This article was downloaded by: [155.33.130.32] On: 17 June 2026, At: 08:49
Publisher: Institute for Operations Research and the Management Sciences (INFORMS)
INFORMS is located in Maryland, USA

Organization Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Gender Differences in Responses to Competitive Organization? A Field Experiment on Differences Between STEM and Non-STEM Fields from an Internet-of-Things Platform

Kevin J. Boudreau, Nilam Kaushik

To cite this article:
Kevin J. Boudreau, Nilam Kaushik (2023) Gender Differences in Responses to Competitive Organization? A Field Experiment on Differences Between STEM and Non-STEM Fields from an Internet-of-Things Platform. Organization Science 34(6):2119-2142. https://doi.org/10.1287/orsc.2022.1624

This work is licensed under a Creative Commons Attribution 4.0 International License. You are free to copy, distribute, transmit and adapt this work, but you must attribute this work as "*Organization Science*. Copyright © 2023 The Author(s). https://doi.org/10.1287/orsc.2022.1624, used under a Creative Commons Attribution License: https://creativecommons.org/licenses/by/4.0/."

Copyright © 2023 The Author(s)

Please scroll down for article—it is on subsequent pages

With 12,500 members from nearly 90 countries, INFORMS is the largest international association of operations research (O.R.) and analytics professionals and students. INFORMS provides unique networking and learning opportunities for individual professionals, and organizations of all types and sizes, to better understand and use O.R. and analytics tools and methods to transform strategic visions and achieve better outcomes.
For more information on INFORMS, its publications, membership, or meetings visit http://www.informs.org

https://pubsonline.informs.org/journal/orsc

ORGANIZATION SCIENCE
Vol. 34, No. 6, November–December 2023, pp. 2119–2142
ISSN 1047-7039 (print), ISSN 1526-5455 (online)

Gender Differences in Responses to Competitive Organization? A Field Experiment on Differences Between STEM and Non-STEM Fields from an Internet-of-Things Platform

Kevin J. Boudreau,[a,b,*] **Nilam Kaushik**[c]

[a] D'Amore-McKim School of Business, Northeastern University, Boston, Massachusetts 02120; [b] National Bureau of Economic Research, Cambridge, Massachusetts 02138; [c] Indian Institute of Management Bangalore, Bangalore 560076, India

*Corresponding author

Contact: k.boudreau@northeastern.edu, https://orcid.org/0000-0003-2787-9599 (KJB); nilam.kaushik@iimb.ac.in, https://orcid.org/0000-0002-7684-6737 (NK)

Received: February 10, 2022
Accepted: July 14, 2022
Published Online in Articles in Advance: January 9, 2023

https://doi.org/10.1287/orsc.2022.1624

Copyright: © 2023 The Author(s)

Abstract. Prior research, primarily based on laboratory experiments of children and students, suggests that women might be more averse to competition than are men; women might, instead, be more inclined toward collaboration. Were these findings to generalize to working-age men and women across the workforce, there could be profound implications for organizational design and personnel management. We report on a field experiment in which 97,678 adults from a wide range of fields of training and career stages were invited to join a product development platform. Individuals were randomly assigned to treatments framing the opportunity as either involving competitive or collaborative interactions with other participants. Among those outside of science, technology, engineering, and math (STEM) fields, we find differences in the willingness of men and women to participate under competition. Thus, patterns in non-STEM fields conform to the usual claims of gender differences. However, among those in STEM fields, we find no statistical gender differences. Results hold under a series of alternative specifications, controls, and stratified analyses of 17 narrowly defined STEM subfields. The results are consistent with sorting into fields on the basis of competitiveness, as suggested by prior research, as well as other explanations we discuss. Overall, heterogeneity among women and heterogeneity among men appear to be at least as important as population-wide gender differences.

History: This paper has been accepted for the *Organization Science* Special Issue on Experiments in Organizational Theory.

Open Access Statement: This work is licensed under a Creative Commons Attribution 4.0 International License. You are free to copy, distribute, transmit and adapt this work, but you must attribute this work as "*Organization Science*. Copyright © 2023 The Author(s). https://doi.org/10.1287/orsc.2022.1624, used under a Creative Commons Attribution License: https://creativecommons.org/licenses/by/4.0/."

Funding: This work was supported by Ewing Marion Kauffman Foundation [Grant G00005624].

Supplemental Material: The online appendix is available at https://doi.org/10.1287/orsc.2022.1624.

Keywords: Platforms • innovation • diversity • STEM • online distributed work • field experiment • sorting • gender

1. Introduction

A stream of laboratory-based studies has reported gender differences in the probability of subjects choosing to engage in tasks under competitive conditions (e.g., Niederle and Vesterlund 2007, Sutter and Glätzle-Rützler 2015, Saccardo et al. 2017; see Section 2).[1] The gender differences recorded in these studies have been interpreted as indicating that men have a greater preference for working under competitive conditions (e.g., Croson and Gneezy, 2009). Women have, instead, been interpreted to prefer noncompetitive piece-rate regimes and collaborative team-based regimes (e.g., Healy and Pate 2011, Dargnies 2012, Abramo et al. 2013, Kuhn and Villeval 2015). These provocative findings and interpretations are supported by numerous replication studies—and have even begun to diffuse to wider popular media audiences (Eswaran 2012, Eswaran 2015, Guo 2015).

Nonetheless, the generalizability of these findings remains little understood (Flory et al. 2015), and there are several reasons for further cautious investigation. For example, many existing results are drawn from relatively narrow contexts and study populations, especially children and students. There is also yet little theoretical consensus regarding underlying mechanisms that might produce gender-based differences (see Section 2), curtailing the ability to theoretically extrapolate beyond the existing evidence. Moreover, inasmuch as gender cannot be randomly assigned, there are fundamental limits to ruling out confounds and interpreting

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

a definitive causal "gender effect," whether in laboratory experiments or otherwise. Adding to these reasons for caution, a number of studies have emerged that report results contrary to the usual findings of gender-based differences, as we will review herein. Of course, gender is itself hotly debated in academia and in wider society, with plausible empirical implications.[2] Our primary contribution here is to study behaviors within a considerably more widely sampled population of working-age adults in a field experimental context.

It is important to better understand whether working-age men and women might somehow systematically differ in their responses to competition. Scholars in research on gender and competition regularly speculate that gender-based differences in competitiveness could explain part of "why women are under-represented in many high-profile jobs and in whole professions" (Niederle and Vesterlund 2007, p. 1096). For example, if girls and women are more averse to competition, they might systematically sort out of fields and occupations that are perceived to be competitive. These arguments have been the basis of hypothesized disparities in gender representation particularly among senior executive positions; science, technology, engineering, and math (STEM) fields; and politics (e.g., Niederle and Vesterlund 2010, Buser et al. 2014, Balafoutas et al. 2018). Clearer understanding might therefore shed light on whether "women's talents are sometimes wasted because they avoid competitive environments" (Kuhn and Villeval 2015, p. 115).

Diversity, including gender diversity, is also regularly suggested to be a potential source of productivity gains (e.g., Page 2008, Jones 2009). Attaining a better understanding of responses to competition could point to ways of improving organizational designs to better harness different workers' talents and efforts. This is because the "levers" of organizational design—internal incentive systems, hiring and selection processes, decision-making and political processes, work norms, and values—are the very things that regulate the intensity of competition experienced by workers (Lee and Puranam 2017, Obloj and Zenger 2017, Song et al. 2018, Baumann et al. 2019). Regulating the intensity of competition could be especially relevant for a new generation of digital forms of organizing—such as crowdsourcing, gig platforms, open communities, and open innovation—where interactions among participants can be readily governed, designed, and "tuned" to be more or less competitive or collaborative (Boudreau and Hagiu 2009, Boudreau 2017, Liang et al. 2018, Hunt and Samman 2019). Research on actors working on digital platforms (e.g., Jeppesen and Lakhani 2010, Boudreau et al. 2011), has itself presented evidence consistent with advantages of diverse work populations, under certain conditions.

In this paper, we take steps toward theorizing and documenting limits and boundary conditions regarding gender differences in competitiveness. At the core of this paper is a field experimental approach that allows us to observe responses to competition across a wide range of college-educated, working-age adults ranging from college students to retirees. We proceed by first developing theoretical predictions to guide our investigation. In short, we predict that gender differences in competitiveness should differ according to individuals' fields of training, and that gender differences should be significantly smaller among those who sort into STEM fields, relative to the general population.

Given the current lack of theoretical consensus on underlying mechanisms shaping responses to competition and possible gender differences (Section 2.2), our approach is to develop predictions based on only the most consistent claims and assumptions across the existing literature. A first point we build on is that there exists some (yet little understood or measured) degree of heterogeneity in competitiveness (i.e., differences in propensity for or aversion to competition) across the population of adult workers. The second point supposed across the existing literature that we build on is that individuals' competitiveness might serve as a meaningful basis for *sorting into different fields*. Any such sorting may be especially important, as young people make path-dependent choices throughout their education, culminating into longer-term career pathways (Kahn and Ginther 2017). A simplest possible implication of these two presumptions is that men and women sorting into STEM fields should be relatively similar in their competitiveness—in the sense that those sorting into STEM might each be relatively competitive.

However, whether and to what extent men's and women's responses to competition converge in STEM fields and do so in a manner consistent with current presumptions in the literature remains an empirical question. To test for gender differences in responses to competition across working-age adults and to investigate possible differences across fields, we report results from a field experiment covering 97,678 adults from a range of fields of training and ages.

Each individual in our study population was invited to participate in a three-week, part-time product development activity. This multidisciplinary product development activity was designed with the intent of being accessible, relevant, and meaningful to a wide cross section of invitees—whatever their (technical or nontechnical) field of training (see Section 3.1). The experiment focused on randomly assigning individuals to treatments that framed interactions with other participants as either *competitive* or *collaborative*. We, therefore, derive inferences by investigating how the likelihood of participation depended on assignment to competition versus collaboration treatments, conditional on gender and field of training (i.e., college majors in humanities, business, sciences, computer science, etc.), along with other personal characteristics.

In non-STEM fields, we find results that are consistent with the usual intuitions of gender-based differences in

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

competitiveness. Non-STEM men's and women's participation rates under the collaboration treatment were statistically equivalent, with roughly 3% choosing to participate. Non-STEM men's participation was also statistically the same under the competitive treatment. By contrast, non-STEM women participated significantly less frequently under competition, with a participation rate about a half percentage point lower (a 25.5% drop, relative to the participation rate in the collaboration treatment).

In STEM fields, we find patterns that are indeed consistent with men and women responding similarly to competition. Baseline participation rates were higher among those in STEM fields, with overall participation at roughly four percentage points. Participation rates for both STEM men and STEM women were about one percentage point lower under the competition treatment than under the collaboration treatment. Apart from simply being similar, this response to competition among STEM men and women is statistically indistinguishable from zero. (Sections 5.2 and 6 provide a fuller presentation and discussion of these results.) The results are robust to a series of alternative controls and specifications. We also validated these results in tests of 17 more narrowly defined STEM subfields.

Although, on the one hand, we find evidence wholly consistent with STEM men and women responding similarly to competition, the specifics of how they respond is not entirely consistent with simplest presumptions of prior behavioral research on responses to competition. Whereas we found similarities between STEM men and women, we did not find that these were because they both exhibited a similarly higher preference for participating under competition. Both STEM men and women were in fact more willing to participate under the collaboration regime. As we discuss in Section 6, we interpret this finding as consistent with those in STEM fields possessing a more contingent willingness to work under either competitive or collaborative conditions, depending on the demands of the context. In this context of a multidisciplinary novel product development task, the STEM subjects may have perceived advantages to collaborating. We provide a fuller interpretation of each of a range of documented patterns in Section 6.

Overall, this study takes steps toward clarifying limits of generalizing gender differences in competitiveness. By doing so, this paper continues to build bridges between research on gender and competition and questions of firms and organizations, outside of the laboratory. Organizational scholarship considering the implications of possible gender differences in competitiveness remains scarce (for an exception, see Brands and Fernandez-Mateo (2017). This paper also contributes to a growing number of studies examining how organizational designs and processes shape gender representation in STEM fields (e.g., Fernandez and Campero 2017, Wynn and Correll 2017, Murciano-Goroff 2022).

This paper proceeds as follows. Section 2 reviews the prior literature and develops our theoretical hypothesis. Section 3 describes the field experimental research design. Section 4 describes the data and variables. Section 5 reports the results. Section 6 summarizes and discusses the results. Section 7 concludes.

2. Background and Literature

This section reviews prior research on gender-based differences in responses to competition, clarifying the limits of generalizability and extrapolation beyond the existing studies. We also build on the existing consensus in the literature to develop our main predictions.

2.1. Existing Evidence Suggesting Gender Differences in Competitiveness

The bulk of existing evidence on gender differences in response to competition comes from laboratory experiments (e.g., Gneezy et al. 2003, Gneezy and Rustichini 2004, Niederle and Vesterlund 2011). The canonical experimental approaches have involved either comparing whether male and female laboratory subjects choose to work under competitive or noncompetitive conditions or, alternatively, evaluating the effect of competition on the performance of male and female subjects.

(Please note: We are somewhat constrained to refer to "males" and "females" in discussing the prior literature, given that the prior literature does not often or always observe men and women, and often instead observes boys and girls and young students in inferring binary gender differences. We will also follow convention within this literature of reporting empirical results in relation to a binary 1-0 variable, Female.)

To consider questions of generalizability, it is useful to review details of the existing research. For example, Niederle and Vesterlund's (2007) seminal laboratory experiment studied the behavior of 80 college students recruited from the University of Pittsburgh. This study has emerged as the canonical experimental protocol in the literature. The subjects sat in groups of two men and two women at a time and were asked to add two-digit numbers for five minutes. The subjects were asked to choose whether they would be paid according to a competitive scheme in which they would be paid \$2 for each correct answer if they correctly solved more problems than the other three subjects (i.e., a rank order tournament) or, alternatively, a noncompetitive piece rate of 50¢ per correct answer. The striking finding in this study was that twice as many male subjects chose competition as did female subjects (73% versus 35%). To help make the claim that the differences between male and female subjects could be interpreted as related to gender differences rather than unobserved factors correlated with the recruited subjects' gender, the authors pointed out that they found no statistical differences in male and female

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

subjects' ability to solve problems in preexperimental trials.[3] The authors also showed that a residual mean difference remained between male and female subjects after controlling for measures they constructed to reflect risk tolerance, aversion to receiving feedback, and self-confidence.[4] Additionally, men with low ability were interpreted as being overconfident, as they chose competition too often relative to their odds of winning. Women with high ability choose competition too infrequently relative to their odds of winning, and thus were interpreted as being averse to competition.[5]

These findings of male subjects exhibiting willingness to participate under competition, or otherwise performing better under competitive conditions than female subjects, have been replicated over other experimental tasks, subject pools, and variants on the original protocols (Paserman 2010, Healy and Pate 2011, Shurchkov 2012, Gupta et al. 2013, Dato and Nieken 2014, Dittrich et al. 2014, Morin 2015, Reuben et al. 2015, Sutter and Glätzle-Rützler 2015, Buser 2016, Comeig et al. 2016, Saccardo et al. 2017, Iriberri and Rey-Biel 2019).

In relation to the questions of this study, there are yet few studies concerning working-age adults and in relation to roles in the workforce. Reuben et al. (2015) found that a laboratory-based measure of the competitiveness in a set of MBA students differed between men and women and that this measure was correlated with entering high-paying industries after graduation. Additionally, Buser et al. (2021) used online survey data and found that a measure of competitiveness among those responding to the survey was associated with participants' completed level of education, field of study in college, occupation, and income. Research by Flory et al. (2015) is especially notable, as they reported on a field experiment that tested how rates of applications by administrative assistants to online job postings in multiple U.S. cities vary depending on the posted compensation scheme. The study finds that in cities where there are higher wages, women are less likely to apply to competitive pay schemes. The authors pointed out that this result can be interpreted as consistent with female administrative assistants avoiding competitive jobs if they have outside options.

2.2. Existing Evidence on Competition vs. Collaboration

Whereas many studies contrast competition with a lack of competition, particularly piece-rate regimes, a closely related stream of papers has contrasted female subjects' aversion to competition with an inversely related preference for collaborative or team-based work (Healy and Pate 2011, Dargnies 2012, Abramo et al. 2013, Kuhn and Villeval 2015). Much of this work follows the same basic outlines of the Niederle and Versterlund (2007) experimental protocol. In addition to comparing forms of competition versus noncompetitive (piece-rate) payment, these protocols include tests contrasting collaboration with competition or collaboration with a piece rate.

For example, in a study representative of this work, Dargnies (2012) evaluated 78 people recruited through an online system. She reported that women were more likely than men to choose to team, where team was operationalized as combining (averaging) scores when solving arithmetic problems with an anonymous unobserved teammate, as opposed to payoffs based on individual performance. Specifically, she found that men with high skills were less likely to accept this version of teaming when they were uncertain of the skills of their teammate. Healy and Pate (2011) carried out a similar protocol in an experiment involving 192 students from Loyola Marymount University, finding similar patterns. Kuhn and Villeval (2015) also implemented a similar protocol in a study of 174 students interacting online at a French University. The protocol was similar, in this case, except the choice between individual pay and pooled average outcomes was made without their being competition among teams. Again, female students disproportionately choose the nominally cooperative (shared payoffs) regime. The authors emphasize an interpretation of women experiencing inequity aversion and that the same confidence deficit that pushes women out of competitions pulls women into teams, where it is beneficial to have an abler teammate. The field experiment by Flory et al. (2015) involving online applicants for administrative assistant jobs included a treatment that mentioning teams in the compensation description for an administrative assistant job had a positive influence on the likelihood of women applying.

2.3. Limits to Extrapolating Beyond Existing Findings

Notwithstanding a considerable number of replication studies, there are important limitations to generalization that are well known to authors in this literature. A first challenge to extrapolating beyond the existing results is that the evidence is drawn from narrow contexts and narrow study populations, concentrated on schoolchildren and campus laboratory experiments with synthetic tasks. Important advances in field studies themselves remain somewhat pinpointed in coverage, such as the pathbreaking study by Flory et al. (2015), which focused on administrative assistants.

Narrow sampling of evidence places an especially large burden on theory to interpret generalizability. However, there is yet little consensus on underlying theoretical explanations and mechanisms. The prior research has suggested numerous plausible explanations for observed gender differences, emphasizing attitudes toward or preferences and tastes for competition (Croson and Gneezy 2009, Kleinjans 2009, Dohmen and Falk 2011), with an implication of possible biological and/or evolutionary factors playing some role (Lippa

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

1998, Knight 2002, Kivlighan et al. 2005, van Vugt et al. 2007, Buser 2009, Apicella et al. 2011, Wozniak et al. 2014). Other explanations include possible learned, socialized, or innate differences in overconfidence and self-efficacy (e.g., Niederle and Vesterlund 2007, Comeig et al. 2016), socialization of the stereotypes of gender roles (e.g., Gneezy et al. 2006), gender differences in subjective beliefs about the implications and meaning of competition (e.g., Kesebir et al. 2019), and differing psychophysiological tendencies of men and women to feel stress (Holt-Lunstad et al. 2001, Buckert et al. 2017). We might also interpret related streams of laboratory studies reporting analogous residual differences in risk attitudes, tastes for high-powered incentives, and aversion to feedback on performance as alternatives or complementary explanations for differences in preferences for competition (e.g., Byrnes et al. 1999, Eckel and Grossman 2008, Croson and Gneezy 2009). Despite the best efforts of the authors in this literature, the inability to randomize subjects' gender means it is not possible to entirely rule out the possibility of spurious factors, especially in small and highly selective study groups.

Apart from the limitations, above, a third challenge is the number of published results that run counter to findings of gender differences (many by the same authors). The authors of these contrarian studies have interpreted results to hypothesize that gender differences could depend on any number of added factors, including socialization, context, individual characteristics, and even how competition is operationalized (e.g., Gneezy et al. 2003, 2009; Günther et al. 2010; Dreber et al. 2011; Andersen et al. 2013; Boschini et al. 2019). More generally, these contrarian results point to a need for further research into possible boundary conditions and contingencies. At the same time, these contrary studies are not themselves immune to the same limitations as the studies described above. A number of these findings that are contrarian to popular intuitions are also contrarian to one another (see Appendix A).

2.4. Differences Across STEM and Non-STEM Fields?

Given the above limits to generalization in the literature, Flory et al. (2015, p. 122) note: "Whether, and to what extent, gender differences in attitudes toward competition lead to differences in naturally occurring labor markets remains an open question." Our empirical analysis to follow will make progress by reporting more widely sampled evidence on adults across the workforce than has been possible in the prior literature.

However, we first build on earlier research to develop theoretical predictions to better guide and support a generalizable interpretation of the analysis to follow. Below, we enumerate multiple arguments and behavioral mechanisms that suggest that *competitiveness among men and women should be significantly more similar among those in STEM fields than those in non-STEM fields and the wider population.*

Despite a lack of consensus on the theoretical mechanisms (Section 2.2), there are two widely accepted presumptions across much of the prior research that allow us to develop simple predictions. The first presumption is that individuals across the population are heterogeneous and somehow distributed in their propensity toward or aversion to competition. Where prior research has focused on mean gender differences, the presumption also implies there could potentially be considerable variance more generally, both among males and females. Some degree of variance of behavior among men and among women is observed in all prior studies, even small studies.

A second key presumption of the prior literature is that competitive individuals tend to sort themselves into competitive fields (Antonovics et al. 2009, Niederle and Vesterlund 2010, Buser et al. 2014, Balafoutas et al. 2018), and particularly within education and within careers thereafter. The greatest available evidence supporting this presumption relates to mathematics and STEM fields. Specifically, the literature has gone as far to report correlations between measures of competitiveness and sorting into math and STEM fields (Antonovics et al. 2009, Buser et al. 2014, Reuben et al. 2015, Pregaldini et al. 2020). Strictly speaking, this evidence cannot rule out the possibility that sorting occurs based on unobserved characteristics that are merely correlated with competitiveness. This point remains a fundamental limitation in interpreting empirical results, even those of experiments, in this area.

To the extent that these premises are correct and produce economically significant effects, the competitiveness of working-age adults in the economy should reflect some degree of sorting into fields based on competitiveness. Thus, inasmuch as STEM fields are perceived to be more competitive, they should tend to attract more competitive men and women, leading to greater similarities among the men and women selecting these fields. This is an empirical question—and the one studied here.

3. Experimental Research Design

The goal of the latter half of this paper is to empirically investigate gender differences in competitiveness across a widely sampled study population of working-age adults, and to test our prediction that gender differences in response to competition should vary by field (Section 2.3).[6]

3.1. Research Context

This research was carried out in partnership with a large R1 research-oriented university in the United States with roughly 20,000 undergraduate students, 8,000 graduate students, and several hundred thousand alumni in its network. The university is in the top 40 ranked colleges and universities according to the *U.S. News & World Report* list

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

of the best U.S. universities with ranked undergraduate programs in engineering, computer science, and business.

The university runs an online platform-based program to allow alumni and students to gather in teams and compete with each other to design new products related to internet-of-things (IoT).[7] The objective of the program is to provide participants with opportunities to design IoT products ("applications"), to gain an understanding of IoT technologies and opportunities, and to learn how these technologies can be relevant to participants' work organizations and sectors. The program also provides experience in increasingly standard product development work practices from "use case" design to technical design and business case design. These goals are achieved through a series of part-time learning-by-doing product development activities. These exercises are organized as team-based competitive "challenges" or rank-order tournaments. Although people sign up as individuals, they are assigned to teams by the platform. To make the program as readily and widely accessible as possible, all activities are hosted on an online platform that allows individuals to participate from any location during off hours outside of work or school.

The program involves a minimum of three weeks of part-time commitment of one's off hours, participating in at least one product development exercise. For this opportunity cost, individuals can benefit from participating in interesting projects, learning, interacting with members of the university community, receiving feedback on designs, and receiving cash prizes. Several teams also benefited by taking the ideas and designs they developed on the platform into follow-up entrepreneurial development (off the platform). The opportunity is promoted as highly relevant to all students and alumni, in terms of developing multidisciplinary product development skills, and in terms of exposing both nontechnical and technical individuals to technical and business opportunities made possible by the internet-of-things. The platform work and learning process was designed with the philosophy of low floors and high ceilings (Boaler 2016) to engage a wide range of participants. Thus, relative neophytes could productively engage in learning about the technology and contributing to designs, by following defined steps and platform tools. Meanwhile, the platform also provides pathways for relative experts in the fields to channel their expertise to develop designs. The platform has grown to more than 5,500 participants and includes participants from all fields of training and career stages in all U.S. states and five continents.

3.2. Timeline and Procedure

Embedding our experiment in the initial launch of the platform allowed us to be part of a one-time process of mass communication with 97,678 potential adopters under highly controlled conditions. By tracking responses of this known set of individuals for whom descriptive data are available, the effect of random assignment to the competition collaboration treatments can be assessed.

3.2.1. Randomized Assignment to Competition and Collaboration Treatments. An introductory email introduced individuals to the opportunity, inviting them to the platform to learn more details and join. Invitation emails were sent over 60 business days, with individuals randomly assigned to each day. Spreading invitations over time allowed the engineering team to monitor platform scaling while minimizing the risk that any one day could produce eccentric results.

Individuals were randomly assigned to competition or collaboration treatments with the aim of influencing subjects' perceptions of interactions they would encounter with other participants. Subjects were assigned to receive different emails depending on their treatment. Within the email invitation, they could click on a link in the email to send them to the platform ("Click HERE to learn more and to sign up to the platform"). The platform landing page also provided additional details including high-level descriptions of the technical nature of IoT and the opportunity to create new products and applications. The version of the platform landing page to which they were sent also depended on whether they were in the competition or collaboration treatment, where these platforms differed only in the sense of repeating the distinct language used in the emails.

The details of both the emails and landing pages varied in the same way, depending on the treatment. What follows are the relevant subset of distinguishing words from both the email and the platform, respectively, for the competition treatment (emphasis added):

> This is a two-sided *competitive* platform to ideate and innovate "smart" Internet-of-Things (IoT) products and services—using hardware, software, networking, data and algorithms.
>
> On one side of the platform, companies seek solutions to their IoT innovation challenges. On the other side, *you will compete with other participants to solve IoT innovation problems* of companies for cash and other benefits.

For the collaboration treatment, the italic words were replaced with "*collaborative platform*" and "*you will work within a team to solve IoT innovation*." Therefore, the content and length were virtually identical for both treatments, except for these key words.

Individuals who did not act on the email were sent a single reminder seven days later. We explicitly added a line in the email stating that the invitation was not transferable or to be forwarded. Nonetheless, there were 26 instances of forwarding of emails. We were

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

able to detect such forwarding, and we removed these instances from our analyses.

Once on the platform, individuals could choose to participate by clicking on a red "join and participate" button prominently displayed on the site. Users were prompted to log in with their LinkedIn passwords. This sign-in and authentication allowed their LinkedIn picture, name, link, and brief blurb to be used to create their platform profiles.

The analytics generated by the email management system (Mailchimp) and the platform allowed us to determine the number of people among the 97,678 receiving invitations who positively double-clicked to open the invitation they received and then proceeded to the platform. Positive confirmation of opening rates for females and males were statistically identical, with 46.5% of females and 45.9% of males opening. The true rate at which individuals read emails will be higher, as the email management system tracked active clicking on emails. However, most modern browsers allow one to read an email without double-clicking to open an email. Furthermore, even the title of the email mentioned the institution's "competitive platform" or "collaborative platform" for IoT product development. Therefore, even reading the title implied exposure and treatment. We cannot be sure of the true share of emails that were not read. To the extent that there is some fraction of our study population that did not, in fact, read the invitation, we should expect weaker statistical results in our analysis.

3.2.2. Controlled and Independent Bilateral Communications. A crucial aspect of running this experiment was to carefully control the information environment. Running the experiment during the initial launch campaign, at a time when prospective adopters had no prior experience or preconceived notions of the platform, allowed us to selectively emphasize the competitive or collaborative aspects of the platform in our communications. By implementing alternative emails and entirely separate platforms with distinct communications, we could present separate and controlled information to each subject, depending on the treatment. Importantly, the information presented in both the competitive and collaboration treatments was also truthful, as the platform and program within which subjects would eventually participate would involve competition among teams.

In controlling the information environment, it was also important that the *only* form of communication and marketing of this initial 60-day campaign be this sequence of bilateral interactions with the platform that would occur prior to opening the platform to development events. For example, there was no simultaneous broad-based marketing campaign. We were also aware of the possibility that individuals within the experiment might potentially, themselves, share messages with their peers. If messages were to be shared with other subjects in our study population, resulting in the mixing of treatments, this would likely weaken any treatment effect by mixing messages. We attempted to minimize such interactions by adding a line to all communications indicating that the subjects should not forward any messages. Using tracking and analytics, we found that among the tens of thousands of communications, there were only 26 instances of forwarding. We removed these instances from our data set; doing so had no effect on the results. We also considered the possibility that any interactions and information diffusion occurring between individuals could be more likely toward the end of the 60-day campaign. However, including time controls, even individual-day fixed effects, showed no effect on results.

3.3. Links with the Prior Experimental Literature

The experimental protocol here is based directly on previous research in the literature on competition and gender (Section 2.1). To observe whether individuals participate conditional on the organizational regime, our experimental protocol follows prior work from Samek (2019), for example. The advantage of this approach is that it allows us to assess preferences to participate under each regime independently (relative to an outside option of not participating). The alternative in the literature is to recruit only those subjects who are willing to participate (as when recruiting to a campus laboratory experiment) and then ask individuals to choose the regime they would prefer, effectively providing a rank-order preference for one regime versus the other, rather than an independent evaluation of each regime. Another advantage of studying whether people participate or not under either regime independently is that we are able to explicitly observe the selection process into participation in the exercise, rather than having the selection process be part of recruitment to the experiment.

Our approach also follows the approach of prior studies that compare willingness to work under competition with willingness under collaborative regimes (e.g., Healy and Pate 2011, Dargnies 2012, Abramo et al. 2013, Kuhn and Villeval 2015), as opposed to comparing preferences with a piece-rate regime (e.g., Niederle and Vesterlund 2007). This approach has natural advantages in our context, as it is simply not feasible to implement a piece rate for innovation, development, and uncertain learning and problem solving in our context of developing novel IoT projects. In practice, we also exploited the organization of competitions on the platform between teams as a means of focusing on competitive or collaborative and team-based treatments while scrupulously avoiding deception of any of our subjects in any of our communications.

Prior research tends to operationalize competition and collaboration as a matter of either a small (often

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

two-person) winner-take-all rank-order tournament for competition or averaging performance payoffs for collaboration (see Section 2.1). Here, we simply directly use the words "competitive" and "collaborative" to describe the organizational context, allowing subjects to discern for themselves what should be meant by these terms in an organizational context where they carry out work and learning akin to activities in industry.

The largest and most important departure from the bulk of previous research in the literature focused on gender-based differences in competitiveness is that ours is a field experiment rather than a laboratory experiment involving synthetic tasks. Among the field experiments in this study, this paper comes closest to that of Samek (2019), in the sense of examining who applies for an office support job, conditional on organizational regime. She focuses on a study population of students. This work is also arguably closely related to the study by Flory et al. (2015), which also involved a large field experiment, involving nearly 9,000 subjects; although that study focused on only a market for administrative assistants. Here, we examine a considerably larger number of college-educated adults from all fields.

4. Data, Variables, and Descriptive Statistics

Our study population included 97,678 people in the risk set of potential platform adopters. (A broader population was targeted by the platform, but this number includes the individuals identified and assigned to treatments during the experiment.) Data for these individuals were kindly provided by the institution, matched and anonymized before the launch. The data set included data on majors, graduation years, and academic performance (cumulative undergraduate grade point averages (GPAs)) for 13,926 individuals from cohorts after 2009. Furthermore, we used an online application programming interface–based service (https://gender-api.com) to probabilistically assign the vast majority of names in our data set to genders. Table 1 describes the main variables used in the analysis. Figure 1 summarizes the distribution of individuals and the gender breakdowns by GPA and cohort (reported in terms of age).

The participation rates of men and women in STEM fields were 3.97% and 4.47%, respectively; in non-STEM fields, they were 2.62% and 1.98%, respectively. Participation was higher for men than for women, and this was true across ages and academic performance, shown in Figure 1.[8]

Therefore, the initial platform launch attracted thousands of adopters from the risk set. According to university officials, these participation rates were (very) high relative to most other university programs and clubs directed at both students and alumni. These levels of participation are also higher than in most comparable prior studies. For example, Samek (2019) advertised a research assistant position to 35,462 university students and received applications from 1.38%, from which she derived inferences by comparing differences in participation across treatments. These adoption rates might also be regarded to be high in relation to, say, a

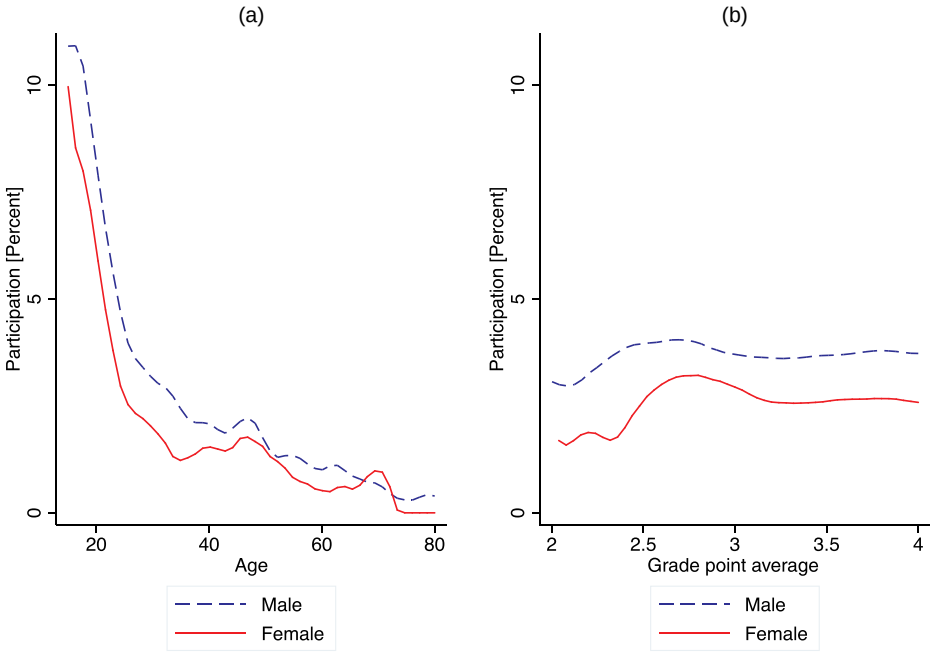
Table 1. Descriptive Statistics of the Main Variables

Variable	Mean	SD	Description
Participation	0.03	0.17	An indicator variable that is switched to one for those subjects who chose to participate
Competition	0.50	0.50	An indicator variable that is switched to one for those randomly assigned to the competitive treatment (as opposed to the collaborative comparison group)
Female	0.44	0.50	An indicator variable that is switched to one for female subjects
STEM	0.33	0.47	An indicator variable that is switched to one for those in computer science, engineering, or sciences
Student	0.08	0.27	An indicator variable that is switched to one for subjects currently enrolled as students
CohortYear	1998.7	16.0	Year of matriculation
GPA	3.01	1.17	Cumulative undergraduate college grade point average
Day	30.5	17.3	Count variable from 1 to 60 for each of the days in which invitations were sent (not including weekends and
Engineering	20%	40%	Indicator variable for business major
Law	4%	19%	Indicator variable for computer science major
Computer Science	4%	19%	Indicator variable for design and media major
Health and Nursing	17%	37%	Indicator variable for engineering major
Design and Media	7%	25%	Indicator variable for health and nursing major
Business	25%	43%	Indicator variable for humanities major
Humanities	14%	35%	Indicator variable for law major
Sciences	9%	28%	Indicator variable for sciences major

Notes. The number of observations is 97,678 for all variables with the exception of *CohortYear*, for which we have 90,087 observations. Data for *GPA* were available for only a subset of 13,926 observations in the post-2009 data. SD, Standard deviation.

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Figure 1. Gender Differences in Participation by Age and Academic Performance



Notes. In panel (a), age is used rather than graduation year in the interest of more direct interpretation. Age is based on graduation year and approximated according to the approximation that graduation occurs at the age of 22 or thereabouts. Panel (b) summarizes differences in participation across males and females in relation to GPA with a quadratic fitted curve.

typical platform launch by a private company, who might typically not expect to achieve multiple percentage points of adoption among the general population in the first couple months of operation. By contrast, those studies that nonrandomly select their participants conditional on an expression of interest in participating, of course, tend to find higher eventual participation rates (e.g., Niederle and Vesterlund 2007, Flory et al. 2015).

Although randomization should ex ante lead to equal groups in treatment and control, Table 2 tests and confirms that observable characteristics of those assigned to competition and collaboration treatments were virtually identical.

5. Results

5.1. Baseline Study Population Average Gender Differences

This first subsection begins by replicating findings from previous research.[9] We show that response to competition (in terms of percentage difference in participation rates between the competition treatment and collaboration treatment) is greater for women than for men in the study population average. The magnitude of the gender difference is only marginally statistically significant and smaller than in prior laboratory experimental research (Section 2).

Model (1) of Table 3 reports gender differences in participation rates, regressing the participation indicator on the gender dummy *Female* and constant in a linear probability model. Heteroskedasticity-robust standard errors are reported.[10] Coefficients are expressed as percentage points (i.e., 100 = 100%). The constant term, or probability of males participating, is 3.19. The coefficient in the female dummy is highly significant, −0.67 percentage points (p = 0.0001).[11] This result means that women are 21% (i.e., −0.67/3.19) less likely to participate on average than are men, overall.[12]

Model (2) adds the indicator for the dummy variable for *Competition* to the model, revealing that those assigned

Table 2. Balance of Assignment Groups

	Competition treatment		Collaboration comparison group	
Variable	Mean	SD	Mean	SD
Female	44.63%	49.71%	44.33%	49.68%
STEM	32.68%	46.91%	32.68%	46.91%
Student	7.88%	26.95%	7.65%	26.57%
CohortYear	1998.8	16.0	1998.7	16.0
GPA	3.01	1.17	3.00	1.18
Day	30.5	17.3	30.4	17.3
Engineering	20.44%	40.32%	20.17%	40.13%
Law	3.70%	18.87%	3.76%	19.02%
Computer Science	3.65%	18.76%	3.62%	18.67%
Health and Nursing	16.82%	37.40%	16.95%	37.52%
Media and Design	6.67%	24.95%	6.57%	24.77%
Business	24.74%	43.15%	25.02%	43.31%
Humanities	14.22%	34.93%	13.98%	34.68%
Sciences	8.59%	28.03%	8.89%	28.46%

Note. SD, Standard deviation.

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Table 3. Baseline Ordinary Least Squares Model Estimates of Participation Rates for Study Population Averages

	Dependent variable: *Participation* (percentage points)								
	(1) Gender	(2) Treatment	(3) Interaction	(4) Day controls	(5) Student controls	(6) Cohort controls	(7) Subsample with GPA	(8) GPA controls	(9) All controls
Female	−0.67***	−0.67***	−0.67***	−0.67***	−0.81***	−1.04***	−1.15***	−1.13***	−1.31***
	(0.11)	(0.11)	(0.16)	(0.16)	(0.16)	(0.15)	(0.28)	(0.28)	(0.28)
Competition		−0.71***	−0.71***	−0.71***	−0.73***	−0.61***	−1.22***	−1.22***	−1.09***
		(0.11)	(0.15)	(0.15)	(0.15)	(0.14)	(0.27)	(0.27)	(0.27)
Female × Competition			0.00	−0.01	0.02	−0.06	0.30	0.30	0.19
			(0.21)	(0.21)	(0.21)	(0.20)	(0.37)	(0.37)	(0.37)
Student					6.75***				2.95***
					(0.33)				(0.50)
CohortYear						0.078***			−0.09***
						(0.00)			(0.01)
GPA								−0.16*	-0.030
								(0.08)	(0.08)
Day FEs				Yes					Yes
Constant	3.19***	3.54***	3.54***		3.09***	−151.89***	4.35***	4.81***	
	(0.08)	(0.10)	(0.11)		(0.11)	(5.83)	(0.21)	(0.33)	
Adjusted R^2	0.000	0.001	0.001	0.001	0.012	0.011	0.002	0.002	0.008

Notes. Ordinary least squares linear probability model coefficients are reported as percentage points (i.e., 100% = 100). Heteroskedasticity-robust standard errors reported in parentheses. FEs, Fixed effects.

*$p < 0.1$; ***$p < 0.01$.

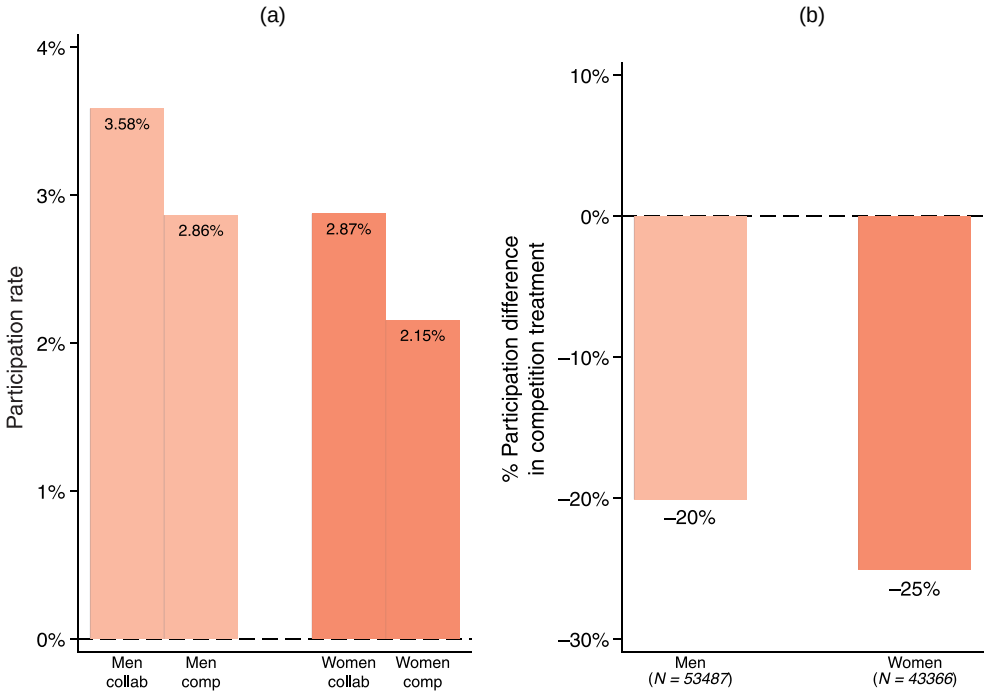
to the competition treatment are 0.71 percentage points ($p = 0.0001$) less likely to participate than those assigned to the collaboration treatment. Model (3) introduces an interaction between competition and gender. The coefficient of this interaction is statistically zero, which means that there is no absolute change difference between men and women. These basic differences between men's and women's responses are summarized in an equivalent comparison of unconditional participation rates in panel (a) of Figure 2.

Therefore, the absolute difference in participation differences across competition and collaboration treatments is statistically the same for men and women. However, as baseline levels of participation differ, we also test whether the *percentage* differences across competition and collaboration for men and women statistically differ. A comparison of percentage changes arguably also provides a more direct comparison with prior experimental results (Section 2), in which subjects necessarily proceed to participate, and the percentage of subjects choosing one work regime or another is reported. Figure 2 summarizes the results of model (3) (equivalently, Figure 2) in terms of percentage changes, that is, $\frac{Participation(Competition) - Participation(Collaboration)}{Participation(Collaboration)}$. The difference in women's participation rates in the collaboration and competition treatments is $\frac{\beta_{Competition} + \beta_{Female \times Competition}}{constant + \beta_{Female}} = -24.86$ percent. For men, this difference in participation rates is $\frac{\beta_{Competition}}{constant} = -20.08$ percent. A Wald test of the nonlinear restriction that these percentages are the same, $H_0 : \frac{\beta_{Competition}}{constant} = \frac{\beta_{Competition} + \beta_{Female \times Competition}}{constant + \beta_{Female}}$, is significant at $p = 0.097$. These differences are summarized graphically in panel (b) of Figure 2.

These population-average results would appear to be robust to numerous alternative controls and specifications (aside from accounting for field differences, as in Section 5.2). The pattern of negative coefficient estimates on *Female* and *Competition*, implying a greater negative percentage response to competition among women, does not change when controlling for a series of dummies corresponding to the day an individual was invited to join (model (4)), whether subjects are students or graduates (model (5)), or age (equivalently, cohort; model (6)). We also find similar patterns when controlling for college cumulative GPA (model (8)) or all controls at once (model (9)). Note that because tests with college GPA data include only the 13,926 individuals from cohorts after 2009, for which we have GPA data, we also report main model results with just this subset of observations (model (7)) to provide a more direct comparison of results in models (8) and (9). The coefficients in model (7), estimated in the subsample, and those of model (3) are the same in sign and similar in the relative size ratios between the model coefficients. However, the magnitudes are larger in model (7), as this subsample comes from more recent graduates, where overall participation is higher in younger cohorts (see Figure 1). This is consistent with possible higher returns or lower opportunity costs to participate in this exercise among younger cohorts.

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Figure 2. Differences in Participation and Response to Treatment by Sex, Overall Averages



Notes. Panel (a) is the graphical equivalent of regression results presented in model (3) of Table 3. Panel (b) presents the equivalent information in terms of percentage differences in participation under competition, that is, $\frac{Participation(Competition)-Participation(Collaboration)}{Participation(Collaboration)}$. The difference between percentage differences in responses of men and women in panel (b) is weakly significant at $p = 0.097$, based on a nonlinear Wald test of their equivalence. Collab, Collaboration; comp, competition.

5.2. Main Results: Differences Between Fields

This subsection investigates our main prediction that gender responses to competition differ by field (Section 2.3).

5.2.1. Controlling for Fields. As a first step, we investigate whether simply controlling for a series of dummies for field of training affects the earlier result of Section 5.1. In Table 4, models (1) and (3) rereport population average results, both without and with the competition treatment effects. Models (2) and (4) then reestimate these models with field dummies. Whereas results of Section 5.1 were highly robust to a wide range of alternative controls and tests, here we see that including controls for field fundamentally alters key coefficient estimates. Most striking, comparing model (1) to model (2) shows that controlling for field differences leads the coefficient on *Female* to reverse its sign. Comparing models (3) and (4) also finds this reversal of the sign on the *Female* coefficient, once controlling for field fixed effects.

The coefficients on the field dummies are reported in Table 4, ordered by their magnitude. The estimates indicate that those in the STEM fields of computer science, engineering, and science are more willing to participate than those in other fields. This is consistent with product development in the internet-of-things perhaps being more immediately accessible or interesting to those in STEM fields (even despite the considerable efforts to make this activity relevant, accessible, and interesting to all fields; see Section 3.1).

5.2.2. Gender Differences in STEM vs. Non-STEM Fields. We now test our specific hypothesis of Section 2.3, that gender differences in STEM fields should be significantly smaller than those in non-STEM fields. Our approach is simply to stratify results from the above model by those in STEM versus non-STEM fields. (Recall that *STEM* is defined in this context to include engineering, computer science, and sciences.) Model (1) of Table 5 begins by simply restating overall results, controlling for fields, as a basis for comparison. Models (2) and (3) reestimate the results stratified by subsets of non-STEM and STEM observations. Model (2) reports that in non-STEM fields, the difference between participation under competition and that under collaboration for women is 0.47 percentage points more negative than that for male counterparts in the same fields, significant at $p = 0.05$ (i.e., the coefficient on *Female* × *Competition*). Model (3) reports that in STEM fields, this difference of participation versus competition is not statistically different between women and men. Note, too, in model (3), that those in STEM fields are generally more willing to participate in the collaboration regime than they are in the competition regime (i.e., negative coefficient

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Table 4. Ordinary Least Squares Model Estimates of Participation Rates, Controlling for Fields

	Dependent variable: *Participation* (percentage points)			
	(1) Population average	(2) Field controls	(3) Population average	(4) Field controls
Female	−0.67***	0.25**	−0.67***	0.40**
	(0.11)	(0.12)	(0.16)	(0.17)
Competition			−0.71***	−0.43***
			(0.15)	(0.15)
Female × Competition			0.00	−0.29
			(0.21)	(0.21)
Computer Science		7.03***		7.25***
		(0.43)		(0.44)
Engineering		3.97***		4.18***
		(0.14)		(0.16)
Sciences		2.98***		3.18***
		(0.20)		(0.22)
Business		2.75***		2.96***
		(0.11)		(0.14)
Design and Media		2.59***		2.80***
		(0.22)		(0.24)
Humanities		2.07***		2.28***
		(0.14)		(0.16)
Law		1.43***		1.63***
		(0.22)		(0.23)
Health and Nursing		1.06***		1.27***
		(0.13)		(0.16)
Constant	3.19***		3.54***	
	(0.08)		(0.11)	
Adjusted R^2	0.000	0.030	0.000	0.030

Notes. Ordinary least squares linear probability model coefficients are reported as percentage points (i.e., 100% = 100). Heteroskedasticity-robust standard errors reported in parentheses.
**$p < 0.05$; ***$p < 0.01$.

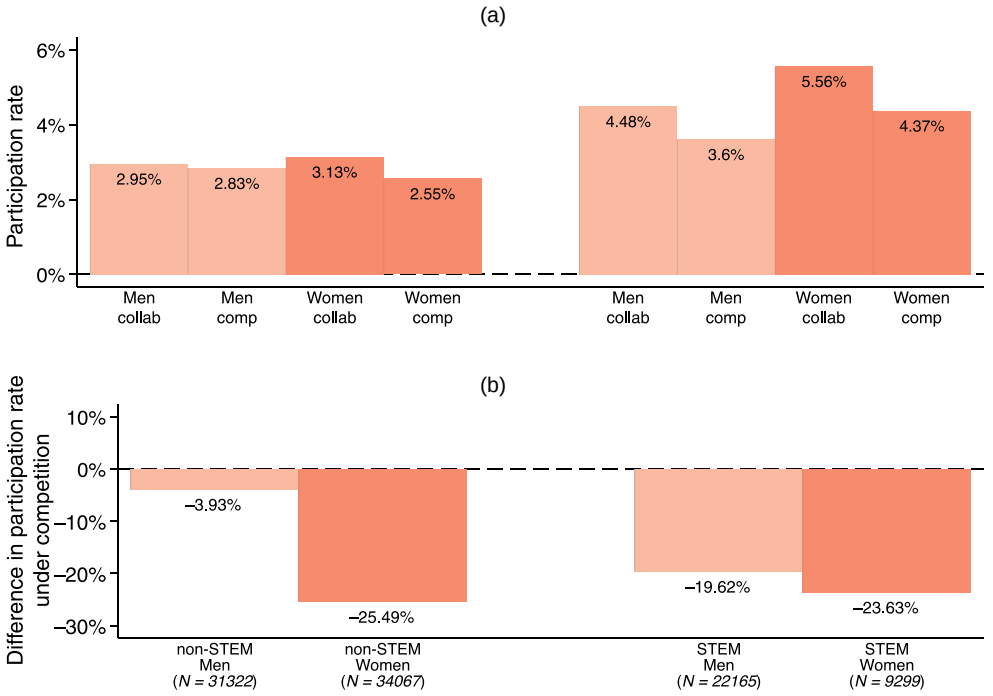
Table 5. Ordinary Least Squares Model Estimates of Participation Rates Stratified by STEM and Non-STEM

	Dependent variable: *Participation* (percentage points)			
	(1)	(2) Non-STEM subset	(3) STEM subset	(4) Pooled interactions
Female	0.40**	0.20	1.13***	0.20
	(0.17)	(0.19)	(0.40)	(0.19)
Competition	−0.43***	−0.11	−0.87***	−0.11
	(0.15)	(0.18)	(0.26)	(0.18)
Female × Competition	−0.29	−0.47**	−0.32	−0.47**
	(0.21)	(0.23)	(0.50)	(0.23)
STEM Field × Female				0.93**
				(0.44)
STEM Field × Competition				−0.77**
				(0.32)
STEM Field × Female × Competition				0.16
				(0.55)
Field FEs	Yes	Yes	Yes	Yes
Adjusted R^2	0.03	0.02	0.05	0.03

Notes. Ordinary least squares linear probability model coefficients are reported as percentage points (i.e., 100% = 100). Heteroskedasticity-robust standard errors reported in parentheses. Note that among the 97,678 observations, 31,923 are associated with those trained in STEM fields, and 65,755 are associated with non-STEM fields. FEs, Fixed effects.
**$p < 0.05$; ***$p < 0.01$.

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Figure 3. Treatment Effects, Conditional on Field, by STEM and Non-STEM



Notes. Panel (a) is the graphical equivalent of regression results presented in models (2) and (3) or, equivalently, model (4) of Table 6. Panel (b) presents the equivalent information in terms of percentage differences in participation under competition, that is, $\frac{Participation(Competition)-Participation(Collaboration)}{Participation(Collaboration)}$. The difference in non-STEM men's and women's percentage differences between competition and collaboration (i.e., panel (b)) is significant at $p = 0.01$, based on a nonlinear Wald test of their equivalence. This gender difference in percentage difference for STEM fields is significant at $p = 0.73$—or, not statistically significant in the least. Collab, Collaboration; comp, competition.

estimated on the *Competition* variable). These responses, stratified by men and women and by non-STEM and STEM fields, are graphically summarized in panel (a) of Figure 3. Model (4) summarizes the same information of models (2) and (3), or panel (a) of Figure 3, within a single regression specification. (This alternative compact way of summarizing results will be referred to in robustness results, below.)

We also test whether the *percentage* differences across competition and collaboration for men and women in STEM and non-STEM fields are significantly different from one another. Panel (b) of Figure 3 presents our results of models (2) and (3) as percentage differences in participation rates, stratified by gender and STEM versus non-STEM fields, that is, $\frac{Participation(Competition)-Participation(Collaboration)}{Participation(Collaboration)}$.

As summarized in Figure 3, men and women in non-STEM fields show large differences in their responses to the competition treatment, with differences in participation of −3.93% and −25.49% in relation to the collaboration treatment, respectively. A Wald test of the nonlinear restriction that these percentages are the same, $H_0 : \frac{\beta_{Competition}}{\mu_{Non-STEM\ Female,\ Collaboration}} = \frac{\beta_{Competition}+\beta_{Female\times Competition}}{\mu_{Non-STEM\ Female,\ Collaboration}}$ in model (4), is significant at $p = 0.01$.

Consistent with our main prediction, and in stark contrast to the above patterns in non-STEM fields, men and women in STEM fields respond similarly to the competition treatment. The differences in participation for men and women in response to the competitive treatment are −19.62% and −23.63%, in relation to participation in the collaboration treatment. A Wald test of the nonlinear restriction that these percentages are the same, $H_0 : \frac{\beta_{Competition}}{\mu_{Non-STEM\ Female,\ Collaboration}} = \frac{\beta_{Competition}+\beta_{Female\times Competition}}{\mu_{Non-STEM\ Female,\ Collaboration}}$, is not statistically significant in the least (i.e., $p = 0.73$).

5.2.3. Robustness of Main Results. Additional tests reported in Table 6 assess whether results in model (4) of Table 6, are robust to controls for other factors influencing benefits and costs of participating. We indeed find the results to be robust.

For example, model (1) begins by rereporting the earlier patterns for comparison. Model (2) tests the possibility that the age and cohort distributions of men and women could vary between fields in ways that lead to spurious findings, and adds age as a control. There is no effect on the coefficients of the main model. Controlling for a quadratic time trend or distinct time trend for each gender does not affect results (not reported).

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Table 6. Robustness Tests

	Dependent variable: *Participation* (percentage points)				
	(1) Main result	(2) Cohort	(3) Opportunity cost	(5) GPA subsample	(6) GPA
Female	0.20	−0.10	0.01	−0.17	0.79
	(0.19)	(0.19)	(0.20)	(0.35)	(0.60)
Competition	−0.11	−0.01	−0.01	−0.40	−0.42
	(0.18)	(0.18)	(0.18)	(0.34)	(0.34)
Female × Competition	−0.47**	−0.57**	−0.58**	−0.73*	−0.71
	(0.23)	(0.23)	(0.23)	(0.44)	(0.44)
STEM Field × Female	0.93**	0.44	0.38	−0.89	−0.87
	(0.44)	(0.44)	(0.44)	(0.66)	(0.66)
STEM Field × Competition	−0.76**	−0.84***	−0.83***	−1.33**	−1.31**
	(0.32)	(0.31)	(0.31)	(0.56)	(0.56)
STEM Field × Female × Competition	0.15	0.20	0.22	2.10**	2.09**
	(0.55)	(0.55)	(0.55)	(0.84)	(0.84)
Child-Rearing Years			−0.98***		
			(0.22)		
Child-Rearing Year × Female			−0.43		
			(0.27)		
GPA					0.12
					(0.12)
GPA × Female					−0.33**
					(0.16)
Age		−0.09***	−0.09***	−0.08***	−0.08***
		(0.00)	(0.00)	(0.01)	(0.01)
Field FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.03	0.04	0.04	0.04	0.04
No. of observations	97,696	97,696	97,696	36,345	36,345

Notes. Ordinary least squares linear probability model coefficients are reported as percentage points. (i.e., 100% = 100). Heteroskedasticity-robust standard errors reported in parentheses. FEs, Fixed effects.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

We also test whether variation in opportunity costs could be a spurious factor. To test for this possibility, we include a measure of an important source of opportunity costs, being in one's child-rearing years.[13] Model (3) includes an indicator switched on for ages 29 through 35 along with an interaction with gender. The years of child rearing are associated with lower participation, but the main results remain unchanged.

Model (4) tests whether a measure of aptitude (academic achievement) might somehow be a spurious factor in the model. We first reestimate the main model on the subsample for which we have GPA data to confirm similar patterns (model (4)). Model (5) then reestimates the model while including GPA and GPA interacting with gender. A first point to observe is that accounting for GPA does not alter main coefficients, comparing coefficient estimates in models (4) and (5). In this sense the results are robust to including GPA. We remark, too, that the considerably larger coefficient on the three-way interaction *STEM Field* × *Female* × *Competition* suggests even greater (more positive) differences in response to competition among women in STEM for whom we have GPA data (i.e., younger cohorts).

5.3. Gender Differences Across STEM Subfields

This section reestimates our model over 17 more narrowly defined STEM subfields in order to determine whether we continue to see similarities in men's and women's responses to competition at the level of individual subfields.

In short, despite considerable variation in overall participation rates across individual STEM subfields, we see that responses to competition among men and women are similar when examined at the level of subfields. To study patterns at the level of subfields, we worked with university staff familiar with the dozens of degrees offered in these fields to map them to subfields, listed in Table 7. Degrees with ambiguous mappings were removed from this subfield analysis. (Computer science during the study period does not break down into separate degrees or subfields.[14]) We kept within the analysis here all STEM subfields with at least 200 individuals.

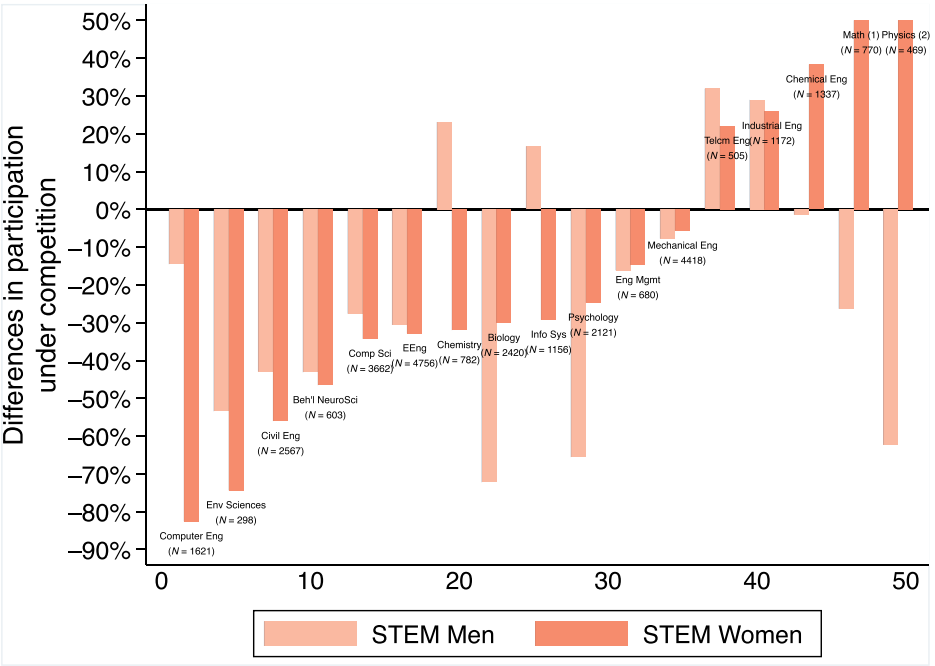
Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Table 7. Ordinary Least Squares Model Estimates of Participation Rates, Estimated Separately on STEM Subfields

		Dependent variable: *Participation* (percentage points)							
		Female		*Competition*		*Female × Competition*		Constant	
	No. of observations	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Behavioral neuroscience	603	1.49	(2.01)	−0.95	(1.98)	−0.77	(2.56)	2.20	(1.54)
Biology	2,420	−0.79	(0.96)	−2.26	(0.84)	1.55	(1.15)	3.13	(0.75)
Chemical engineering	1,337	1.11	(1.48)	−0.03	(0.88)	1.20	(2.24)	1.94	(0.61)
Chemistry	782	1.57	(1.78)	0.45	(1.37)	−1.58	(2.39)	1.95	(0.87)
Civil engineering	2,567	3.52	(1.65)	−0.61	(0.45)	−2.16	(1.99)	1.42	(0.36)
Computer engineering	1,621	1.10	(2.59)	−0.87	(1.26)	−4.98	(2.86)	5.98	(0.93)
Computer science	3,662	0.87	(1.55)	−2.24	(0.99)	−0.84	(2.00)	8.11	(0.75)
Electrical engineering	4,756	1.64	(1.31)	−0.86	(0.47)	−0.60	(1.70)	2.80	(0.36)
Engineering management	680	2.21	(3.18)	−0.72	(1.80)	−0.27	(4.21)	4.45	(1.32)
Environmental sciences	298	2.12	(3.23)	−1.57	(2.48)	−2.19	(3.74)	2.94	(2.06)
Industrial engineering	1,172	2.71	(2.14)	0.79	(1.16)	0.62	(3.29)	2.72	(0.78)
Information systems	1,156	−0.91	(2.00)	0.99	(1.94)	−2.48	(2.74)	5.97	(1.33)
Mathematics	770	−2.49	(1.47)	−0.94	(1.64)	6.40	(2.89)	3.59	(1.25)
Mechanical engineering	4,418	0.56	(1.17)	−0.20	(0.51)	0.02	(1.61)	2.64	(0.37)
Physics	469	−4.26	(1.48)	−2.65	(1.74)	4.87	(2.81)	4.26	(1.48)
Psychology	2,121	−0.82	(1.08)	−1.90	(1.11)	1.38	(1.31)	2.89	(0.95)
Telecommunications engineering	505	−3.18	(3.69)	3.32	(3.64)	−1.73	(5.77)	10.40	(2.33)

Note. This table reports participation percentage changes in the competition treatment for both men and women, stratified by STEM subfield. SE, Standard error.

Figure 4. Percentage Differences in Participation Under the Competition Treatment in STEM Subfields



Notes. The graph presents percentage differences in participation between those in the competition treatment and those in the collaboration comparison group for both men and women, that is, $\frac{Participation(Competition)-Participation(Collaboration)}{Participation(Collaboration)}$, stratified by both sex and STEM subfields. Only gender differences for computer science are found to be statistically significant at conventional levels ($p = 0.01$), based on nonlinear Wald test of $H_0 : \frac{\beta_{Competition}}{constant} = \frac{\beta_{Competition}+\beta_{Female\times Competition}}{constant+\beta_{Female}}$, where $Participation_i = constant + \beta_{Female\times Compete} \cdot \text{Female}_i \times \text{Compete}_i + \beta_{Female} \cdot \text{Female}_i + \beta_{Compete} \cdot \text{Compete}_i + \varepsilon_i$. The estimated percentage changes for females in mathematics (1) and physics (2) are truncated in the graph; that for math is 497% ($p = 0.27$), and that for physics (2) is undefined (zero women participated in the collaboration treatment). Beh'l, Behavioral; Eng, engineering; EEng, electrical engineering; Env, environmental; Info Sys, information systems; Telcm, telecommunications.

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Table 7 reports model estimates of participation rates for each subfield. Figure 4 reports the corresponding percent changes in response to competition for both men and women. We must be somewhat cautious in interpreting the results, as this fine-grained stratification of the analysis reduces statistical power, and we might expect large differences in gender dynamics between STEM subfields.

Consistent with previous findings of an average negative response to competition of approximately 20%, the coefficient estimates in Table 7 are largely negative, and the percentage responses to competition shown in Figure 4 are also largely negative. Examining the percentage changes in response to competition in Figure 4, we found no evidence of statistical significance of the subfields in 16 of 17 subfields. The only gender difference that is statistically significant at a conventional level is in computer engineering ($p = 0.01$), where women are much more averse to competition (−83% change in response to competition for women versus −15% change for men).[15]

Although we must be cautious in interpreting statistical significance, particularly now as we stratify our analysis into fine-grained subsets, what is most strikingly consistent with the earlier results and theoretical hypotheses is that it is overwhelmingly the case that men's and women's responses to competition appear to be much more similar within subfields than between subfields. As can be seen in Figure 4, in most cases, the responses of men and women follow the same sign, and even the magnitudes of the responses are very similar within the individual subfields. These patterns are broadly consistent with the general claim and earlier documented patterns suggesting that men and women sorting into STEM fields are more likely to respond similarly to competition.

6. Summary and Discussion of Results

6.1. Main Finding: Smaller (Negligible) Gender Differences in STEM Fields

We found that within our field context with working-age adults—at least for those in non-STEM fields—the results followed earlier research (Section 2) in that women were more averse to competition than were men. Non-STEM men and women participated at similar rates under the collaboration treatment. However, non-STEM women were 25.49% less likely to participate under competition, whereas the non-STEM men's rate of participation did not statistically change under competition (Figure 3 and Table 5).

In Section 2.3, we hypothesized that gender differences in STEM fields should be smaller than those in non-STEM fields. Indeed, we found that differences in participation for STEM men and women in the competition treatment, relative to their participation rates in the collaboration treatment, were statistically identical: 19.62% lower participation for STEM men under competition, and 23.63% lower participation for STEM women under competition (Figure 3 and Table 5).

In finding no statistical differences in responses to competition between men and women in STEM fields, should we interpret the result as reflecting truly small differences, or just an inability to detect differences with sufficient statistical power? A variety of patterns suggests our tests are sufficiently powered and the differences are indeed negligible. Most starkly, in those instances where we do find gender differences (such as in non-STEM fields), the observed gender differences are indeed large and highly statistically significant (i.e., at $p = 1\%$). Furthermore, where we do not detect differences in STEM, the reason is not a lack of precision in our estimates; rather than standard errors being relatively large, it is the point estimates of coefficients that are relatively small (e.g., compare models (3) and (4) in Table 3). It is noteworthy, too, and particularly so in relation to the prior literature, that these findings of no statistical differences are found in data covering 31,923 STEM subjects. Just this subset of our data is orders of magnitude larger than the bulk of study groups in prior research (Section 2). We also found estimates to be robust to a series of controls (Table 4), and we found similar responses among men and women in 17 narrower STEM subfields (Section 5.3). Last, it is only, precisely, where we theoretically predicted to find small(er) differences that we indeed found small differences. Therefore, the evidence and arguments point to gender differences being small among STEM subjects.

6.2. Secondary Finding: STEM Subjects Prefer Collaboration over Competition

Although our primary research question focuses on relative gender differences in responses to competition, our research design also allowed us to gain insight on preferences for working under competition versus collaboration in a widely sampled study population, more generally. Here, we find that *both* men and women in STEM fields have an absolute preference for working under a collaborative regime, as summarized in Figure 3 and Table 5. STEM men participated 19.62 less frequently under competition—a 3.60% participation rate under competition versus a 4.48% participation rate under collaboration. STEM women participated 23.63% less frequently under competition—a 4.37% participation rate under competition versus a 5.56% participation rate under collaboration.

6.3. Interpretation of Results

Here we review several explanations for the reported patterns.

6.3.1. STEM Sorting, Socialization, Training, and Experience. It is widely presumed in research on gender and competition that individuals may sort into distinct

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

fields and occupations on the basis of differences in competitiveness.[16] We hypothesized that to the extent such a true causal sorting effect exists, we should observe smaller gender differences in fields presumed to attract competitive individuals. The prior literature most often presumes that STEM fields should be regarded as most competitive.

Therefore, a simplest interpretation that directly follows from the prior research is that men and women in STEM should be more similar, in that they should both have a relatively high preference for competition. However, rather than find that STEM men and women generally preferred competition, we instead found the opposite: both STEM men and STEM women had a greater willingness to participate under collaboration in our context. Therefore, a more nuanced explanation than pointing to a greater "preference" for competition is required, as we described in the review of Section 2.

One possible explanation for similar responses to competition among STEM men and women but greater willingness to participate under collaboration is suggested by prior research on the particulars of learning and working in STEM fields. We might expect, for example, more moderated or contingent responses to both competition and to collaboration among those in STEM fields. On the one hand, competition is well documented to be a regular feature of work in industrial firms, such as in laboratories, both within and between organizations (e.g., Lam 2011, Ali et al. 2018). On the other hand, the demanding nature of problem solving and the advance of knowledge demands in STEM fields has made it increasingly common for technical problem solving to be carried out in collaborative teams—whether in the laboratory, in the product development department, within the software development community, or other context (e.g., Shah 2006, Jones 2009, Mortensen 2014). In this sense, the ability to work under *both* competition and collaboration is a regular and routine aspect of working and learning in modern STEM fields (e.g., Menekse et al. 2017). It is also plausible, in a context where both competition and collaboration are regular work modes, that STEM workers might perhaps, to some degree, be able to recognize the organizational approach most suited to a certain context and set of circumstances. For example, in our context, the task was one of (inherently multidisciplinary) product conception and development, for which team-based collaboration might have naturally been favorable. Therefore, it is possible that although those in STEM were able and willing to participate under competition, they might have recognized the relative merits of collaborating in this context.

Other research documenting gender dynamics in STEM fields hints at other possible interpretations for smaller gender differences in STEM. Descriptive case study evidence suggests that STEM women may be ambivalent to both competition and collaboration. For example, female engineers have been reported to exhibit ambivalence or aversion to collaborations in cases in which they anticipate gender-stereotyped expectations and work role assignments (McIlwee and Robinson 1992; Cech et al. 2011; Choi 2013; Foor et al. 2013; Coffman 2014; Silbey 2015; Cheryan et al. 2017; Moss-Racusin et al. 2018). At the same time, competitions have been shown in instances to be important means of engaging and socializing women and girls in STEM fields (Kuyath and Yoder 2004, Notter 2010, Friesel and Timcenko 2011). These points at least open the possibility that STEM women may be more moderated in their willingness or desire to work under collaboration and competition.

Other strands of research focused on STEM students and workers have argued that these fields can promote cultures promoting practices and norms associated with masculinity, including competitiveness and assertiveness (McIlwee and Robinson 1992, Kvande 1999, Etzkowitz et al. 2000, Cheryan et al. 2009).

Furthermore, women scientists and engineers have been documented to sometimes adopt practices and behaviors to conform with their field's culture (Kvande 1999, Ong 2005, Powell et al. 2009), including emulating competitive behaviors (Cheryan et al. 2017). These arguments, on their own, would suggest that women who remain in STEM fields might converge to the behavior of their male peers as a matter of socialization rather than sorting. At the same time, most straightforward interpretations of these claims are inconsistent with the finding that both STEM men and women in our study preferred to work under collaboration.

6.3.2. "Intellectually Distant" Non-STEM Men and Overconfidence. It is notable too that among men and women in STEM and non-STEM fields, only non-STEM men appeared to be indifferent between participating under competition or collaboration (model (2) of Table 5). On the one hand, these results might simply be considered consistent with women responding more negatively to competition than men do, as in the prior research (Sections 1 and 2).

This exceptional indifference of non-STEM men between competition and collaboration is consistent with overconfidence. Overconfidence among men has been previously suggested as an explanation for gender differences in competitiveness, particularly so among lower-skilled men (e.g., Niederle and Vesterlund 2007). Of course, men in non-STEM fields cannot as a group be judged to be lower skilled; but in this instance, they may be less familiar with or more intellectually distant

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

from the task at hand. It is possible that more intellectually distant males are more susceptible to misconstruing the work to be performed and to exhibit overconfidence in their choices.

This explanation of intellectually distant men being overconfident is consistent with prior research finding that domain-specific knowledge and familiarity with a task can be an important factor shaping responses to competition (Wieland and Sarin 2012). Also supporting this interpretation, Comeig et al. (2016) also show that experience and expertise in an area alters attitudes toward competition by moderating confidence. Kamas and Preston (2012) found in their laboratory study of 310 students solving mathematical problems that although women were less willing to choose competition than men, the differences were not statistically significant among science and engineering students, who presumably have greater training in mathematics.

6.3.3. Non-STEM Women, Gender-Role Congruity, and Self-Efficacy. Apart from possible overconfidence of non-STEM men, it is possible that non-STEM gender differences also arise from a range of previously hypothesized reasons for an aversion to competition, at least among non-STEM women. For example, women in non-STEM fields might perceive the technologically intensive product development to be a male-oriented task (Nosek et al. 2002, 2009; Su et al. 2009), and consequent stereotype threat could result in a diminution in self-confidence and resulting willingness to participate under competition (Woodcock et al. 2012, Dreber et al. 2014). Gender stereotyping of the task might also have led to an expectation of disproportionate participation by men, which could itself reduce willingness to compete (Lundeberg et al. 1994, Gneezy et al. 2003, Booth and Nolen 2012).

We emphasize, too, that apart from these prior hypotheses that tend to be emphasized in the literature, it is also possible that non-STEM women are simply responding somewhat sensibly to the available choices in our context. For example, there are in all likelihood natural advantages to collaborating with others in this case of a multidisciplinary development project.

6.3.4. Demand-Side Explanations. Another more general point to raise in interpreting our results is that worker participation in the workforce reflects two-sided matching between worker supply and employer demand. In contrast, this experiment here (as in others in the literature) was designed to focus on the supply-side willingness of individuals to participate or not. (See Murciano-Goroff (2022) and Price (2011) for analyses of demand-side employers.) Nonetheless, it remains plausible that subjects' decisions to participate could have *anticipated* demand-side features of the workplace (Fernandez-Mateo and Kaplan 2018).

For example, Goldin (2014) hypothesized that women's participation and success in the workplace is often curtailed by rigid and long work hours and a need for face time. The collaborative product development platform used in our context was designed with the intent to minimize the costs of inflexible time requirements, including an ability to interact asynchronously. Closer to the crux of this experiment, if collaboration was viewed as requiring more inflexible face-time costs, this might have had the effect of dissuading female participation. In Table 4, we found no evidence that the competition treatment was affected by controlling for a measure of opportunity costs, providing some assurance that there is no such demand-side effect.

More generally, any perceptions of costs or benefits that apply asymmetrically to men and women who interact with the treatment effect could alter our results. For example, women in STEM could potentially have expected higher returns for participating in this developmental activity if women have disproportionately higher returns on education, receiving more callbacks and job offers (Williams and Ceci 2015). However, it is not clear that such an effect should necessarily vary with the competition and collaboration treatments. Nonetheless, we cannot unequivocally rule out this possibility.

6.4. Additional Considerations in Interpreting Results

Of course, gender cannot be randomly assigned or its effects truly measured, all else being equal; there will always be inherent challenges to interpreting results of regressions involving a gender dummy variable, whether in experiments or otherwise—including in this study. Thus, although we included a range of potential confounds as explicit model regressors, more important is that our results and interpretation do not depend on a causal interpretation. Importantly, we also found that the results remain remarkably unperturbed under a wide range of specifications (although our main results clearly turn on introducing variables that account for field differences, as predicted).

We should also again emphasize the importance of study sampling, particularly in the case of attempting to draw inferences on differences or similarities on a topic so general as men and women. Although our study population is unusually large and widely sampled, relative to the existing literature, it nonetheless only covers U.S. college-educated individuals. Thus, the group we observe, strictly speaking, covers but a narrow range of human experience and circumstances, relative to the wider world of billions of men and women. For this reason, we emphasize the demonstration of the *existence* of

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

smaller (here, statistically zero) gender differences under the predicted conditions (in STEM fields).

It should also be emphasized that although this experiment was carried out in the field and involved a work activity that occurs across most firms and sectors (product development), this is but one work task, and the nature of the work task was not varied experimentally. Several of the interpretations above refer to the nature of work and the nature of knowledge. Strictly speaking, these interpretations are consistent with observed patterns, but not explicitly tested. Such claims might be better supported in future research that varies the nature of the work task. It was not practicable to vary the work task holding all else equal in this case. Nor were the results and interpretations above perfectly foreseen on the basis of the prior research, even had we been able to vary the work task as part of the experiment.

We also wish to highlight that although, on the one hand, the task and work process here were purposely designed with "low floors and high ceilings" (Boaler 2016; Section 3) to grant access and opportunity to a wide range of people from a wide range of fields, the internet-of-things focus might well have been perceived as somewhat technical in nature. Therefore, among the many thousands of people within the study population, it remains possible that the variation we observe is limited to just those people who were open to engaging in the tech sector.

Several points regarding the research design should also be highlighted when comparing the current results to those of other studies in the literature on gender and competition. Most basic, the canonical approach in prior laboratory research (Section 2) is to recruit laboratory participants, who then necessarily participate, and then record whether subjects choose to work under competition or collaboration. By contrast, here, we randomly assigned each subject to *either* competition or collaboration, and we then observed whether they chose to participate or not. Therefore, the prior laboratory experiments measure the percentages of laboratory subjects who prefer one regime over the other, and here, we measure whether individuals choose to participate—at all—conditional on the regime.

Given that competition and collaboration within an organization might imply a wide range of things, from the internal culture to payoffs to modes of work organization, we operationalized these concepts by simply making the words "competition" and "collaboration" salient to our treatments. Subjects were then free to interpret what these would mean. Prior laboratory experimental literature tends, in most cases, to instead operationalize competition and collaboration as a structure of compensation. For example, most commonly, competition is operationalized as a winner-take-all payoff scheme; collaboration is shared or correlated payoffs.

In some cases, the prior laboratory experimental literature has emphasized that gender differences in responses to competition cannot be explained by gender differences in attitudes to risky payoffs (despite gender differences in competition preferences and risk preferences tending to go in the same direction within observed experimental study groups). We do not (and cannot) parse out attitudes to risk here. Competition should generally produce more risky outcomes, and within our context, competition and risk should go hand in hand.

7. Conclusion

Are women more averse to working within competitive organizations than men? We investigated this question by studying the willingness of individuals across all fields to participate in a platform-based product development activity depending on whether individuals were randomly assigned to competition or collaboration treatments. These treatments were based on framing the event in ways that either emphasized competitive or collaborative interactions with other participants.

Our main novel contribution was to present evidence (Section 5) that gender differences in competitiveness differ by field (Section 5.2). Specifically, we theorized and found evidence that gender differences are smaller in STEM fields than in other fields. In our context, not only were gender differences appreciably smaller in STEM than in non-STEM fields, but these differences were statistically indistinguishable from zero (see Section 6.1 summary). Our results were robust to cohort and age and various controls for factors shaping benefits and costs of participation (Section 5.2, Table 4), and similar patterns were found when examining finer-grained STEM subfields (Section 5.3).

It is also the case that STEM men and women were both more willing to participate under collaboration than under competition. This result is inconsistent with a simplest characterization of sorting on "preferences" for competition, where individuals who simply prefer competition sort into STEM fields. As we discussed in Section 6, these results might reflect a more nuanced combination of, say, tolerance and skills for competing under competition, rather than a simple preference. Furthermore, given that work and problem solving and training in STEM fields routinely involves both competition and collaboration, it is possible that we might expect a more nuanced, moderated, and contingent willingness to work under either competition or collaboration. In our case of an inherently multidisciplinary product development task, those in STEM perhaps expected superior performance when organizing collaboratively.

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

These findings begin to outline systematic boundary conditions in relation to the increasingly well-known literature on gender and competition (Sections 2.1 and 2.3). Although our results contrast with those of many prior studies showing gender differences in smaller studies, our theoretical predictions were in fact derived from generally accepted presumptions of the prior research (Section 2.4). Furthermore, our results are consistent with prior results finding systematic gender differences in laboratory-based studies if a majority of those subjects came from non-STEM fields of training. Indeed, even in broad study population averages in our study, we found that competition effects were more negative for women. It was only when accounting for fields that we observed striking differences.

7.1. Organizational Implications

We began the introduction by observing that any behavioral regularities in competitiveness across working-age adults could—if better understood—create opportunities for unlocking the talents of workers through organizational design. Prior research, for example, has shown that in the context of gender differences in a laboratory experiment, affirmative action can increase female productivity along with representation (Niederle et al. 2013), and priming females subjects or alternative framings of participation choices can also increase female participation under competitive treatments (Balafoutas et al. 2018, He et al. 2019). We ourselves suggested that, in field settings, "tuning" the competitiveness of internal organizational environments might also better harness workers' talents and willingness to participate (Section 1).

Our findings suggest that any practical organizational interventions will need to consider contingencies (across fields, discussed in Section 6.1) and possible nuances (regarding mechanisms, discussed in Section 6.3), as we find evidence contrary to claims of *general* gender differences. For example, our results provided no indication that altering the competitiveness of a work environment in the case of STEM workers will affect gender composition—at least among those already sorted into STEM fields of training and careers. It remains plausible that managing the intensity of the competition faced by boys and girls in STEM education earlier in life could affect sorting into STEM fields and thus affect the composition of the STEM pipeline and workforce (Niederle and Vesterlund 2010, Buser et al. 2014, Buser 2016).

Acknowledgments

The authors thank members of supporting organizations, and particularly Maria Costa De Sousa, Hugh Courtney, Mavez Dabas, Sylvain Demortier, Anthony Donaldson, Raj Echambadi, Koreen Geisler-Wagner, Austen Keene, Afan Khan, Atif Khan, Abhinav Kharbanda, Dyan Khor, Raghavi Kirouchenaradjou, Sreerag Sreenath Mandakathil, Patrick McGrath, Tucker Marion, Marc Meyer, Robert Hughes, Michael Orr, Olga Ozhereleva, Kaushik Padmanabhan, Edwige Poinssot, Fernando Suarez, Prathamesh Kisan Tajane, Nikin Tharan, Emery Trahan, Maureen Underhill, Robert Whelan, and Katherine Wilhoit. For helpful comments, they thank Victor Bennett, Roberto Fernandez, Sharique Hasan, Olga Shurchkov, and seminar participants at Duke University, Danish Research Unit for Industrial Dynamics (DRUID) Conference, the Max Planck Institute for Innovation and Competition, the National Bureau of Economic Research, and the Academy of Management. They also acknowledge generous financial support from the Ewing Marion Kauffman Foundation. Boudreau also thanks Charlotte, Donna, Elizabeth, Jackson, Rochelle, and Ruth Ann for motivating this study. The views expressed here are those of the authors alone and do not necessarily reflect those of supporting institutions, funders, or supporters involved with this study. All errors are the authors'.

Appendix A. Studies on Gender and Competition Reporting Contradictory Findings to Usual Findings of Gender Differences

As noted in Section 2.2, one challenge to extrapolating beyond existing results suggesting that females might be relatively averse to competition is a growing number of published results that run counter to these original findings. (Please note, again: We are somewhat constrained to refer to "males" and "females" in discussing the prior literature, given that the prior literature does not often or always observe men and women, and often instead observes boys and girls and young students in inferring binary gender differences.) This appendix provides a brief review to illustrate the important contributions of this research, while also highlighting how it is difficult to derive a simple set of lessons from these studies—as these results sometimes also contradict one another.

The seminal study by Gneezy et al. (2003) found that 30 male students solving mazes at an Israeli university were more positively affected by competition than 30 female Israeli university students who were recruited to the experiment. However, whereas Günther et al. (2010) found similar results for solving similar maze problems, they did not find these results for problems involving writing out words beginning with a certain letter or for memory games in a group of Spanish students. Günther et al. (2010) suggested that their findings might be explained by a theory of "stereotype threat," whereby gendered associations of tasks negatively impact task performance of the negatively stereotyped group.

Whereas Gneezy and Rustichini's (2004) highly influential study of 140 fourth-grade Israeli schoolchildren found that the boys ran faster when facing competition, Dreber et al. (2011) found no such gender differences in a group of 149 Swedish schoolchildren in either running, dancing, or skipping rope—clearly gender-stereotyped activities. We might then perhaps consider possible differences between Swedish versus Israeli culture. However, Boschini et al. (2019) had a market research firm randomly telephone Swedish adults, performing laboratory-style verbal and math tasks to assess the effects of competition. In collecting the responses of 997 Swedes between the ages of 18 and 73, they find some evidence of gender differences in responses to competition

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

in the case of the math task, while controlling for income, age, and level of education.

Gneezy et al. (2009) further examined the possible role of cultural context, recruiting 155 people from the Maasai in Tanzania and the Khasi in India, asking them to throw tennis balls into a bucket, while choosing either competitive or noncompetitive payment schemes (i.e., the Niederle–Vesterlund protocol). The Maasai men more frequently chose competition, whereas the Khasi women more frequently chose competition. The authors interpreted the results as evidence that gender differences are tied to societal culture. They speculated further that gender differences in prior research (i.e., Sections 2.1 and 2.3) could be a fixture of Western societies.

Other results suggest that narrower socialized differences could shape gender differences. Andersen et al. (2013) recruited 318 Indian schoolchildren, 9–15 years old, to similarly throw tennis balls into a bucket in a Niederle–Vesterlund protocol. Most subgroups (by gender, age, and village type) did not statistically differ, when stratifying the data by sex, village, and for ages 9–12 or 13–15. The authors found differences between boys and girls in the case of patriarchal villages for the age 13–15 group. The authors interpreted the results to mean that gender differences emerge only in the older girls within patriarchal societies, after a process of socialization for some years. In other research, Gneezy and Rustichini (2004) reported gender differences occurring before the age of 13.

(A series of findings on gender differences in auctions, where female subjects tend to bid higher than males (e.g., Casari et al. 2007), also appears to run counter to the findings in research on gender and competition.)

Endnotes

[1] See Inglehart et al. (1994) for a discussion of this hypothesis predating the more recent experimental literature.

[2] Here we follow the literature and data availability in being limited to a simple binary indicator measure.

[3] As with any study using gender as an explanatory variable, including laboratory experiments, there are unavoidable challenges in interpreting differences as all-else-being-equal "gender effects." As it is not possible to randomly assign a subject's sex (Holland 1986), it is therefore not possible to unequivocally rule out spurious differences, even with "control" variables (Oster 2019).

[4] Note that from a practical perspective, one's risk tolerance, willingness to receive feedback, and self-confidence might alternatively simply be viewed as part and parcel of one's willingness to compete.

[5] Gneezy et al. (2003, p. 1049) illustrate an alternative canonical protocol, recruiting 324 students to solve maze problems for 15 minutes. Students were randomly assigned to competitive or piece-rate pay schemes in groups of six. Men outperformed women in all treatments, but the differences were not statistically significant in the noncompetitive regime. The authors interpreted the results as indicating that men are more competitive, providing a possible explanation for "gender differences … in competitive high-ranking positions."

[6] Other experiments and A/B tests were embedded in the launch campaign. However, these assignments were orthogonal to the assignments described here and balanced across all subjects, and therefore have no effect on the results reported here.

[7] The internet-of-things refers to a wide set of largely yet-to-be-imagined products, services, and systems that connect machines, infrastructure, consumer products, and other things while making use of the intelligence created by data collection and networking. The IoT is widely expected to generate an impact as wide as the internet, impacting occupations and firms across the economy in a fourth industrial revolution or second machine age (Brynjolfsson and McAfee 2014). These technologies are widely predicted to affect most sectors across the economy.

[8] Gender differences in participation are also observed when stratifying between undergraduate, graduate, and alumni subgroups.

[9] Instructions for accessing data and code to replicate the analysis reside on the Open Science Framework at https://osf.io/6dsn8/.

[10] Linear models ease the interpretation of interactions that are central to this investigation.

[11] We ran an analysis in which we replaced participation here with a measure of participation in other university-sponsored activities (counts of university clubs and activities listed on LinkedIn). The patterns are starkly different, confirming that the patterns observed here do not simply reflect some general inclination to participate in university activities in general.

[12] A low adjusted R^2 statistic is consistent with high variance with a low mean incidence of ones.

[13] The average college-educated American women has her first child at the age of 30.3 (Bui and Miller 2018). We did not find a definitive source of the distribution over time, but results are insensitive to shifting this age range by three years on upper or lower bounds. Note that in this cross section, the age is also the graduation cohort, and therefore open to multiple interpretations.

[14] Estimating the model separately for computer science, engineering, and sciences shows similar results as for STEM overall, with men and women responding with statistically similar percentage changes in participation under the competition treatment relative to the collaboration treatment.

[15] The next most statistically significant gender difference was in biology, where differences are significant at $p = 0.18$.

[16] The prior evidence goes as far as reporting correlations between measures of competitiveness and the probability of pursuing certain fields (Section 2).

References

Abramo G, D'Angelo CA, Murgia G (2013) Gender differences in research collaboration. *J. Informetrics* 7(4):811–822.

Ali M, Talib CA, Surif J, Ibrahim NH, Abdullah AH (2018) Effect of STEM competition on STEM career interest. *IEEE 10th Internat. Conf. Engrg. Ed.* (IEEE), 111–116.

Andersen S, Ertac S, Gneezy U, List JA, Maximiano S (2013) Gender, competitiveness, and socialization at a young age: Evidence from a matrilineal and a patriarchal society. *Rev. Econom. Statist.* 95(4):1438–1443.

Antonovics K, Arcidiacono P, Walsh R (2009) The effects of gender interactions in the laboratory and in the field. *Rev. Econom. Statist.* 91(1):152–162.

Apicella CL, Dreber A, Gray PB, Hoffman M, Little AC, Campbell BC (2011) Androgens and competitiveness in men. *J. Neurosci. Psych. Econom.* 4(1):54–62.

Balafoutas L, Fornwagner H, Sutter M (2018) Closing the gender gap in competitiveness through priming. *Nat. Comm.* 9(1):4359.

Baumann O, Eggers JP, Stieglitz N (2019) Colleagues and competitors: How internal social comparisons shape organizational search and adaptation. *Admin. Sci. Quart.* 64(2):275–309.

Boaler J (2016) *Mathematical Mindsets: Unleashing Students' Potential Through Creative Math, Inspiring Messages and Innovative Teaching* (John Wiley and Sons, New York).

Booth A, Nolen P (2012) Choosing to compete: How different are girls and boys? *J. Econom. Behav. Organ.* 81(2):542–555.

Boschini A, Dreber A, von Essen E, Muren A, Ranehill E (2019) Gender, risk preferences and willingness to compete in a random

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

sample of the Swedish population. *J. Behav. Experimental Econom.* 83:101467.

Boudreau KJ (2017) Platform boundary choices & governance: Opening-up while still coordinating and orchestrating. Furman JL, Gawer A, Silverman BS, Stern S, eds. *Entrepreneurship, Innovation, and Platforms* (Emerald Publishing Limited, Bingley, UK), 227–297.

Boudreau KJ, Hagiu A (2009) Platform rules: Multi-sided platforms as regulators. Gawer A, ed. *Platforms, Markets and Innovation*, vol. 1 (Edward Elgar, Cheltenham, UK), 163–191.

Boudreau KJ, Lacetera N, Lakhani KR (2011) Incentives and problem uncertainty in innovation contests: An empirical analysis. *Management Sci.* 57(5):843–863.

Brands RA, Fernandez-Mateo I (2017) Leaning out: How negative recruitment experiences shape women's decisions to compete for executive roles. *Admin. Sci. Quart.* 62(3):405–442.

Brynjolfsson E, McAfee A (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies* (W. W. Norton and Company, New York).

Buckert M, Schwieren C, Kudielka BM, Fiebach CJ (2017) How stressful are economic competitions in the laboratory? An investigation with physiological measures. *J. Econom. Psych.* 62:231–245.

Bui Q, Miller C (2018) The age that women have babies: How a gap divides America. *New York Times* (August 4), https://www.nytimes.com/interactive/2018/08/04/upshot/up-birth-age-gap.html.

Buser T (2009) The impact of female sex hormones on competitiveness. Discussion paper, Tinbergen Institute, Amsterdam.

Buser T (2016) The impact of losing in a competition on the willingness to seek further challenges. *Management Sci.* 62(12):3439–3449.

Buser T, Niederle M, Oosterbeek H (2014) Gender, competitiveness, and career choices. *Quart. J. Econom.* 129(3):1409–1447.

Buser T, Niederle M, Oosterbeek H (2021) Can competitiveness predict education and labor market outcomes? Evidence from incentivized choice and survey measures. Working Paper No. w28916, National Bureau of Economic Research.

Byrnes JP, Miller DC, Schafer WD (1999) Gender differences in risk taking: A meta-analysis. *Psych. Bull.* 125(3):367–383.

Casari M, Ham JC, Kagel JH (2007) Selection bias, demographic effects, and ability effects in common value auction experiments. *Amer. Econom. Rev.* 97(4):1278–304.

Cech E, Rubineau B, Silbey S, Seron C (2011) Professional role confidence and gendered persistence in engineering. *Amer. Sociol. Rev.* 76(5):641–666.

Cheryan S, Plaut VC, Davies PG, Steele CM (2009) Ambient belonging: How stereotypical cues impact gender participation in computer science. *J. Personality Soc. Psych.* 97(6):1045.

Cheryan S, Ziegler SA, Montoya AK, Jiang L (2017) Why are some STEM fields more gender balanced than others? *Psych. Bull.* 143(1):1–35.

Choi KS (2013) Evaluating gender significance within a pair programming context. *Proc.* 2013 46*th Hawaii Internat. Conf. System Sci.*, 4817–4825.

Coffman KB (2014) Evidence on self-stereotyping and the contribution of ideas. *Quart. J. Econom.* 129(4):1625–1660.

Comeig I, Grau-Grau A, Jaramillo-Gutiérrez A, Ramőrez F (2016) Gender, self-confidence, sports, and preferences for competition. *J. Bus. Res.* 69(4):1418–1422.

Croson R, Gneezy U (2009) Gender differences in preferences. *J. Econom. Lit.* 47(2):448–474.

Dargnies MP (2012) Men too sometimes shy away from competition: The case of team competition. *Management Sci.* 58(11):1982–2000.

Dato S, Nieken P (2014) Gender differences in competition and sabotage. *J. Econom. Behav. Organ.* 100:64–80.

Dittrich M, Knabe A, Leipold K (2014) Gender differences in experimental wage negotiations. *Econom. Inquiry* 52(2):862–873.

Dohmen T, Falk A (2011) Performance pay and multidimensional sorting: Productivity, preferences, and gender. *Amer. Econom. Rev.* 101(2):556–590.

Dreber A, von Essen E, Ranehill E (2011) Outrunning the gender gap—Boys and girls compete equally. *Experiment. Econom.* 14(4):560–582.

Dreber A, von Essen E, Ranehill E (2014) Gender and competition in adolescence: Task matters. *Experiment. Econom.* 17(1):154–72.

Eckel CC, Grossman PJ (2008) Men, women and risk aversion: Experimental evidence. Plott CR, Smith VL, *Handbook of Experimental Economics Results*, vol. 1 (Elsevier, Amsterdam), 1061–1073.

Eswaran M (2015) Why we think the way we do about men, women and work. *PBS News Hour* (January 5), https://www.pbs.org/newshour/nation/the-lasting-impact-of-the-plow-on-our-attitudes-about-gender-and-work.

Etzkowitz H, Kemelgor C, Uzzi B (2000) *Athena Unbound: The Advancement of Women in Science and Technology* (Cambridge University Press, New York).

Fernandez RM, Campero S (2017) Gender sorting and the glass ceiling in high-tech firms. *Indust. Labor Relations Rev.* 70(1):73–104.

Fernandez-Mateo I, Kaplan S (2018) Gender and organization science: Introduction to a virtual special issue. *Organ. Sci.* 29(6):1229–1236.

Flory JA, Leibbrandt A, List JA (2015) Do competitive workplaces deter female workers? A large-scale natural field experiment on job entry decisions. *Rev. Econom. Stud.* 82(1):122–155.

Foor CE, Walden SE, Shehab RL, Trytten DA (2013) "We weren't intentionally excluding them … just old habits": Women, (lack of) interest and an engineering student competition team. *Proc.* 2013 *IEEE Frontiers Ed. Conf.* (Institute of Electrical and Electronics Engineers, Piscataway, NJ), 349–355.

Friesel A, Timcenko O (2011) Competition-motivated teamwork and narratives to motivate girls for engineering. Welzer T, Hoffmann M, eds. *Proc.* 22*nd Eur. Assoc. Ed. Electrical Inform. Engrg. Annual Conf.* (University of Maribor, Maribor, Slovenia).

Gneezy U, Rustichini A (2004) Gender and competition at a young age. *Amer. Econom. Rev.* 94(2):377–381.

Gneezy U, Leonard KL, List JA (2006) *Gender Differences in Competition: The Role of Socialization* (University of Chicago).

Gneezy U, Leonard KL, List JA (2009) Gender differences in competition: Evidence from a matrilineal and a patriarchal society. *Econometrica* 77(5):1637–1664.

Gneezy U, Niederle M, Rustichini A (2003) Performance in competitive environments: Gender differences. *Quart. J. Econom.* 118:1049–1074.

Goldin C (2014) A grand gender convergence: Its last chapter. *Amer. Econom. Rev.* 104(4):1091–1119.

Günther C, Ekinci NA, Schwieren C, Strobel M (2010) Women can't jump?—An experiment on competitive attitudes and stereotype threat. *J. Econom. Behav. Organ.* 75(3):395–401.

Guo J (2015) Why do some studies show that women are less competitive than men? *Washington Post* (January 2), https://www.washingtonpost.com/news/storyline/wp/2015/01/02/why-do-some-studies-show-that-women-are-less-competitive-then-men/.

Gupta ND, Poulsen A, Villeval MC (2013) Gender matching and competitiveness: Experimental evidence. *Econom. Inquiry* 51(1):816–835.

He JC, Kang SK, Lacetera N (2021) Opt-out choice framing attenuates gender differences in the decision to compete in the laboratory and in the field. *Proc. Natl. Acad. Sci.* 118(42).

Healy A, Pate J (2011) Can teams help to close the gender competition gap? *Econom. J.* 121(555):1192–1204.

Holland PW (1986) Statistics and causal inference. *J. Amer. Statist. Assoc.* 81(396):945–960.

Holt-Lunstad J, Clayton CJ, Uchino BN (2001) Gender differences in cardiovascular reactivity to competitive stress: The impact of gender of competitor and competition outcome. *Internat. J. Behav. Medicine* 8(2):91–102.

Hunt A, Samman E (2019) Gender and the gig economy. Working Paper 546, Overseas Dev. Institute, London.

Inglehart M, Brown DR, Vida M (1994) Competition, achievement, and gender: A stress theoretical analysis. Pintrich PR, Brown DR,

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.

Weinstein CE, eds. *Student Motivation, Cognition, and Learning: Essays in Honor of Wilbert. J. McKeachie* (Routledge, Abingdon, UK), 311–330.

Iriberri N, Rey-Biel P (2019) Competitive pressure widens the gender gap in performance: Evidence from a two-stage competition in mathematics. *Econom. J.* 129(620):1863–1893.

Jeppesen LB, Lakhani KR (2010) Marginality and problem-solving effectiveness in broadcast search. *Organ. Sci.* 21(5):1016–1033.

Jones BF (2009) The burden of knowledge and the "death of the renaissance man": Is innovation getting harder? *Rev. Econom. Stud.* 76(1):283–317.

Kahn S, Ginther D (2017) Women and STEM. NBER Working Paper No. 23525, National Bureau of Economic Research, Cambridge, MA.

Kamas L, Preston A (2012) The importance of being confident; gender, career choice, and willingness to compete. *J. Econom. Behav. Organ.* 83(1):82–97.

Kesebir S, Lee SY, Elliot AJ, Pillutla MM (2019) Lay beliefs about competition: Scale development and gender differences. *Motivation Emotion* 43(5):719–739.

Kivlighan KT, Granger DA, Booth A (2005) Gender differences in testosterone and cortisol response to competition. *Psychoneuroendocrinology* 30(1):58–71.

Kleinjans KJ (2009) Do gender differences in preferences for competition matter for occupational expectations? *J. Econom. Psych.* 30(5):701–710.

Knight J (2002) *Sexual Stereotypes* (Nature Publishing Group, Berlin).

Kuhn P, Villeval MC (2015) Are women more attracted to co-operation than men? *Econom. J.* 125(582):115–140.

Kuyath SJ, Yoder L (2004) Diversity in engineering technology: Competitions. *Age* (Melbourne, Vic.) 9:1.

Kvande E (1999) "In the belly of the beast": Constructing femininities in engineering organizations. *Eur. J. Women's Stud.* 6(3):305–328.

Lam A (2011) What motivates academic scientists to engage in research commercialization: 'Gold', 'ribbon' or 'puzzle'? *Res. Policy* 40(10):1354–1368.

Lee S, Puranam P (2017) Incentive redesign and collaboration in organizations: Evidence from a natural experiment. *Strategic Management J.* 38(12):2333–2352.

Liang C, Hong Y, Gu B, Peng J (2018) Gender wage gap in online gig economy and gender differences in job preferences. Preprint, submitted November 9, http://dx.doi.org/10.2139/ssrn.3266249.

Lippa R (1998) Gender-related individual differences and the structure of vocational interests: The importance of the people–things dimension. *J. Personality Soc. Psych.* 74(4):996–1009.

Lundeberg MA, Fox PW, Punćcohaŕ J (1994) Highly confident but wrong: Gender differences and similarities in confidence judgments. *J. Ed. Psych.* 86(1):114–121.

McIlwee JS, Robinson JG (1992) *Women in Engineering: Gender, Power, and Workplace Culture* (SUNY Press, Albany, NY).

Menekse M, Higashi R, Schunn CD, Baehr E (2017) The role of robotics teams' collaboration quality on team performance in a robotics tournament. *J. Engrg. Ed.* 106(4):564–584.

Morin LP (2015) Do men and women respond differently to competition? Evidence from a major education reform. *J. Labor Econom.* 33(2):443–491.

Mortensen M (2014) Constructing the team: The antecedents and effects of membership model divergence. *Organ. Sci.* 25(3):909–931.

Moss-Racusin CA, Sanzari C, Caluori N, Rabasco H (2018) Gender bias produces gender gaps in STEM engagement. *Sex Roles* 79(11–12):651–670.

Murciano-Goroff R (2022) Missing women in tech: The labor market for highly skilled software engineers. *Management Sci.* 68(5):3262–3281.

Niederle M, Vesterlund L (2007) Do women shy away from competition? Do men compete too much? *Quart. J. Econom.* 122(3): 1060–1101.

Niederle M, Vesterlund L (2010) Explaining the gender gap in math test scores: The role of competition. *J. Econom. Perspect.* 24(2): 129–144.

Niederle M, Vesterlund L (2011) Gender and competition. *Annu. Rev. Econom.* 3(1):601–630.

Niederle M, Segal C, Vesterlund L (2013) How costly is diversity? Affirmative action in light of gender differences in competitiveness. *Management Sci.* 59(1):1–16.

Notter KB (2010) Is competition making a comeback? Discovering methods to keep female adolescents engaged in STEM: A phenomenological approach. Working paper, University of Nebraska-Lincoln.

Nosek BA, Banaji MR, Greenwald AG (2002) Math = male, me = female, therefore math ≠ me. *J. Personality Soc. Psych.* 83(1):44.

Nosek BA, Smyth FL, Sriram N, Lindner NM, Devos T, Ayala A, Bar-Anan Y, et al. (2009) National differences in gender–science stereotypes predict national sex differences in science and math achievement. Proc. Natl. Acad. Sci. USA 106(26):10593-10597.

Obloj T, Zenger T (2017) Organization design, proximity, and productivity responses to upward social comparison. *Organ. Sci.* 28(1):1–18.

Ong M (2005) Body projects of young women of color in physics: Intersections of gender, race, and science. *Soc. Problems* 52(4): 593–617.

Oster E (2019) Unobservable selection and coefficient stability: Theory and evidence. *J. Bus. Econom. Statist.* 37(2):187–204.

Page S (2008) *The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies* (Princeton University Press).

Paserman MD (2010) Gender differences in performance in competitive environments? Evidence from professional tennis players. NBER Working Paper No. 27154, National Bureau of Economic Research, Cambridge, MA.

Powell A, Bagilhole B, Dainty A (2009) How women engineers do and undo gender: Consequences for gender equality. *Gender, Work Organ.* 16(4):411–428.

Pregaldini D, Backes-Gellner U, Eisenkopf G (2020) Girls' preferences for STEM and the effects of classroom gender composition: New evidence from a natural experiment. *J. Econom. Behav. Organ.* 178:102–123.

Price CR (2011) Gender, competition, and managerial decisions. *Management Sci.* 58(1):114–122.

Reuben E, Sapienza P, Zingales L (2015) Taste for competition and the gender gap among young business professionals. NBER Working Paper No. 21695, National Bureau of Economic Research, Cambridge, MA.

Saccardo S, Pietrasz A, Gneezy U (2017) On the size of the gender difference in competitiveness. *Management Sci.* 64(4):1541–1554.

Samek A (2019) Gender differences in job entry decisions: A university-wide field experiment. *Management Sci.* 65(7):3272–3281.

Shah SK (2006) Motivation, governance, and the viability of hybrid forms in open source software development. *Management Sci.* 52(7):1000–1014.

Shurchkov O (2012) Under pressure: Gender differences in output quality and quantity under competition and time constraints. *J. Eur. Econom. Assoc.* 10(5):1189–1213.

Song H, Tucker AL, Murrell KL, Vinson DR (2018) Closing the productivity gap: Improving worker productivity through public relative performance feedback and validation of best practices. *Management Sci.* 64(6):2628–2649.

Silbey SS (2015) The elephant in the room: Constraints and consequences of a four-year undergraduate engineering degree. *Engrg. Stud.* 7(2–3):164–167.

Su R, Rounds J, Armstrong PI (2009) Men and things, women and people: A meta-analysis of sex differences in interests. *Psych. Bull.* 135(6):859–884.

Sutter M, Glätzle-Rützler D (2015) Gender differences in the willingness to compete emerge early in life and persist. *Management Sci.* 61(10):2339–2354.

van Vugt M, Cremer DD, Janssen DP (2007) Gender differences in cooperation and competition: The male-warrior hypothesis. *Psych. Sci.* 18(1):19–23.

Villeval MC (2012) Ready, steady, compete. *Sci.* 335(6068):544–545.

Wieland A, Sarin R (2012) Domain specificity of sex differences in competition. *J. Econom. Behav. Organ.* 83(1):151–157.

Williams WM, Ceci SJ (2015) National hiring experiments reveal 2:1 faculty preference for women on STEM tenure track. *Proc. Natl. Acad. Sci. USA* 112(17):5360–5365.

Woodcock A, Hernandez PR, Estrada M, Schultz P (2012) The consequences of chronic stereotype threat: Domain disidentification and abandonment. *J. Personality Soc. Psychol.* 103(4):635–646.

Wozniak D, Harbaugh WT, Mayr U (2014) The menstrual cycle and performance feedback alter gender differences in competitive choices. *J. Labor Econom.* 32(1):161–198.

Wynn AT, Correll SJ (2017) Gendered perceptions of cultural and skill alignment in technology companies. *Soc. Sci.* 6(2):45–73.

Kevin J. Boudreau is an associate professor at Northeastern University, the Fulbright Canada Distinguished Chair in Entrepreneurship, and a research associate of the National Bureau of Economic Research. He received his PhD from the Massachusetts Institute of Technology. His research interests are in strategy, entrepreneurship, and innovation, with particular emphasis on scaling and organizing large groups of diverse innovators around platforms and digital organizations.

Nilam Kaushik is an assistant professor in the Strategy area at the Indian Institute of Management Bangalore. She received her PhD from the UCL School of Management in London. Her research interests broadly lie in innovation and entrepreneurship.

Downloaded from informs.org by [155.33.130.32] on 17 June 2026, at 08:49 . For personal use only, all rights reserved.