague. This finding sheds light on how status and gender interact and affect men's and women's differences in tie formation. Future research, however, should explore other factors that influence tie formation. For example, most of the research on personality and networks has focused on how individuals' personality traits are related to their position in the network structure (Burt, Jannotta, & Mahoney, 1998; Oh & Kilduff, 2008; Wolff & Kim, 2012). Notably, this research has primarily focused on explaining how differences in individual self-monitoring personality lead to brokerage positions (Sasovova et al, 2010). Nevertheless, less is known about how different personality dimensions, besides self-monitoring, affect the formation of networks. What is more, there is no prior work that explores gender differences in how personality affects the creation of networks. An experimental approach that combines the network literature with the personality literature to examine how interactions between different personality types lead to tie formation can help us to understand

other mechanisms that lead to the creation of networks and explore gender differences in network creation.

### 5.4.2. Selection and treatment effects

The lack of R&D scientists' career data makes it challenging to disentangle selection and treatment effects in **Chapter 3**. A future project with data on R&D scientists' career data would allow us to understand whether organizational-level gender diversity affects scientists' innovative performance - i.e., treatment effects - or if gender diversity at the organizational level influences how scientists self-select into workplaces - i.e., selection effects. For instance, if women prefer to work in more gender-diverse workplaces, and only more skilled women can choose where to work, the effect of gender diversity on scientists' performance can be explained by self-selection. Given this reasoning, future work that accounts for selection is essential to understand other mechanisms that may affect gender inequality in the workplace.

In **Chapter 4**, my main goal was to disentangle between selection and treatment effects. Nevertheless, the findings of this chapter lead to two avenues for future research. First, replicating the study on the R&D scientists studied in **Chapter 2** and **Chapter 3** and observe whether the results hold beyond academia. There is evidence of how societal attitudes affect gender wage gaps in industrial settings (e.g., Janssen, Sartore, and Backes-Gellner (2016)). However, it is less clear how the same societal attitudes affect individuals' performance. Therefore, future research that builds on the findings of **Chapter 4** and generalizes to different industries may illuminate other sources of gender inequality in the workplace. Second, future work should dig into the mechanisms that explain why controlling for selection reduces the effect of regional gender bias on the gender performance gap. For example, getting more precise information on women's qualifications and personal status can help us to learn more about how

self-selection works. That is, whether women who prefer less biased regions are indeed the ones with higher qualifications and/or less personal constraints.

### 5.4.3. Men's and women's differences in performance and career outcomes

It has been argued that connections to star scientists can boost non-stars' careers and determine their success (Lin, 1999; Son & Lin, 2012). However, little empirical evidence has been provided to support such a claim. Future research should operationalize and show how connections with stars affect non-stars' careers. For instance, future work should examine how by becoming part of a star scientist's network, non-star scientists' career is affected. Future projects examining whether non-stars are more productive, advance in the organizational ladder, or even become star scientists after entering star scientists' networks are needed. This kind of evidence would help us enhance our knowledge of how exactly becoming part of a star's network contributes to non-star scientists' success. Importantly, identifying whether and how men's and women's career outcomes may differ once entering star scientists' networks can also be crucial to deepen our understanding of other determinants of gender disparities.

**Chapter 3** shows that both female and male scientists benefit equally from gender diversity. One potential avenue for future work should build on this exciting finding by exploring the mechanisms driving these patterns of results. For example, future work should explore whether having more women available also benefits men because they are exposed to different knowledge, which improves their innovativeness. This could be potentially developed in the context of R&D labs by exploring differences in the subfields men and women work in and how by having more women, those subfields are modified for men. Another potential avenue to explain why also men benefit from gender diversity may be exploring how men's network structures are changed by having more women in the organization. For instance, by having more

women within the organization, men may need to reach women outside their intra-organizational networks, which can lead them to occupy new brokerage positions. This, in turn, could explain the positive effect of gender diversity on men's innovativeness.

In **Chapter 4**, I explained how the societal attitudes of a region affect the gender performance gap in academics. Future research should take advantage of the existing variance in regional societal attitudes in the US to understand how such societal attitudes evolve. For instance, in the last years, the level of gender bias has, in general, decreased across most US regions. Nevertheless, regional gender bias may still change because of ideological changes happening in the country. That is, regional gender bias could increase as a function of the societal changes happening within the country at a certain point in time. As an example, think about some social movements that in the latest years have reinforced discriminatory behaviors against racial minorities and/or women. This can reflect the increase of gender bias in regions that support this way of thinking, affecting, therefore, how women are treated at work.

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