Gender Diversity and Diversity of Ideas*

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Abstract

This paper examines the relationship between gender diversity and the diversification of ideas in Academia and in the knowledge sector. Diversity in employee representation is often advocated for its potential to foster diversity in ideas, and thereby innovation. However, this process of 'diversifying ideas' critically depends on decisions of incumbents, such as hiring and funding. If interests and ideas differ between incumbents and minorities, it may be difficult for minorities to 'break through'. We first present evidence from the Academic Economics junior job market, where numerous initiatives have been launched in recent years to boost the representation of women. We find that women fare as well as men on the market, but they fare substantially better if they specialize in a more male-dominated field. In an Online Experiment, we study the demand for ideas in a college-educated population. We find large gender differences in the topics men and women choose to engage with. We then show that incentives encouraging the selection of topics that are typically more female are more effective at increasing their representation than incentives encouraging the selection of women.

JEL codes: J16, O30 ***Keywords:*** *Gender diversity, Innovation, Hiring, Academia*

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> We couldn't get funding. We couldn't get publications. We couldn't get people to notice RNA as something interesting ...Pretty much everybody gave up on it.
>
> Drew Weismann, co-winner of the Nobel Prize 2023 with Katalyn Kariko

1 Introduction

In many professional environments, ideas are a key input to productivity. Innovation is defined as the exploration and implementation of novel ideas, and is central to economic growth (Aghion et al., 1998). In this context, efforts towards increasing diversity in the workforce are often motivated by their potential productive benefit (Abramitzky et al., 2024), in addition to fairness arguments (Hamilton et al., 2012, Richard et al., 2013 and Ali and Konrad, 2017). For example, in Economics, it is well-known that men and women tend to specialize in different research fields (Dolado et al., 2012, Kahn and Ginther, 2017, Beneito et al., 2021, Fortin et al., 2021, Auriol et al., 2022, Owen, 2022, Sierminska and Oaxaca, 2022, Truffa and Wong, 2022). However, this is also true for other STEM fields (Shishkova et al., 2017, Holman et al., 2018, Thelwall et al., 2019). Efforts to increase gender diversity could therefore lead to significant expansions in knowledge in areas that are relatively under-researched (Truffa and Wong, 2022).

This paper examines the relationship between gender diversity and idea diversity. Our starting point is the observation that the process of 'diversifying ideas' critically depends on decisions taken by incumbents. Incumbents decide which ideas deserve attention, whether it is through hiring and promotion decisions, grant and investment decisions, etc. If their research interests and ideas differ, it may be difficult for under-represented minorities to 'break through'. Diversity initiatives may increase the demographic representation of under-represented groups, but the question is whether they increase the representation of their ideas and interests to the same extent.

We first present evidence from recent trends in the Economics Academic junior job market. In Academia and in our discipline of Economics in particular, diversity and inclusion have received substantial attention over the last decade, with many professional associations such as the American Economic Association, the European Economic Association or the Women in Economics Initiative investing resources aimed at increasing the representation of under-represented groups, such as women and ethnic minorities. Our first exercise and contribution is to examine placements of men and women, and compare how they fare depending on their research fields, which we use as a proxy for 'clusters of ideas'. The Economics Academic junior market has the great advantage of being relatively standardized, and information is available both about the supply (the pool of candidates) and about selection (placements). It is an ideal setting to examine how different groups and different 'ideas' fare.

Using web-scraped data about the job market candidates from the 2018-2019, 2019-2020 and 2022-2023 job market, we document placements by gender and field, controlling for a range of quality and productivity measures. We find that women in male fields fare substantially better than women in female fields and men (in all fields). Women in male fields are 14.9 percentage points (or 30% in relative terms) more likely to be placed as assistant professors than those specializing in other fields. We do not find a comparable gender gap in other fields. This difference subsists even when controlling for a wide range of productivity measures.

We show that this phenomenon is a novel phenomenon and contrasts to placement outcomes observed in the early 2000s. We also present additional data from the Economics profession related to publications and show that the share of publications by women has increased over time, but proportionally more so than the share of publications in more female fields.

Second, we present evidence from an Online experiment, which allows us to study the demand for ideas in a more controlled manner. We recruit a sample of college-educated, working population, who may presumably be involved in hiring decisions at some point in their career. The setup replicates key features of an 'employment hiring setting'. Participants are asked to pick video presentations from a curated set of presentations - in this case, TED Talks. Presentations are either by male or female speakers and are in a female field (health, environment) or in a male field (tech, business). We provide an incentive to choose a presentation of higher expected quality (as assessed by external raters), and also provide incentives to pay attention to the presentation itself. The goal is to capture the range of incentives involved in hiring decisions in professional contexts: Presumably, there are incentives to hire high-quality candidates, but hiring also has implications for exposure and engagement with their ideas.

The advantage of the controlled setting is that the choices we observe are entirely demand-driven and are not contaminated by supply factors. We implement a first treatment variation to disentangle the role of taste and expertise in choices. The tendency to favor ideas that are similar to one's own interests could be driven by both – taste and expertise. For example, if one is specialized in a given field, one may be both interested in that field, but also feel more competent in evaluating a candidate in that field. We contrast two sub-treatments where we vary the relevance of expertise to gauge to what extent choices are driven by taste or by expertise. We implement a second treatment variation to compare the effects of different incentives aimed at encouraging diversity, such as an incentive to choose a presentation by a woman, or an incentive to pick a presentation in a female field.

We find substantial gender differences in the ideas participants are interested in being exposed to. Men choose disproportionately more presentations in male fields while women choose more presentations in female fields. As a result, male participants are more likely to choose male presenters, because they are over-represented among male fields (and vice versa for female participants and female presenters). The first treatment variation doesn't affect choices much, which means that the reason why men and women choose differently is not because of differences in expertise, but rather, in taste. The second treatment shows that different 'diversity incentives' have very different implications for the representation of women and of ideas that are typically more of female interest. A direct incentive to pick a presentation by a woman increases the share of female speakers chosen within each field, but especially so within male fields. With this incentive, women in male fields become the most demanded group among the selected speakers, followed closely by women in female fields. In contrast, incentives to choose a presentation in a female field do not lead to gender imbalances in choices, but boost substantially the selection of presentations in female fields. As a consequence, men in female fields become the most demanded group.

This paper contributes to the growing literature on gender diversity in the labor market and in Academia in particular. There are several papers which show how trajectories for women have evolved over time both in Academia in general (Lunnemann et al., 2019, Janys, 2020, Card et al., 2023, Iaria et al., 2024) as well as in Economics more specifically (Boustan and Langan, 2019, Lundberg and Stearns, 2019, Meade et al., 2021, Auriol et al., 2022, Card et al., 2022, Bateman and Hengel, 2023, Ayarza and Iriberri, 2024, Blau and Lynch, 2024), which typically find that while there has been progress for women, women remain underrepresented. Furthermore, many recent papers focus specifically on various key points of the career process where women appear to be disadvantaged: During the PhD (Boustan and Langan, 2019); in hiring and promotion processes (Sarsons, 2017, Sarsons et al., 2021), in citations by peers (Koffi, 2021, Iaria et al., 2024) or in recognition by peers (Card et al., 2022, Card et al., 2023), even though the trend appears to be changing at least for the latter. Recent studies have also shown that women are treated differently than men while publishing (Hengel and Moon, 2020, Hengel, 2022, [1]), in seminars (Dupas et al., 2021), in conference acceptance (Chari and Goldsmith-Pinkham, 2017, Hospido and Sanz, 2021) and in how they are described in reference letters (Baltrunaite et al., 2022, Eberhardt et al., 2023). Other research shows that women and men differ in further respects, which might be crucial for their academic careers: in their willingness to express opinions (Sievertsen and Smith, 2024) or in their research networks, which again leads to different publication patterns (Ductor et al., 2021). Some studies have focused on designing initiatives to combat differences between men and women at different stages (Ginther et al., 2020, Avilova and Goldin, 2018, Avilova and Goldin, 2024). A recent study by Bello et al. (2023), particularly relevant for our work here, shows that the similarity in research fields between junior researchers and hiring committee members increases the probability of promotion in Italian Academia and can partially explain the gap in promotions between men and women.

Our main contribution is to highlight that diversity initiatives focusing on attributes such as gender may have limited impact on the diversification of ideas in a world where the ideas and interests of incumbents differ from those

[1] Winkler et al., 2014 also show that while the number of women in the faculty has increased it is still very small.

of under-represented groups. We find that women specializing in traditionally male fields fare significantly better than their counterparts in female fields and even outperform their male peers. Our study also presents results from an experiment that allows us to focus on the 'demand' for ideas with incentives that resemble those present in hiring decisions. We show that the role of 'expertise' is limited in the demand for ideas, and that relatively small incentives for gender or field diversity, can substantially affect which ideas people are willing to engage with. We also find that encouraging engagement with female ideas may increase their representation but that men disproportionately favor ideas from women in male fields. In contrast, incentives encouraging engagement with ideas from female fields may be more successful in diversifying ideas.

These results suggest that the selection of ideas and job candidates in the knowledge sector may be influenced by an element of taste. Since there appears to be large gender differences in these tastes and since most Academic departments are still male-dominated, we conjecture that these taste differences may challenge efforts to increase gender diversity, and may limit the knowledge benefits from diversification based on demographics.

The remainder of this paper is structured as follows: Section 2 presents the data from the Economics Academic junior job market as well as the results obtained with this data. Section 3 presents the Online Experiment, the main hypotheses, as well as the results obtained using the experimental data. Section 4 concludes.

2 Field Study

We first present evidence from the Economics Academic junior job market and examine how men and women fare as a function of their fields of specialization. We use 'research fields' as a proxy for clusters of ideas. That is, we assume that researchers specializing in the same field have ideas that are closer to each other than those who work in different fields. In Section 2.3 we will discuss diversification within fields, and examine how gender diversity contributes to idea diversity within fields.

2.1 Data

We collected data on job market candidates from the top 33 U.S. Economics departments (according to U.S. news ranking as of December 2018) for 2018-2019, 2019-2020 and 2022-2023 [2], in total 1507 candidates (see descriptive statistics in Table A.1). We collected the lists of job market candidates from university websites in December of the respective year.

The key variables of interest are the following:

Gender. Out of 1,507 candidates, we identify the gender of 1,496 candidates based on their first name: women are clearly a minority - they make up 30% of the sample.[3]

Placement. We track candidate placement either through the placement web page of the university, through their personal website or through their LinkedIn site. Most candidates (59%) find jobs in Academia, while the second biggest placement type is in government, private, or international organizations (18%) most often doing research. The remaining big placement groups include consulting (12%) and tech firms (4%). For those placed in Academia, we also differentiate between tenure-track assistant professors (79% of Academic placement) and other types of positions (e.g., postdocs). If a candidate is placed as an assistant professor with a delayed start and gets a postdoc before starting this main position, we only consider the main (delayed) placement as the placement outcome.

Placement rank. If the candidate is placed in a research institution (Academic or non-Academic), we find the rank of that institution using the REPEC Economic Institution rankings (as of April 2022). The REPEC list includes only the top 429 research institutions. For example, the National Bureau of Economic Research has rank 1, followed by the Economics Department of Harvard University (rank 2), and so on. Slightly less than half (43%) of the job

[2]We did not collect data for the job market years of 2020-2021 and 2021-2022, since these years coincided with the Covid pandemic

[3]We assign gender based on the candidate's first name, if the first name is unambiguously associated with a certain gender (e.g., Mary would be female and John would be male). We use the dataset of first names for the U.S. by Blevins and Mullen (2015). If the proportion of women of men per given name is above 98%, we assign that name to be female or male, respectively. For those with more ambiguous names, we assign gender manually based on online information. Additionally, we check many Asian names by hand, since the dataset of first names often assigns them incorrectly.

market candidates are placed at research institutions on the REPEC list.[4] See Figure A.2 in the Appendix for the cumulative distribution of male and female candidates by their placement rank.

Publications. Additionally, we collect information from resumes on whether a candidate has publications at the time of the job market and if so, in which journals. We use the journal rankings provided by Combes and Linnemer (2010). Based on this list, we categorize the first top-7 journals [5] as AA journals, the next 23 journals (up to top-30) as A journals, and the remaining journals up to top-60 as B journals (See Figure A.1 in the Appendix). We also include newer journals that are missing from Combes and Linnemer (2010) like the American Economic Journals (Applied Microeconomics, Macroeconomics, and Economic Policy), as well as AER insights into the list of A journals. A bit more than one third of the candidates has at least one publication, but only 3% have a publication in an AA journal. Around 16% of candidates have a Revise and Resubmit (R&R), but only 5% have an R&R in an AA journal. In general, men are more likely to have a publication or an R&R in an AA or A journal than women (See Figure A.4 in the Appendix).

Supervisor. We retrieved the names of the PhD supervisors for 1,445 job market candidates based on the information on their CVs (62 names are missing).[6] We identify female supervisors based on their first name or assign gender manually. On average, 16% of candidates have a female PhD supervisor, and female candidates are almost twice as likely to have a female supervisor (See Table A.1 in the Appendix).

Research fields. We think of research fields as 'clusters of ideas' and individuals within the same 'cluster of ideas' are potentially closer to one another than across clusters. This type of closeness or similarity has been shown to be important in hiring decisions (Bello et al., 2023). Economics departments will often organize their recruitment around these fields: they may for example determine which fields may be prioritized. For that reason, it is useful to rely on field categories that are commonly used.

To classify research fields as more or less male-dominated, we use data on

[4] Institutions that are not ranked are assigned the lowest rank of 430)

[5] American Economic Review, Quarterly Journal of Economics, Journal of Political Economy, Econometrica, ReStud, Journal of Finance, Journal of Financial Economics

[6] We either use the name, which is mentioned first in the references section, or additionally search for the members of the PhD committee or explicit mentions of advisors and supervisors.

publications in economics from EconLit.[7] Our analysis includes all publications in ranked journals between 2007 and 2017. We assign each paper to research fields using JEL codes, adapting the procedure of Card and DellaVigna (2013) to classify each JEL code into one of 23 research fields.[8] Each publication may be associated with multiple fields depending on its JEL codes.

For each year and field, we calculate the total number of publications authored by women and the same for men.[9] We then compute the fraction of female authors per field per year and calculate the average fraction of females per field over the entire 2007–2017 period. Based on these averages, we classify the eight fields with the lowest female representation as 'male fields' and the eight fields with the highest female representation as 'female fields'.

It is important to note that, even in the most female fields, economics remains a male-dominated discipline overall. A more precise—though potentially confusing—terminology would be "more male-dominated" and "less male-dominated" fields rather than 'male' and 'female'. The final classification of research fields is shown in Figure 1.

In a similar fashion, we extract research fields from the resumes of job market candidates, focusing on the primary (first) research field for our main analysis.[10] We successfully identify a research field for 93% of candidates: 48% of candidates report a first field, which we classify as male and 35% report a female first field. By construction men report male fields more often (45%) and female fields less often (29%) and the contrary holds for women (32% and 48%).

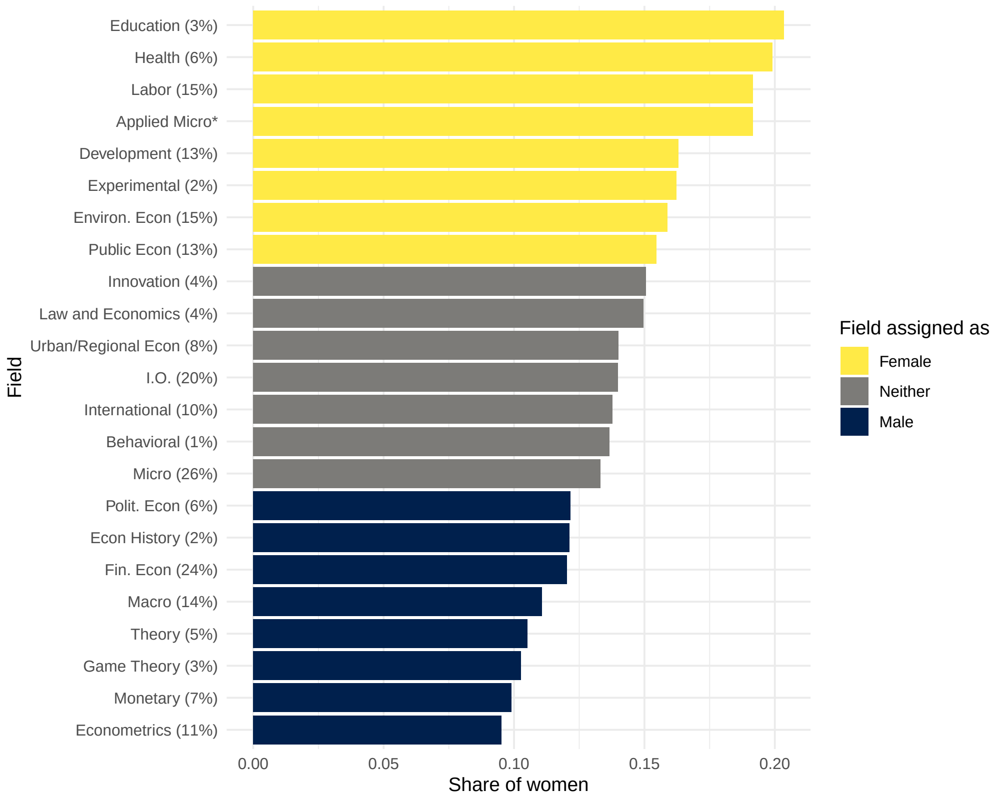
[7]We thank Ductor et al., 2021 for kindly providing the data.

[8]The research fields are: Microeconomics, Theory, Macroeconomics, Labor, Econometrics, Industrial Organization, International Economics, Financial Economics, Public Economics, Urban and Regional, Development, Economic History, Experimental, Health, Education, Innovation, Political Economy, Monetary, Environmental, Game Theory, Law and Economics, Behavioral Economics, and Other.

[9]Counting the number of publications authored by women involves the following: If a field has two publications, where the first is co-authored by two women and the second by one man, the female fraction is calculated as $\frac{2}{3}$. This method counts paper-author combinations, meaning papers with more co-authors are weighted more heavily. Since papers can belong to multiple fields, calculations are conducted within each field.

[10]To match the research field as described in candidates' CVs to our classification based on JEL codes, we rely on detailed JEL code information, which is available for most fields. However, one exception is the field "Applied Micro," for which no specific JEL code exists. After extensive checks of correlations between research fields, we conclude that "Applied Micro" most closely aligns with Labor Economics. Consequently, candidates listing "Applied Micro" as their primary field are assigned to Labor Economics. For all other fields, there is a straightforward mapping between the field stated on CVs and those defined by JEL codes.

Figure 1: Fields in Publication Data by Share of Women



Note: The parentheses next to the field name reports the share of publications in a certain field, e.g., 15% of publications have at least one JEL code which is associated with Labor Economics. Since papers can be associated to multiple fields these shares do not add up to one. The share of women on the x-axis is the share of women among all individuals publishing in this field. Source: EconLit Data

Figure A.3 in the Appendix shows the share of women by fields based on the data from the CVs.

2.2 Placement Outcomes by Gender and Fields

We first look at placement outcomes. We observe that women are as likely (if not more likely) to be placed as tenure-track assistant professors as men: 48.2% vs. 46.2% (See Panel A in Figure 2). The key question though, is how these placement probabilities vary across fields. Panel B in Figure 2 shows placement probabilities splitting the sample in two different ways: by whether the first field is a female field or not, and by whether the first field is a male field or not. From Panel B in Figure 2 it becomes clear that the placement probability for women who specialize in a male field is substantially higher (both in comparison to women with no male field, and to men with a male field). The placement probability for a woman specializing in a male field is 59.3%. If a woman does not specialize in a male field, her placement probability is 44.1%. The difference is a staggering 15 percentage points.

While there are notable differences in placement probabilities, there are no notable differences for women in the placement rank: conditional on being placed as an AP, women in male fields are as likely to be placed in Top-50 Economic Research Institutions as women in female fields (See Panel C in Figure 2). Figure 2 shows clearly that while women in male fields outperform others in terms of placement probabilities, they do not outperform others in terms of placement rank: This is a first indication that these female candidates in male fields are not better candidates than the others.

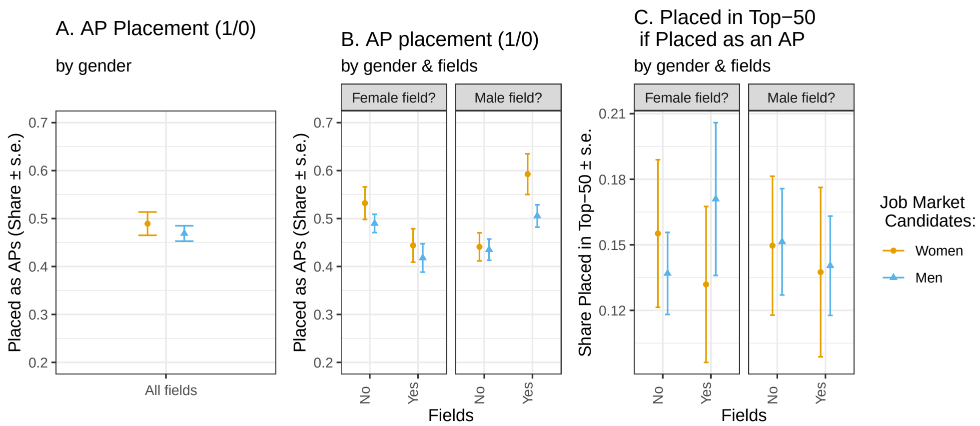
This relationship – the premium in placement probability for women in male fields – also holds for other types of placement outcomes. These women have higher placement chances in Academia in general, which includes non-tenure track APs, postdocs, adjunct, teaching, and other positions (see Panel B in Figure A.5 in the Appendix). The premium also holds if we consider placements in the top economic research institutions that are ranked in REPEC (Panel C in Figure A.5), which also includes placements in the top non-Academic research departments, such as the Federal Reserve Board, the IMF, the World Bank, etc. Hence, the premium for women in male fields is robust and observed across the board.

Our conjecture is that the placement premium may be driven by efforts to increase gender diversity in economics departments and by a stronger demand for male fields in general, the latter due to the fact that Economics is a male-dominated discipline.

There could however be alternative explanations. For instance, the quality of candidates could differ across fields (supply-side differences). There might also be a ‘supervisor effect’: women in male fields are more likely to have a male supervisor (87% vs. 73% for women who have a non-male first field) and male supervisors have access to broader networks (Ductor et al., 2021) allowing for better placements for their PhD students.

If these alternative explanations are relevant, the estimated premium for

Figure 2: Placement Outcomes – Probability of Being Placed as an Assistant Professor and Placement Rank



Note: Panel A displays the probability of being placed as an Assistant Professor (AP) separately for men and women. Panel B does the same but partitioning the data on whether the first research field is female or male. Panel C displays the probability of being placed as an Assistant Professor in a top-50 institution, conditional on AP placement. All panels display the point estimate plus/minus one standard error. All panels are based on data collected on job market candidates and their placements.

women in male fields (over women in female fields) should shrink when we introduce controls for the quality of the candidate (the rank of the PhD-granting institution, publication records at the time of the job market) or when we control for the supervisor's gender.

To test this formally, we run the following regression:

$$\begin{aligned} Y_{i,s,y} =& \beta \cdot \mathbb{1}\{i = \textit{Woman in male field}\} + \mu \cdot \mathbb{1}\{i = \textit{Man in male field}\} \\ &+ \delta \cdot \mathbb{1}\{i = \textit{Man not in male field}\} + \kappa \cdot \textit{quality-proxies}_i \\ &+ \sigma \cdot female\_supervisor_i + \gamma_s + \xi_y + u_{i,s,y} \end{aligned} \tag{1}$$

where $Y_{i,s,y}$ is either a placement indicator for the placement as an assistant professor[11] (0/1) for candidate i; from PhD-granting institution s in year y; the indicator functions $\mathbb{1}\{i = \textit{Woman in male field}\}$, $\mathbb{1}\{i = \textit{Man in male field}\}$ and $\mathbb{1}\{i = \textit{Man no male field}\}$ take value 1 if and only if candidate i is a female with a male research field, a man with a male research field and a man without

[11] or the placement rank – whether the placement rank is within the Top-50 Economics Research Institutions for those placed as assistant professors (0/1)

a male field. Therefore, the baseline category against which one is comparing are women with no male fields. The variable $quality\text{-}proxies_i$ include the quality of journals where the candidate has published or has a revise and resubmit. The dummy variable $female\_supervisor_i$ controls for the gender of the supervisor. Coefficients γ_s and ξ_y capture PhD-granting institution and year fixed effects, and $u_{i,s,y}$ is the residual.

Table 1: Regression Results: Placement as Assistant Professor

	Placed as an AP (1/0)		In Top-50 (1/0), if placed as an AP	
	(1)	(2)	(3)	(4)
β: Woman in Male Field	0.149**	0.143**	-0.025	0.002
	(0.052)	(0.050)	(0.051)	(0.043)
μ: Man in Male Field	0.063	0.028	-0.010	-0.046
	(0.038)	(0.037)	(0.039)	(0.042)
δ: Man not in Male Field	-0.012	-0.021	0.003	0.010
	(0.037)	(0.039)	(0.040)	(0.047)
H0: $\beta = \mu$ (p-val)	0.078	0.023	0.744	0.350
N obs	1,365	1,365	650	650
N clusters		33		33
R^2	0.01	0.05	0.00	0.05
Mean Y	0.48	0.48	0.15	0.15
publication records controls		✓		✓
PhD supervisor's gender		✓		✓
institution fixed effects		✓		✓
year fixed effects		✓		✓

* p<0.05, ** p<0.01, *** p<0.001
This table reports selected coefficients for Regression (1). See the full set of coefficients in Table A.3 in the Appendix.

The main parameter of interest is β, which captures the difference in placement outcomes between women in male fields and women in non-male fields. Without any controls, women who specialize in male fields are 14.9 percentage points more likely to be placed as tenure-track assistant professors than women not in male fields (See Row 1, Column 1 of Table 1). Next, in Column 2, we introduce controls for the quality of publications (and R&Rs), supervisor gender and PhD-granting institution (and year) fixed effects, which means that we exploit only the variation in placement outcomes for people graduating from the same institution. In general we find that a better publication record is correlated with better placement outcomes. In particular, a revise-and-resubmit at an AA journal (top-7) "adds" 34 percentage points (See Column 2 of Table A.3 in the Appendix). Nevertheless, the gap (β) remains stable when including the additional controls: the estimate is at 14.3 percentage points with p-value < 5% (See Column 2 of Table 1). We conclude that these controls fail to explain the premium women in male fields experience.

While we find no placement differences between men in male fields and women in non-male fields (See Row 2, Column 1 in Table 1), nor between men in non-male fields and women in non-male fields (See Row 3, Column 1 in Table 1), there is a difference between men and women who specialize in a male field (See Row 4, Column 1 and 2 in Table 1, which tests the $H0$ that $\beta = \mu$). Without controls or fixed effects women with a male field are 8.6 percentage points more likely to be placed as tenure-track assistant professors than men with a male field in without control, however this effect is statistically significant only at the 10 percent level. With controls the effect is larger (11.5 percentage points) and is statistically significant at the 5 percent level. Therefore, the premium for women in male fields also exists when comparing them to men in male fields.

Placement quality, conditional on placement, is not statistically different across the different groups of job market candidates (See Columns 3 and 4 of Table 1).

When we consider alternative placement outcomes – placement in Academia or in the top 429 economic research institutions – the results are similar (See Columns (3)-(7) and (9)-(12) of Table A.3 in the Appendix).

Overall, we show that, indeed, in line with our hypothesis, there appears to be a premium for women who work in male fields over women in non-male fields, but also over men in male fields: women in male fields are more likely to be placed as assistant professors overall, and their higher chances do not appear to be driven by higher quality or better supervisor networks.

2.3 Diversity of Ideas Within Fields

So far we have used fields as a proxy for 'clusters of ideas', and we have shown that the access of women to assistant professorships is much larger if they are in male fields. These results show that trends in the representation of women do not necessarily go hand in hand with trends in the representation of fields women tend to specialize in, thereby possibly limiting the gains from diversification. However, it is plausible that women specializing in male fields contribute to diversification of ideas *within* fields. They may bring different perspectives and approaches within a field. For example Angrist et al. (2017) document a shift in the disciplines that corresponds to a shift in methods rather than topics. Over time all fields have become more empirical. Similarly, it is plausible that the increasing share of women within fields has contributed to more diversity of ideas (topics or methods) within a field.

To shed light on how 'different' candidates are within a field, we construct a measure based on the similarity of the *words* of the abstracts of the job market papers of candidates. We compare the abstract of the job market paper of each candidate to all other abstracts of job market papers of candidates in the same field. Since abstracts summarize key ideas and methods, this measure should provide a good indication of the extent to which women and men's ideas 'stand out' in a given field.[12]

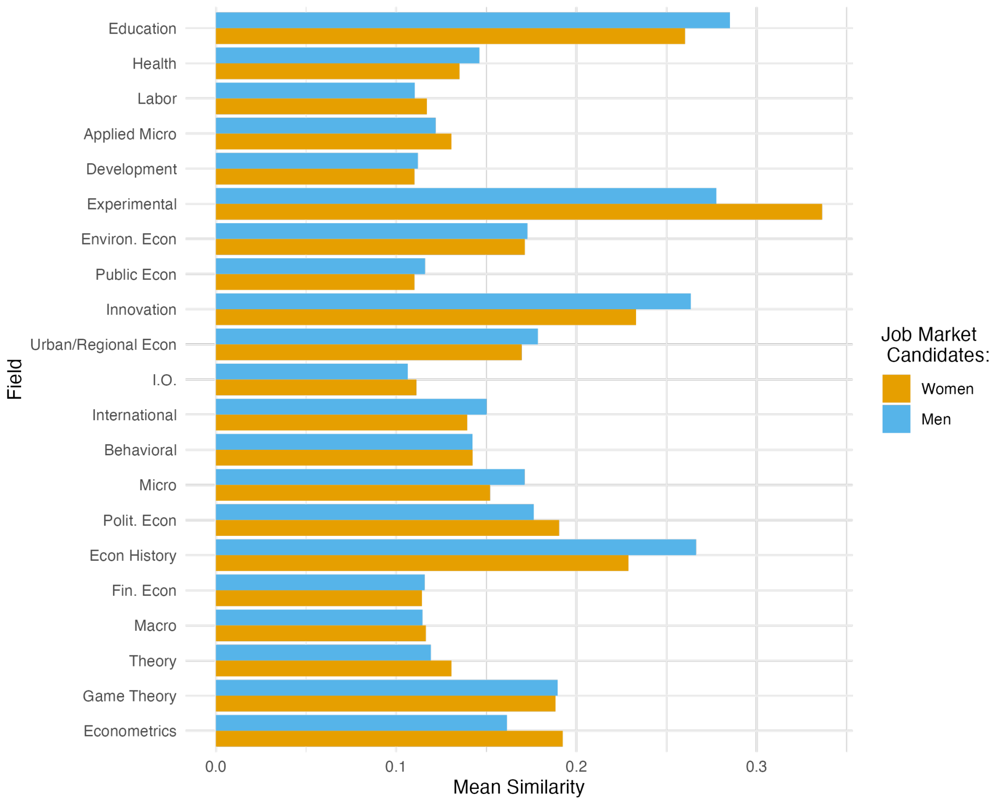
Figure 3 presents the similarity measures for men and women across the different fields in Economics. We do not find large differences in how similar women's and men's ideas are to the rest of the candidates in the same field. That is, there is no strong evidence that women's ideas are very different from men's ideas within any given field, except perhaps for experimental economics, innovation and economic history. However, there is no clear pattern that would suggest that women are more different in terms of ideas in more male fields.

2.4 Historical Perspective on Diversification of Ideas in Economics

In this Section, we present additional evidence on diversification of the Economics discipline specifically by using additional data which allows a more

[12]To be specific, we calculate an "TF-IDF score" for each abstract, which captures a combination of the importance of each word within an abstract (TF: Term Frequency) and the importance across all abstracts within a subfield (IDF: Inverse Document Frequency). The TF-IDF score takes values from zero to infinity, and it has been re-scaled as the cosine similarity. Therefore, all similarity values reported take values from -1 to 1.

Figure 3: Similarity of Abstracts by Gender and Field



Note: Author's own calculations based on abstracts of job market papers. The fields are ordered by the fraction of women publishing in these fields from 2007 to 2017 based on Econlit data.

long run perspective. We do so first, by looking at the Economics Academic Job Market in the early 2000s when gender diversity was not yet an important factor in hiring decisions and see how women in female and male fields performed. Second, we take an even more long run perspective to examine how different fields have evolved over time going back to the 1970s using data on publications.

First, we hand-collected data of individuals on the Economics Academic Junior Job Market from 2005 to 2011. This dataset includes information on job market candidates and their placements, sourced from a subset of 11 universities for which candidate lists were available for some of the years in this period.[13]

[13]The universities include Boston College, Boston University, Brown University, Columbia University, Cornell University, Harvard University, Stanford University, University of California Los Angeles, University of Pennsylvania, University of Virginia, and Yale University.

With this additional data, we again examine whether women in certain research fields performed better than in others during the early 2000s, a time when gender diversity was not yet a prominent factor in hiring decisions. Specifically, we classify research fields as either female or male and compare the placement probabilities of women and men across these categories. Again, our primary focus is on their likelihood of obtaining a position as an assistant professor. The results of this analysis are presented in Figure 4.

Panel A of Figure 4 depicts the comparison of women and men with and without a first research field classified as female (left side) and as male (right side) for the years 2005 to 2011. Panel B shows the same comparison for the years 2018, 2019, and 2022, reflecting a period when gender diversity had become a significant consideration in hiring decisions.

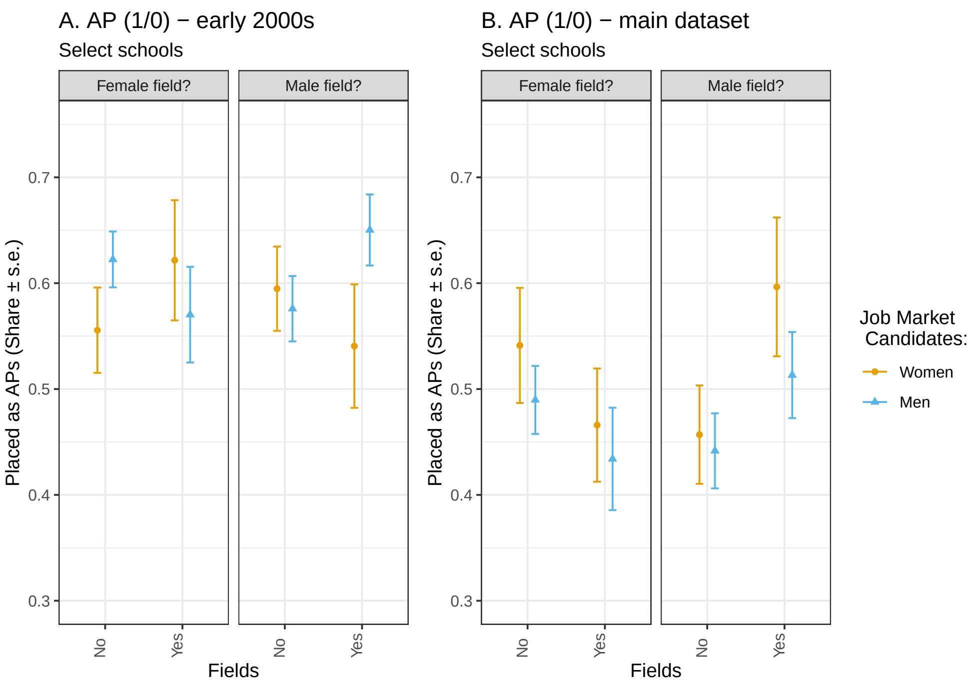
Two key findings emerge from this analysis. First, the results in Panel B, despite being based on a smaller subset of the data, mirror those of our main analysis. When gender diversity is a prominent issue, women in male fields outperform all other candidates in terms of placement probabilities. Second, Panel A illustrates a contrasting pattern: in the early 2000s, when gender diversity was not a priority in hiring decisions, women in male fields did not outperform other job market candidates. In fact, during this earlier period, a woman's primary research field appeared to have little impact on their placement outcome.

This finding is significant because it supports our main hypothesis: while women in male fields currently outperform women in female fields, the reverse was not true in the past. Consequently, it is unlikely that women in female fields historically enjoyed particularly high placement success, leading to women already being over-represented in female fields and now needing to catch up in male fields. Instead, our results suggest that diversity incentives and the predominance of incumbents from male fields have created an advantage for women in male fields in the recent years.

Second, using data on publications we can consider a more long run perspective to shed light on the evolution of fields and performance of women. One interesting statistic to consider for example is how the share of 'female fields' changed over time, especially relative to the share of women who are in

These departments were selected because, among the top 33 departments, they provided the most detailed and accessible records of candidates on the job market during the chosen years.

Figure 4: Job Market placement in earlier years for selected schools



Note: Author's own calculations based on the placements of job market candidates from selected 11 universities in the early 2000s in Panel A and from the 2018, 2019 and 2022 in Panel B.

the profession.

Using data on publications in Economics from EconLit,[14], we find that the share of women in Economics overall has increased substantially over the last five decades: As one can see in Figure 5, in the early 1970s the share of women publishing in economics was only around 6% and has increased to around 16% in 2017. Similarly, also the share of publications in female fields has grown over time, from around 18% in the 1970s to 23% in 2017. While the growth of the share of women has been considerable since the 1970s it has clearly stalled in the last two decades, similar to the growth of publications in female fields, which however started at a much higher level.

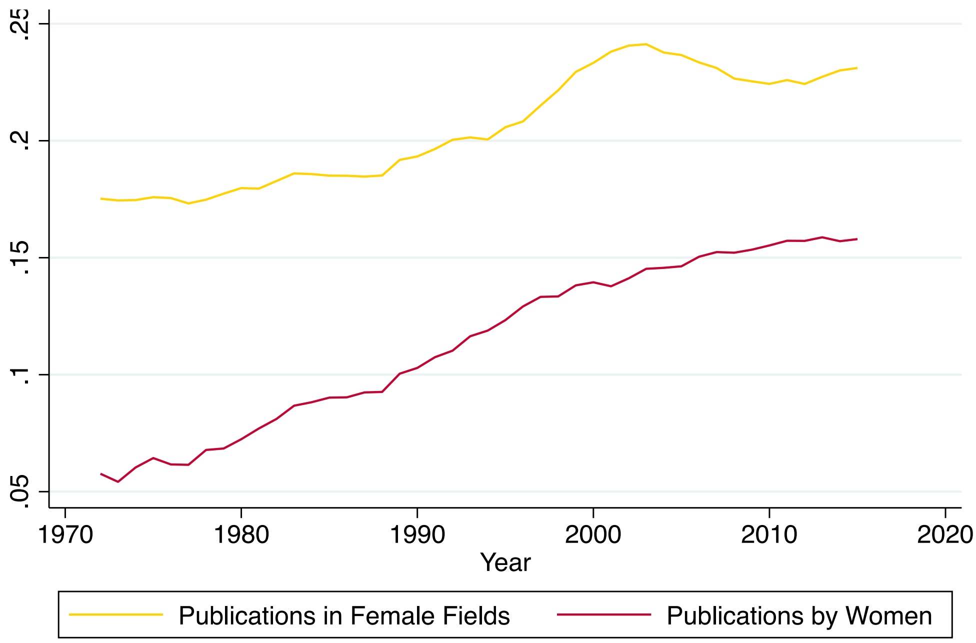
In conclusion, the data from the Academic Economics job market point at

[14]We use data from Econ Lit on all publications in journals ranked by the Tinbergen Institute (we thank Ductor et al. (2021) for providing the data). To calculate the share of female fields we use the JEL codes of publications to categorize publications into (potentially multiple) fields.

a striking pattern, showing that women in male fields fare significantly better than other groups. There is no evidence that their relative advantage is due to higher quality or better access to networks. There is also no evidence that the increase in female representation is associated with increased diversity in ideas in these male fields. Furthermore, data on the representation of women and more female ideas show that women remain underrepresented in the Economics profession.

However, these data have their drawbacks. Job market placements are an equilibrium outcome, and reflect supply and demand factors. There may be unobservables that drive differences in placements that are unaccounted for. The next Section presents experimental evidence from a controlled environment, which allows us to focus entirely on the demand for ideas.

Figure 5: Evolution of Publications in Female Fields and Publications by Women



Note: Author's own calculations based on Econ Lit Data using only ranked journals. The graph shows 5 year moving averages of percentages of publications in female fields and percentages of publications authored by women.

3 Online Experiment

Our second study is based on an Online experiment where we study more broadly the demand for ideas in a college-educated working population. We design an experiment to examine in more detail the demand for ideas when confronted with incentives that are similar to those present in hiring decisions. Presumably, there are incentives to hire high-quality candidates, and hiring decisions have implications for exposure to and engagement with the ideas of the candidate. The goal of this experiment is to first, present evidence on the demand for ideas, and second, to explore to what extent the demand for ideas responds to incentives.

The design is deliberately kept simple and thereby omits important features likely to be relevant in real-world applications, such as real long-term social interactions. Also, we put a general focus on 'ideas', while usually hiring is determined by the specific needs of a firm, its specialization, etc. Nevertheless hiring needs are likely to be partly a choice variable as well. Also, it is likely that when establishing a profile for a candidate, firms have room to focus on certain aspects and less on others. For example, a company looking for an administrative assistant may be interested in someone who values environmental initiatives, or someone who is more business-minded.

The experiment was pre-registered on the AEA RCT website under the title 'What do people choose to watch' (AEARCTR-0011330), and conducted on the platform Prolific in July 2023. [15]

3.1 Basic Setup

We now turn to describing the basic experimental design. Participants, who we will refer to as 'Employers', are asked to choose three talks among a curated set of eight TED talks. The eight talks fall under broad topics ("Tech", "Health", "Business" or "Environment") and are either presented by a woman or a man.

[15] The first pre-registration took place in May 2023, just before any data collection started. We then collected data for Stage 1 of the experiment (ratings of TED Talks by Cornell students as explained below). We indicated that the plan for stage 2 (main experiment) was preliminary, and would be updated before data collection would start for stage 2, which we did on 26 July 2023, prior data collection for the second stage (main experiment). A third amendment was registered on September 28, after we noticed small imbalances in videos shown to participants. 50 additional observations were collected to eliminate these imbalances. None of the results were significantly affected by adding these additional observations

The choice sets presented to employers always had the same structure:

- 4 presentations in a male field (either Tech or Business); 3 by male presenters, 1 by a female presenter.
- 4 presentations in a female field (Health or Environment); 1 by a male presenter, 3 by female presenters.

The order of presentations within any choice set is randomized.[16]

Before selecting their preferred talks, they see basic information about each of the talks: a screenshot showing the speaker (see Figure 6, which displays half of a possible choice set), the title of the talk, the field category (Tech, Health, Environment or Business), and a brief summary of the talk. They are then asked to rank their three choices in order of preference. The higher they rank a presentation, the higher the probability they will get to view this presentation:

- Rank 1: probability of watching equal to $\frac{1}{2}$;
- Rank 2: probability of watching equal to $\frac{1}{3}$;
- Rank 3: probability of watching equal to $\frac{1}{6}$.

One of three talks is then selected at random (according to the procedure described above), each and participant views one presentation. After having watched the presentation, participants are asked to answer four questions related to it. Finally, participants are also asked a series of questions about their occupation and interests, as well as basic background characteristics. [17]

3.2 Baseline Incentives

Participants are told that their earnings are between \$6 and \$18 for participating in the study. The payment of a minimum of \$6 is guaranteed.

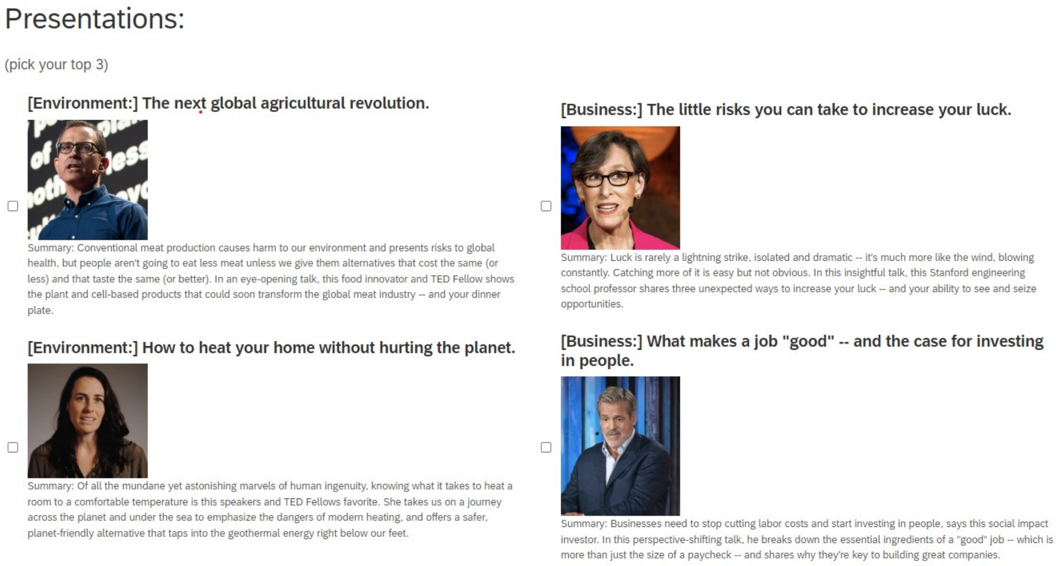
The incentives are set as follows:

- Payment depending on the quality of the talk watched ($\$1 - \$5$).
- Payment of \$3 per correctly answered attention question.

[16] There are two sets of 'choice sets' for each field, such that several employers would be confronted with the same choice set.

[17] The full survey questions are available in an Appendix available on request.

Figure 6: Choice Screen only 4 out 8 Choices Displayed



The quality of talks was assessed prior to the experiment by external raters. We recruited 16 Cornell students, based on topics they reported having expertise in. Each TED Talk was rated by 2 students on three dimensions (how informative was the talk, whether the presenter made it interesting and easy to follow, and whether the talk was convincing). We calculated an average rating for each talk across the three dimensions and two students. We then re-scaled it on a scale from 1 to 5 and rounded the rating to the nearest half unit (0.5, 1, 1.5, 2,...5). Participants are told they earn \$1 times the value of the rating. [18].

The attention questions are a set of four questions related to the talks. These questions were generated by our research team, with the help of two research assistants. As described below, one of the treatment variations relates to the nature of these questions, and whether they are easier to answer when one has expertise in the topic of the talk or not.

3.3 Treatments

We introduce two experimental variations. The first treatment variation relates to the nature of questions asked about the talk and aims to evaluate the extent to which choices are driven by expertise as opposed to taste. The second treatment variation aims at evaluating the effects of diversity initiatives.

[18]Full details of the protocol are provided in an Online Appendix available upon request

We contrast the effects of introducing (small) incentives to choose a female presenter to the effects of an alternative incentive, that subsidizes the choice of presentations in a female field. We are interested in evaluating how these institutions affect the representation of women and the diversity of ideas. For this second variation, we only involve male participants as employers, since the goal is to learn how these incentives can affect decisions in male-dominated workforce environments.

3.3.1 Taste vs Expertise

The first treatment varies the type of attention questions participants are asked about the TED Talk. Depending on the treatment, the questions can be of two types: **content questions** or **listening questions**. Content questions are questions related to the content of the talk and are easier to answer if one has some expertise in the topic. Listening questions are questions that require no knowledge of the topic and simply require having paid attention to the presentation. For the latter, the question is of the type 'Was this sentence said...'. [19].

Both types of questions are single choice questions giving a choice of four possible sentences, with one of them being correct. We use this experimental variation to assess the extent to which expertise or taste drive choices.

3.3.2 Incentivizing Diversity

Diversity initiatives often target specific individual characteristics, such as gender or race. The idea is to encourage a fair representation of candidates, and in particular of those who are under-represented. We introduce a treatment 'Gender Incentive', where participants receive an additional $1 incentive for selecting a presentation by a female speaker.

An alternative incentive that we consider is one that targets under-represented fields, rather than under-represented individuals. The idea is to encourage hiring in fields that are under-represented and more popular among under-represented individuals. We introduce a treatment 'Field Incentive', where participants receive an additional $1 incentive for selecting a presentation in a female field (“Health” or “Environment”).

[19] The full list of questions is available in an Online Appendix upon request

Note that the payment for the gender or field incentive (\$1) is deliberately chosen to be relatively small compared to the other drivers of choices. The quality of the candidate and the need to engage with their ideas are by design intended to matter more in decisions than the diversity incentives. The goal is to replicate the trade-off we perceive in many professional settings, where questions of quality and fit are likely to be key determinants of hiring, and diversity concerns matter but are perhaps not as prime order as quality or fit.

The shifts we observe in choices should therefore be considered with this incentive structure in mind.

Overall, we implement a 3×2 between-subject design, but the two additional incentive treatments only involve male participants.

Female participants are only exposed to the two treatments - taste vs. expertise with baseline incentives, while male participants are additionally exposed to the three different diversity incentives.

3.4 Hypotheses

We pre-registered several hypotheses related to how we expect the choices to depend on (1) the gender of the employer, and on (2) treatment variations.

The key variables of interest are:

- Share of female presenters chosen, $S_{FPresenter}$ = Number of female presenters chosen / Total number of presenters chosen
- Share of presentations in female fields, S_{FField} = Number of chosen presentations in female fields / Total number of presenters chosen
- Share of women in female fields, S_{FF} = Number of chosen presentations by female presenters in female fields / Total number of presenters chosen
- Share of women in male fields S_{FM}= Number of chosen presentations by female presenters in male fields / Total number of presenters chosen

A natural benchmark to which we can compare the shares corresponding to choices is their shares in the choice sets. For each group (gender, field, and combination of gender and field) we calculate a measure of over- and underdemand on based on the ratio of the chosen share to the share in the choice set. This ratio lies between 0 and 8 (e.g., if all employers choose a woman from a male field or a man from a female field). A ratio below 1 indicates that this group is underrepresented, a ratio above 1 shows that this group is over represented. We now turn to the hypotheses to be tested.

Hypothesis 1 We predict there are systematic differences in preferences and expertise for field according to the gender of the employer. We expect the following in the baseline (no gender or field incentive) treatment:

Hypothesis 1a. Presentations by male/female presenters will be over-represented in the shares of presentations chosen by men/women respectively.

- $S_{FPresenter}$ < 50% if employer gender is male.
- $S_{FPresenter}$ > 50% if employer gender is female.
- $S_{FPresenter}$ if employer is male < $S_{FPresenter}$ if employer is female

Hypothesis 1b. Presentations in male/female fields will be over-represented in the shares of presentations chosen by men/women respectively.

- S_{FField} < 50% if employer gender is male.
- S_{FField} > 50% if employer gender is female.
- S_{FField} if employer is male < S_{FField} if employer is female

Hypothesis 1c. The differences observed in (a) and (b) will be larger in the "expertise treatment" than in the "no expertise treatment".

Hypothesis 2 We compare the impact of two treatments: "gender incentive" and "field incentive". We predict the following for male employers:

Hypothesis 2a. Both "incentive treatments" will increase the share of women relative to the baseline.

- $S_{FPresenter}$ under Gender Incentive > $S_{FPresenter}$ under Baseline
- $S_{FPresenter}$ under Field Incentive > $S_{FPresenter}$ under Baseline

Hypothesis 2b. The field incentive will increase the share of presentations in female fields. We do not expect to find a significant effect of the gender incentive treatment on the share of presentations in female fields.

- S_{FField} under Field Incentive > S_{FField} under Baseline
- S_{FField} under Gender Incentive = S_{FField} under Baseline

Hypothesis 2c. We want to explore how the two incentive treatments affect the diversity of ideas. We measure the distance to full diversity as a sum of squared differences between the actual aggregate shares chosen in each field versus 25% – the full-diversity benchmark when each field is represented proportionally (see Equation 2). We then test whether any of the incentive treatments generate more diversity of ideas than in the baseline, and whether the field incentive treatment generates more or less diversity of ideas than the gender incentive treatment.

3.5 Sample

The experiment was conducted via the platform Prolific. We sampled 551 prolific participants (413 men and 138 women), all of whom are US-born, aged between 25 and 60, have a college degree, and currently employed (full-time, part-time or starting a new job within 2 weeks).[20]

3.6 Analysis of Online Experiment Data

On average participants spent 19 minutes on the study and were paid $13.2. Summary statistics on the payment components and time spent by each treatment group are presented in Tables A.7 and A.8.

3.6.1 Sample Descriptives

The realized sample sizes per treatment group and the gender of the employer are in Table A.4). The randomized values are overall balanced across different

[20]We surveyed 501 people on July 27, 2023. Ex-post, we realized that there were some imbalances in the number of observations across different randomization values, which happened completely at random. We amended the Pre-Analysis plan on September 28, 2023, (see the details in an Online Appendix available upon request) and additionally surveyed 50 people on September 29, 2023.

treatment groups: The descriptive statistics for the randomly assigned values are presented in Table A.5 (grouped by the type of the incentive and gender) and in Table A.6 (grouped by the question type and gender).[21]

Women and men in our sample are different in terms of their occupations and topics of interests. Women are less likely than men to have a STEM degree (21% of women vs. 42% of men) or to work in occupations related to ICT, math, engineering or architecture (0% vs. 6%). Women are more likely than men to indicate interest in topics such as Art (46% of women vs. 35% of men), Education (33% vs. 22%), Environment (52% vs. 40%), Health (67% vs. 44%), Lifestyle (55% vs. 29%), and Literature (46% vs. 25%); but they are less interested in Business and Finance (29% vs 48% for men), Politics (33% vs. 45%), Science and Technology (55% vs. 76%), and Sports (21% vs. 51%). See Table A.5.

Overall, the occupational structure among the survey respondents resembles the occupational structure among college-educated labor force in the U.S. (Table A.9).

3.6.2 Baseline Choices

We start with the first hypothesis. The first outcome of interest is the share of women chosen by male and female employers, considering first ranked choices only. Results are presented in more detail in Panel A of Table A.10 in the Appendix. Men choose presentations by female speakers on average in 46.1% of cases, however this is not significantly below 50% (p-value 17.8%, one-sided test). Women choose presentations by female speakers in 58.7% of all cases, which is significantly more than 50% of time (one-sided t-test p-value of 2%). The difference in the probability of choosing a woman between the two groups of employers is 12.6 percentage points and statistically significant (p-value 1.8%), in line with Hypothesis 1a.

Hypothesis 1b relates to the share of presentations in female fields, and how it differs across gender, again considering first ranked choices only. Again, we find systematic gender differences. Figure 7 shows that men are more likely than women to choose Tech and Business (i.e., male fields), while women are more likely to choose Health and Environment (i.e., female fields). Overall, men choose female fields in only 42.6% of cases, which is significantly below

[21]See Footnote 20.

50% (p-value 3.8%, one-sided test, see Panel B of Table A.10). Women choose female fields in 65.2% of cases, which is significantly above 50% (p-value <0.01%). Overall, the gender difference in field choices is 22.6 percentage points and statistically significant (p-value <0.01%). These sharp differences in field choices by men and women are in line with Hypothesis 1b that men and women are interested in different ideas.

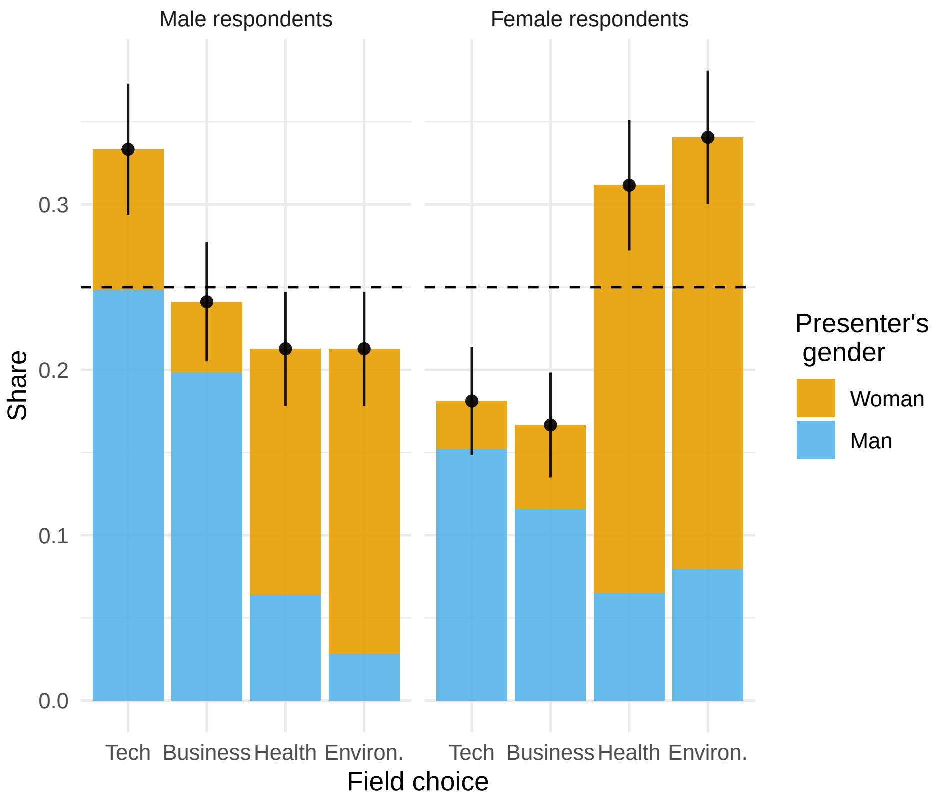
Note that the difference in the shares of female presenters chosen appears mostly driven by different preferences for fields, discussed above. Conditioning on the field chosen, we find no evidence of gender biases in choices. There is no significant association between the gender of the presenter and the gender of the participant (t-statistics = 0.12; See Figure A.7 in the Appendix). To sum up, men are more interested in male fields where male presenters are in the majority, which results in men choosing more men. Similarly, women choose more women because they are interested in fields where women are in the majority. Hence, substantial differences arise in the gender mix of presenters chosen and these are driven clearly by field choices.

3.6.3 The Role of Expertise

Hypothesis 1c relates to whether the nature of the attention questions affects choices, and in particular, whether it is plausible that choices are driven by expertise rather than taste. When employers are asked questions regarding the content of the TED talk, we expect them to have stronger incentives to choose a talk in which they have some prior expertise than when they are simply asked listening questions (i.e., "Was this sentence said?"). In other words, we would expect men to be more likely to choose male fields (or less likely to choose female fields) under content questions than under listening questions, if their choices are driven by expertise.

We do not find significant differences in field choices by the type of questions (See Figure A.6 and Table A.11). Men choose female fields in 39.4% of cases under content questions and 45.7% of cases under listening questions, but the difference of 6.3 percentage points is not statistically significant (p-value of 22.7%, one-sided t-test). Vice versa, we would expect women to choose female fields more often when asked content questions rather than listening questions, but we observe the opposite: women choose female fields in 60% of cases un-

Figure 7: Baseline Choices



Note: The dashed line at 25% shows expected shares for each field if presentations are chosen at random. Sample sizes: 132 male respondents, 126 female respondents.

der content questions, compared to 70.6% under listening questions. Hence, the results indicate that differences in expertise are not the main, or at least not the only driver of the sharp gender differences in field choices, but rather gender-specific tastes play a significant role.

3.6.4 Effect of Gender and Field Incentives

Next, we turn to Hypothesis 2, which relates to the effects of the two incentive treatments and focuses on the sample of male employers.

Hypothesis 2a predicts that both incentive treatments increase the share of women relative to the baseline. We find that the gender incentive increases the share of women much more than the field incentive (See Figure A.9). The share of female presenters increases from 46.1% at baseline to 55.1% under the field incentive (p-value 6.7% for the difference relative to the baseline; one-sided t-test; See Table A.11) and to 75% under the gender incentive (p-value <0.01% for the difference relative to the baseline; one-sided t-test). These results are in line with Hypothesis 2a.

We find that both gender and field incentives significantly increase the share of presentations in female fields (See Figure 8 and Figure A.8). The share of female fields increases from 42.6% at baseline to 64% under the gender incentive (p-value <0.01% for the difference relative to the baseline; one-sided t-test) and to 66.9% under the field incentive (p-value <0.01% for the difference relative to the baseline; two-sided t-test). All the calculations are presented in Table A.11. Hypothesis 2b predicted that the share of presentations in female fields would increase significantly with the field incentive, but not with the gender incentive. We find that *both* incentives increase the share of presentations in female fields. Just like both incentives increase the share of presentations by female speakers.

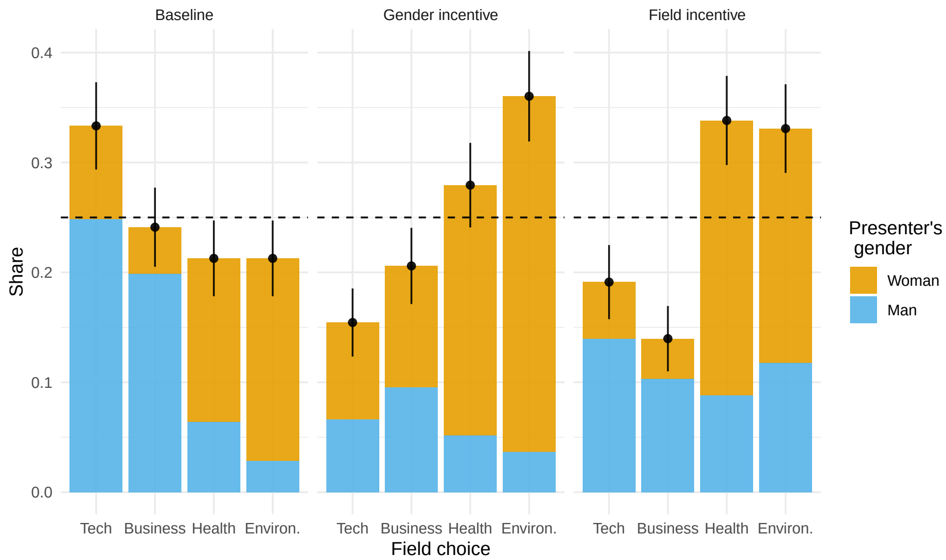
We find that the gender incentive treatment increases the share of women chosen in each field (see Figure 9). Figure 9 shows the distribution of gender conditional on field, for first-ranked choices. We see that women in male fields benefit most from the gender incentive. The share of women in male fields increases from 22.4% up to 55.8% , whereas the share of women in female fields increases from 80% up to 87.8%. In contrast, the field incentive does not benefit one gender over another. While women are substantially over-represented overall with the gender incentive, they are only marginally over-represented with the field incentive. Thus, these two incentive schemes have very different impact on the share of women chosen.

3.6.5 Measures of Over and Under-Demand

Additionally, we construct a measure and over and under-demand of men and women in different fields. This measure is the ratio of demand for each gender-field group relative to its representation in the choice set.

The calculated ratios are shown in Figure 10 for each gender/field combination and incentive treatment, and relate to men's choices only. We find that at the baseline, the only group in over-demand is men in male fields. Under the gender incentive, the most demanded group is women in male fields, followed

Figure 8: Gender and Field Choices of Male Respondents by Incentive



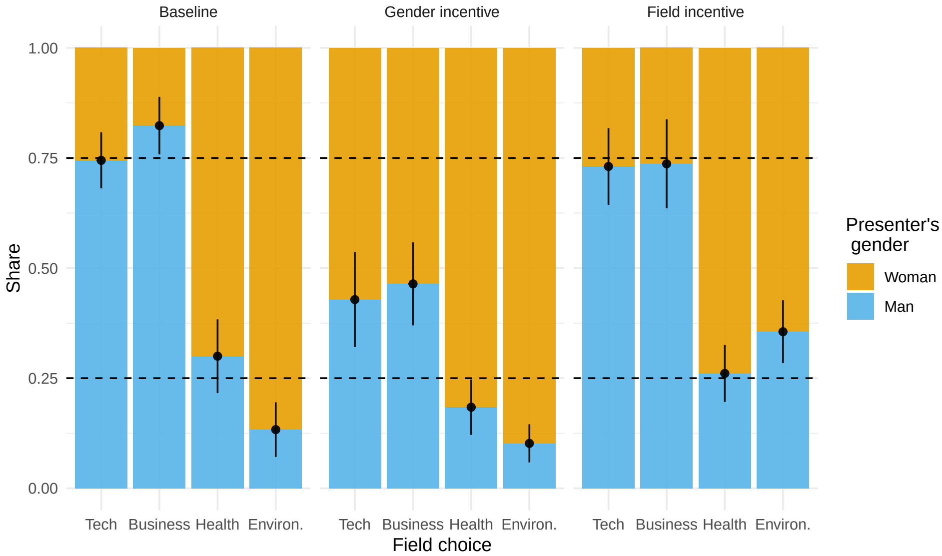
Note: The dashed line at 25% shows expected shares for each field if presentations are chosen at random. Sample sizes: 132 respondents in the baseline group, 117 in the gender incentive group, and 126 in the field incentive group. Male respondents only.

closely by women in female fields. Both are close to 50% over-demanded. Under the field incentive, the most demanded group is men in female fields, with women in female fields being in over-demand as well. That is, the (small) incentives substantially affect the demand for ideas.

We conclude that gender incentives may indeed have a differential effect on demand for women in male fields compared to women in female fields. The takeaway message is that incentives to increase female representation may disproportionately increase the demand for female ideas in male fields, a phenomenon that echoes the pattern we find in the data from the Academic Economics junior job market.

Of course, the magnitude of the changes in the relative demand for these groups depends on the strength of the gender incentive and on the strength of field preferences of the employers. Here the incentives were deliberately chosen to be small relative to the other incentives, in particular relative to the incentives of engaging with the ideas themselves, which we believe is in line with the current incentives in Academia. We find that, perhaps not surprisingly, these incentives have substantial effects on choices, suggesting that the

Figure 9: Gender Choices of Male Participants by Field and Incentive



Note: The dashed line at 75% shows the expected share of men in male fields: and the dashed line at 25%, the expected share of men in female fields, if presentations are chosen at random. Sample sizes: 132 respondents in the baseline group, 117 in the gender incentive group, and 126 in the field incentive group. Male respondents only.

demand for ideas is quite elastic in this setting. Not everyone responds though, there is a significant fraction of people who do not choose female presentations or presentations in female field even when given an incentive to do so.

3.6.6 Distance to Equal Representation of Ideas

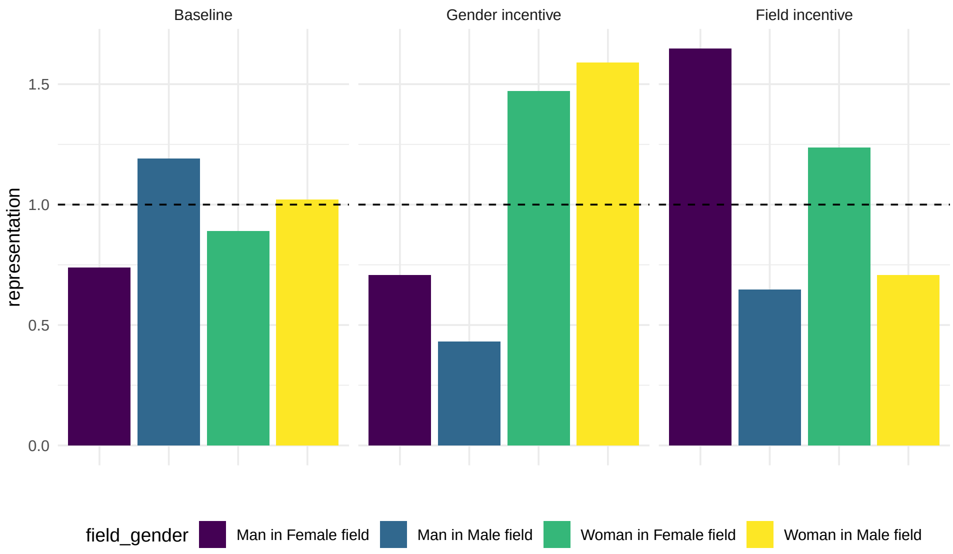
Another way to gauge how the incentive treatments affect diversity of ideas selected is to measure how far the choices are from a situation in which all ideas have the same chance of being selected.

The choice sets of ideas are such that each of the four fields is equally represented. We can therefore calculate a measure of how far the actual choices are from equal representation:

$$DistEqual \equiv \sum_{j \in fields} (S_j - 25\%)^2 \tag{2}$$

where S_j is the share of field $j \in \{Tech, Business, Health, Environment\}$ among the top-1 choices of the employers and 25% is the share of each field in the choice set.

Figure 10: Over and Under-Demanded Groups by Incentive



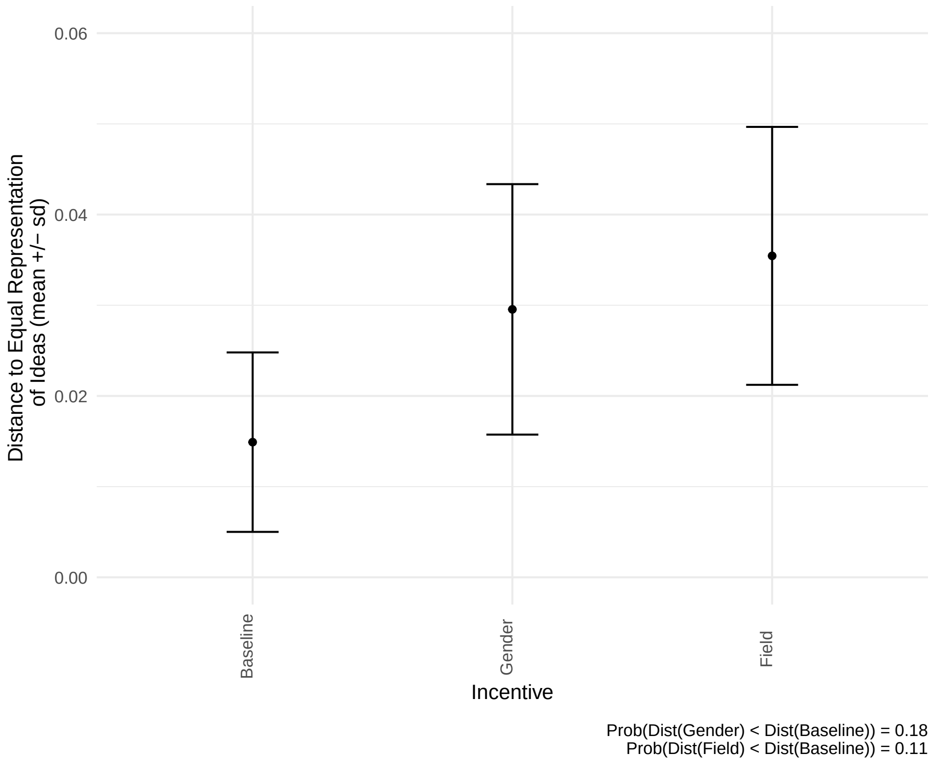
Note: The dashed line at 1 shows the expected demand-ratio if presentation are chosen at random. The representation measure is calculated by dividing actual share by the share in the choice set. When the ratio > 1, the group is over-demanded. When the ratio < 1, the group is under-demanded. Sample sizes: 132 respondents in the baseline group, 117 in the gender incentive group, and 126 in the field incentive group. Male respondents only.

For example, the distance will be equal to zero, if all four fields are equally represented among the top-1 choices, i.e., all are exactly at 25%. The largest distance to equal representation equals to 0.75, when all employers choose only one field as their top-1 choice.

To test if incentives statistically increase diversity (i.e. decrease the distance to equal representation), we bootstrap the sample 10,000 times within each incentive treatment to obtain the mean and standard errors of the distance to equal representation. Figure 11 shows the results.

Both gender and field incentives alter the choices substantially in favor of 'female fields' and the choices are as far from equal representation as the baseline choices or even further (see Figure 11). At baseline, the distance to equal representation is 0.0149 for men's choices, while it rises to 0.0295 under the gender incentive and to 0.0354 under the field incentive. The probability that the gender or field incentives leads to a situation with smaller distance to equal representation than the baseline is just 17.9% or 10.8% (respectively). In all other instances, the incentives lead to bigger distances to equal representation.

Figure 11: Distance to Equal Representation of Ideas



Note: The estimates are based on 10,000 bootstrapped samples.

However, it is important to stress that these effects relate to flows rather than stocks. While at the baseline the top-1 choices favor male fields, gender or field incentives favor female fields. One needs to consider that gender or field incentives are usually introduced to adjust the flow of new hiring to correct for existing imbalances in the representation of fields (stocks). If the current stocks of employers are represented by the historical imbalances favoring male fields, then making the flows favor female fields will likely improve the stock's diversity and help in moving towards more equal representation.

4 Discussion and Conclusion

This paper presents evidence on the relationship between gender diversity and diversity of ideas.

We first present evidence from the Economics Academic junior job market showing that women in male fields fare significantly better than women in non-male fields, and than men in any field. Controlling for available measures of productivity and gender of the supervisor does not explain this advantage. We present other evidence showing that this phenomenon is a recent one, and that over the last 5 decades, the increase in the fraction of female authors has been steeper than the increase in the papers in female fields.

Data from the field confound supply and demand factors though, so we also present evidence from a controlled experiment, conducted Online with a college-educated population. We examine the demand for ideas (TED talks) when there are incentives to engage with high-quality ideas. We find large gender differences in the demand for ideas, and we find that these differences are mostly driven by taste rather than by expertise considerations.

Introducing small incentives to engage with ideas proposed by women or ideas in fields that are typically more female sharply affect choices, suggesting the demand for ideas is quite elastic. We also show that these incentives have different effects on the representation of ideas. Incentives to increase female representation lead to an over-demand of women in male fields, while incentives to increase representation in female fields lead to an over-demand of both men and women in female fields.

The evidence presented here aims to inform initiatives aimed at increasing diversity in Academia. Many recent initiatives are targeting specific demographics. The results presented in this paper point out that these initiatives may well be effective in increasing the demand for under-represented groups, but may not necessarily realize the full potential of diversity in a situation in which ideas are selected by incumbents. Promoting diversity of ideas across the board may be more effective at achieving an increase in representation of under-represented groups, as well as their ideas.

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A Appendix

Table A.1: Descriptive Statistics for Econ Job Market Candidates

		By gender:	
	All	Men	Women
Number of observations:			
Total	1,507	1,044	452
2018-2019 market	506	334	167
2019-2020 market	528	373	155
2022-2023 market	473	337	130
Women (share)	0.30	0.00	1.00
Placement:			
placement unknown	0.04	0.04	0.04
Academia	0.59	0.59	0.58
Research, gvt, international org.	0.18	0.18	0.18
Consulting	0.12	0.11	0.14
Tech firm	0.04	0.05	0.04
in top 429 econ research inst. (share)	0.43	0.43	0.46
among those:			
REPEC rank (mean)	148.66	149.07	147.77
REPEC rank (median)	113.00	115.00	113.00
PhD-granting institution:			
Institution's rank, from 1 to 33 (mean)	14.16	13.92	14.65
Institution's rank, from 1 to 33 (median)	13.00	12.00	13.00
Fields of specialization (First field):			
First field known (share)	0.93	0.93	0.94
First field is a male field (share)	0.43	0.48	0.32
First field is a female field (share)	0.35	0.29	0.48
Macro (share)	0.21	0.22	0.16
Labor (share)	0.12	0.11	0.15
Microeconomics (share)	0.02	0.03	0.01
Publications (at the time of the JM):			
Has a publication (share)	0.36	0.37	0.35
Has a publication in AA journal (share)	0.03	0.04	0.01
Has an R&R (share)	0.16	0.16	0.14
Has an R&R in AA journal (share)	0.05	0.05	0.04
PhD Supervisor:			
No supervisor name on the CV (share)	0.04	0.04	0.04
Has a female supervisor (share)	0.16	0.14	0.23

This table reports descriptive statistics for 1,507 job market candidates in 2018-2019, 2019-2020 and 2022-2023 academic years from top-33 US economics departments (US news December 2018 ranking). The first column provides statistics for the full sample, while the second and third provide statistics for men and women separately.

Table A.2: Fields by share of women

	Field	Women (share)	Field share	Male fields	Female fields
1	Econometrics	0.10	0.11	1	0
2	Monetary	0.10	0.07	1	0
3	Game Theory	0.10	0.03	1	0
4	Theory	0.11	0.05	1	0
5	Macro	0.11	0.14	1	0
6	Fin. Econ	0.12	0.24	1	0
7	Econ History	0.12	0.02	1	0
8	Polit. Econ	0.12	0.06	1	0
9	Micro	0.13	0.26	0	0
10	Behavioral	0.14	0.01	0	0
11	International	0.14	0.10	0	0
12	I.O.	0.14	0.20	0	0
13	Urban/Regional Econ	0.14	0.08	0	0
14	Law and Economics	0.15	0.04	0	0
15	Innovation	0.15	0.04	0	0
16	Public Econ	0.15	0.13	0	1
17	Environ. Econ	0.16	0.15	0	1
18	Experimental	0.16	0.02	0	1
19	Development	0.16	0.13	0	1
20	Applied Micro	0.19		0	1
21	Labor	0.19	0.15	0	1
22	Health	0.20	0.06	0	1
23	Education	0.20	0.03	0	1

This table reports share of women and the share of publications by field. Note that a single publication can belong to several fields due to it having multiple JEL codes. Sample: EconLit Data on publications in ranked (Tinbergen Institute) journals from 2007 to 2017, except for ‘Applied Micro‘, which is introduced by the authors manually.

Table A.3: Regression results: placement outcomes by gender and field

	Placement						Placement rank					
	Assist. professor (1/0)		Academia (1/0)		Top-429 inst. (1/0)		Top-50 inst. (1/0) if Assist. professor		Top-50 inst. (1/0) if in academia		Inst. rank if in Top-429	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β: Woman in Male Field	0.149**	0.143**	0.144**	0.138**	0.122*	0.128*	-0.025	0.002	0.005	0.030	2.722	-3.248
	(0.052)	(0.050)	(0.051)	(0.045)	(0.052)	(0.056)	(0.051)	(0.043)	(0.050)	(0.041)	(17.860)	(20.391)
μ: Man in Male Field	0.063	0.028	0.088*	0.064	0.052	0.023	-0.010	-0.046	-0.011	-0.037	-5.186	5.829
	(0.038)	(0.037)	(0.037)	(0.032)	(0.037)	(0.040)	(0.039)	(0.042)	(0.037)	(0.036)	(13.650)	(18.539)
δ: Man not in Male Field	-0.012	-0.021	0.013	0.008	-0.064	-0.066	0.003	0.010	0.012	0.012	6.202	13.336
	(0.037)	(0.039)	(0.037)	(0.036)	(0.037)	(0.033)	(0.040)	(0.047)	(0.038)	(0.036)	(14.183)	(18.222)
published AA		0.112		0.183*		0.123		0.058		0.064		-21.894
		(0.091)		(0.070)		(0.077)		(0.070)		(0.051)		(14.691)
published A		0.184**		0.133*		0.073		-0.037		-0.028		-1.870
		(0.059)		(0.052)		(0.059)		(0.053)		(0.052)		(21.299)
published B		0.044		0.014		0.172*		0.013		0.019		5.676
		(0.060)		(0.052)		(0.069)		(0.094)		(0.093)		(22.342)
published other		0.008		0.035		0.038		-0.027		-0.013		15.573
		(0.033)		(0.030)		(0.031)		(0.035)		(0.028)		(11.612)
r & r AA		0.344***		0.214***		0.241***		0.186**		0.154**		-12.950
		(0.047)		(0.045)		(0.046)		(0.058)		(0.055)		(16.358)
r & r A		0.169**		0.110*		0.022		0.057		0.028		-3.193
		(0.049)		(0.051)		(0.065)		(0.066)		(0.058)		(17.011)
r & r B		0.165		0.151*		0.108		0.023		-0.003		-5.648
		(0.092)		(0.061)		(0.103)		(0.146)		(0.126)		(38.432)
r & r other		0.102		0.056		0.125*		0.117		0.098		-11.678
		(0.057)		(0.056)		(0.053)		(0.064)		(0.062)		(22.747)
Female supervisor		-0.029		-0.043		0.014		-0.073		-0.040		15.859
		(0.029)		(0.035)		(0.045)		(0.046)		(0.037)		(11.142)
H0: $\beta = \mu$ (p-val)	0.078	0.023	0.249	0.086	0.147	0.049	0.744	0.350	0.716	0.154	0.627	0.605
N obs	1,365	1,365	1,365	1,365	1,365	1,365	650	650	814	814	601	601
N clusters		33		33		33		33		33		33
R^2	0.01	0.05	0.01	0.04	0.02	0.08	0.00	0.05	0.00	0.03	0.00	0.02
Mean Y	0.48	0.48	0.60	0.60	0.44	0.44	0.15	0.15	0.17	0.17	148.03	148.03
institution fixed effects		✓		✓		✓		✓		✓		✓
year fixed effects		✓		✓		✓		✓		✓		✓

This table reports regression results (Eq.1). Columns (1) to (6) estimate placement probabilities, while the other columns show placement quality, according to the REPEC Economic Institution ranking (as of April 2022), conditional on being placed: either whether the placement happened in the Top-50 institutions (Columns (7) to (10)) or the rank itself (Columns (11)-(12)). The results for placements as a tenure-track assistant professor are in Columns (1)-(2) and Columns (7)-(8). The results for placements in Academia are in Columns (3)-(4) and (9)-(10). Finally, the results for placements in top 429 economic research institutions are in Columns (5)-(6) and (11)-(12). Independent variables: *Woman in Male Field* is an indicator variables which equals 1 if the candidate is a woman whose first field is classified as a male field, and zero otherwise. Similarly, *Man in Male Field* and *Man not in Male Field* are indicator variables for male candidates, depending on their first field. The omitted group is women whose first field is not classified as a male field. *AA* refers to the top-7 journals in economics, based on Combes and Linnemer (2010); *A* journals refer to the next journals up to top-30; and *B* journals include the remaining journals (up to top-60). Regressions presented in even columns contain PhD-granting institution and year fixed effects, and standard errors (in parentheses) are clustered at the PhD-granting institution level. Sample: 1365 job market candidates in the 2018-2019, 2019-2020 and 2022-2023 Academic years from top-33 US Economics Departments, with non-missing controls.

* p<0.05, ** p<0.01, *** p<0.001

Table A.4: Sample size by treatment group and employer's gender

	Baseline	Gender Incentive	Field Incentive
Listening questions	Men: 70 Women 68	Men: 70	Men: 67
Content questions	Men: 71 Women: 70	Men: 66	Men: 69

Table A.5: Experiment: Descriptive statistics by the type of incentive

	Male respondents								Female respondents		
	Baseline		Gender incentive			Field incentive			Baseline		
	mean	sd	mean	sd	p-val*	mean	sd	p-val*	mean	sd	p-val*
Randomized values:											
Listening questions (1/0)	0.50	(0.50)	0.51	(0.50)	[0.76]	0.49	(0.50)	[0.95]	0.49	(0.50)	[0.95]
Content questions (1/0)	0.50	(0.50)	0.49	(0.50)	[0.76]	0.51	(0.50)	[0.95]	0.51	(0.50)	[0.95]
Male field:											
Technology (1/0)	0.51	(0.50)	0.46	(0.50)	[0.43]	0.50	(0.50)	[0.86]	0.50	(0.50)	[0.86]
Business (1/0)	0.49	(0.50)	0.54	(0.50)	[0.43]	0.50	(0.50)	[0.86]	0.50	(0.50)	[0.86]
Female field:											
Health (1/0)	0.52	(0.50)	0.46	(0.50)	[0.37]	0.49	(0.50)	[0.59]	0.49	(0.50)	[0.68]
Environment (1/0)	0.48	(0.50)	0.54	(0.50)	[0.37]	0.51	(0.50)	[0.59]	0.51	(0.50)	[0.68]
Video displayed (1 to 3)	1.71	(0.77)	1.74	(0.76)	[0.78]	1.55	(0.70)	[0.07]	1.70	(0.76)	[0.94]
Personal info:											
Age (years)	39.78	(9.64)	40.37	(9.78)	[0.62]	40.01	(9.06)	[0.84]	42.21	(10.25)	[0.04]
Major related to:											
STEM (1/0)	0.43	(0.50)	0.40	(0.49)	[0.63]	0.40	(0.49)	[0.72]	0.21	(0.41)	[0.00]
excluding Medicine	0.37	(0.48)	0.38	(0.49)	[0.92]	0.35	(0.48)	[0.78]	0.17	(0.38)	[0.00]
Business (1/0)	0.21	(0.41)	0.26	(0.44)	[0.38]	0.24	(0.43)	[0.65]	0.17	(0.37)	[0.33]
Health (1/0)	0.14	(0.35)	0.07	(0.26)	[0.07]	0.07	(0.25)	[0.04]	0.17	(0.38)	[0.46]
Environment (1/0)	0.08	(0.27)	0.02	(0.15)	[0.03]	0.07	(0.26)	[0.89]	0.05	(0.22)	[0.35]
Work experience >5 years (1/0)	0.79	(0.41)	0.82	(0.39)	[0.55]	0.86	(0.35)	[0.11]	0.77	(0.42)	[0.70]
Occupation:											
Business or Finance (1/0)	0.09	(0.28)	0.21	(0.41)	[0.00]	0.18	(0.39)	[0.02]	0.10	(0.30)	[0.64]
ICT, Math, Engineering, Architecture (1/0)	0.06	(0.23)	0.05	(0.22)	[0.85]	0.04	(0.19)	[0.43]	0.00	(0.00)	[0.00]
Education (1/0)	0.11	(0.31)	0.09	(0.28)	[0.61]	0.11	(0.31)	[0.92]	0.11	(0.31)	[0.95]
Sales (1/0)	0.07	(0.26)	0.05	(0.22)	[0.50]	0.06	(0.24)	[0.68]	0.08	(0.27)	[0.78]
Management (1/0)	0.06	(0.25)	0.04	(0.21)	[0.47]	0.08	(0.27)	[0.59]	0.05	(0.22)	[0.64]
Healthcare (1/0)	0.09	(0.28)	0.09	(0.28)	[0.93]	0.08	(0.27)	[0.90]	0.12	(0.32)	[0.39]
Topics of interest:											
Arts (1/0)	0.35	(0.48)	0.35	(0.48)	[0.98]	0.36	(0.48)	[0.92]	0.45	(0.50)	[0.11]
Business and Finance (1/0)	0.48	(0.50)	0.44	(0.50)	[0.57]	0.51	(0.50)	[0.51]	0.29	(0.46)	[0.00]
Education (1/0)	0.23	(0.42)	0.21	(0.41)	[0.67]	0.29	(0.46)	[0.20]	0.33	(0.47)	[0.05]
Environment (1/0)	0.43	(0.50)	0.40	(0.49)	[0.64]	0.42	(0.50)	[0.82]	0.53	(0.50)	[0.11]
Health (1/0)	0.47	(0.50)	0.41	(0.49)	[0.35]	0.49	(0.50)	[0.78]	0.64	(0.48)	[0.00]
International relations (1/0)	0.17	(0.38)	0.13	(0.34)	[0.38]	0.21	(0.41)	[0.37]	0.18	(0.39)	[0.81]
Lifestyle (1/0)	0.29	(0.46)	0.27	(0.45)	[0.73]	0.25	(0.43)	[0.45]	0.56	(0.50)	[0.00]
Literature (1/0)	0.24	(0.43)	0.23	(0.42)	[0.80]	0.24	(0.43)	[0.98]	0.43	(0.50)	[0.00]
Politics (1/0)	0.43	(0.50)	0.40	(0.49)	[0.64]	0.43	(0.50)	[0.98]	0.33	(0.47)	[0.09]
Science and Technology (1/0)	0.77	(0.42)	0.75	(0.43)	[0.76]	0.72	(0.45)	[0.39]	0.56	(0.50)	[0.00]
Sports	0.52	(0.50)	0.46	(0.50)	[0.30]	0.58	(0.50)	[0.29]	0.20	(0.40)	[0.00]
	N = 141		N = 136			N = 136			N = 138		

* All p-values are for a two-sample t-test comparing mean values with the baseline Male group.

Table A.6: Experiment: Descriptive statistics by question treatment

	Male respondents					Female respondents				
	Listening		Content			Listening		Content		
	mean	sd	mean	sd	p-val*	mean	sd	mean	sd	p-val*
Randomized values:										
Male field:										
Technology (1/0)	0.54	(0.50)	0.48	(0.50)	[0.45]	0.50	(0.50)	0.50	(0.50)	[1.00]
Business (1/0)	0.46	(0.50)	0.52	(0.50)	[0.45]	0.50	(0.50)	0.50	(0.50)	[1.00]
Female field:										
Health (1/0)	0.53	(0.50)	0.51	(0.50)	[0.80]	0.53	(0.50)	0.46	(0.50)	[0.40]
Environment (1/0)	0.47	(0.50)	0.49	(0.50)	[0.80]	0.47	(0.50)	0.54	(0.50)	[0.40]
Video displayed (1 to 3)	1.73	(0.78)	1.69	(0.77)	[0.77]	1.78	(0.77)	1.63	(0.75)	[0.24]
Personal info:										
Age (years)	40.26	(10.37)	39.31	(8.91)	[0.56]	44.07	(10.20)	40.40	(10.04)	[0.03]
Major related to:										
STEM (1/0)	0.41	(0.50)	0.44	(0.50)	[0.79]	0.16	(0.37)	0.26	(0.44)	[0.17]
excluding Medicine	0.37	(0.49)	0.37	(0.49)	[0.95]	0.15	(0.36)	0.20	(0.40)	[0.41]
Business (1/0)	0.23	(0.42)	0.20	(0.40)	[0.65]	0.15	(0.36)	0.19	(0.39)	[0.55]
Health (1/0)	0.17	(0.38)	0.11	(0.32)	[0.32]	0.15	(0.36)	0.20	(0.40)	[0.41]
Environment (1/0)	0.07	(0.26)	0.08	(0.28)	[0.77]	0.04	(0.21)	0.06	(0.23)	[0.73]
Work experience >5 years (1/0)	0.77	(0.42)	0.80	(0.40)	[0.65]	0.75	(0.44)	0.79	(0.41)	[0.62]
Occupation:										
Business or Finance (1/0)	0.11	(0.32)	0.06	(0.23)	[0.22]	0.09	(0.29)	0.11	(0.32)	[0.61]
ICT, Math, Engineering, Architecture (1/0)	0.09	(0.28)	0.03	(0.17)	[0.14]	0.00	(0.00)	0.00	(0.00)	[NaN]
Education (1/0)	0.07	(0.26)	0.14	(0.35)	[0.18]	0.13	(0.34)	0.09	(0.28)	[0.38]
Sales (1/0)	0.06	(0.23)	0.08	(0.28)	[0.53]	0.07	(0.26)	0.09	(0.28)	[0.79]
Management (1/0)	0.09	(0.28)	0.04	(0.20)	[0.30]	0.03	(0.17)	0.07	(0.26)	[0.26]
Healthcare (1/0)	0.10	(0.30)	0.07	(0.26)	[0.53]	0.09	(0.29)	0.14	(0.35)	[0.32]
Topics of interest:										
Arts (1/0)	0.31	(0.47)	0.39	(0.49)	[0.32]	0.51	(0.50)	0.39	(0.49)	[0.13]
Business and Finance (1/0)	0.50	(0.50)	0.45	(0.50)	[0.56]	0.26	(0.44)	0.31	(0.47)	[0.52]
Education (1/0)	0.21	(0.41)	0.24	(0.43)	[0.72]	0.37	(0.49)	0.30	(0.46)	[0.40]
Environment (1/0)	0.40	(0.49)	0.46	(0.50)	[0.44]	0.53	(0.50)	0.53	(0.50)	[0.99]
Health (1/0)	0.50	(0.50)	0.44	(0.50)	[0.45]	0.62	(0.49)	0.67	(0.47)	[0.51]
International relations (1/0)	0.14	(0.35)	0.20	(0.40)	[0.39]	0.21	(0.41)	0.16	(0.37)	[0.46]
Lifestyle (1/0)	0.23	(0.42)	0.35	(0.48)	[0.11]	0.51	(0.50)	0.60	(0.49)	[0.32]
Literature (1/0)	0.26	(0.44)	0.23	(0.42)	[0.66]	0.49	(0.50)	0.39	(0.49)	[0.24]
Politics (1/0)	0.43	(0.50)	0.44	(0.50)	[0.92]	0.35	(0.48)	0.31	(0.47)	[0.63]
Science and Technology (1/0)	0.76	(0.43)	0.77	(0.42)	[0.81]	0.50	(0.50)	0.61	(0.49)	[0.18]
Sports	0.47	(0.50)	0.56	(0.50)	[0.28]	0.26	(0.44)	0.14	(0.35)	[0.08]
	N = 70		N = 71			N = 68		N = 70		

* The p-value is for a two-sample t-test comparing mean value for the content-question group to the mean value of the listening-questions group).

Table A.7: Experiment: Outcomes and performance by the incentive type

	Male respondents								Female respondents		
	Baseline		Gender incentive			Field incentive			Baseline		
	mean	sd	mean	sd	p-val*	mean	sd	p-val*	mean	sd	p-val*
Rank 1 choice:											
Field:											
Technology (1/0)	0.33	(0.47)	0.15	(0.36)	[0.00]	0.19	(0.39)	[0.01]	0.18	(0.39)	[0.00]
Business (1/0)	0.24	(0.43)	0.21	(0.41)	[0.48]	0.14	(0.35)	[0.03]	0.17	(0.37)	[0.12]
Health (1/0)	0.21	(0.41)	0.28	(0.45)	[0.20]	0.34	(0.47)	[0.02]	0.31	(0.46)	[0.06]
Environment (1/0)	0.21	(0.41)	0.36	(0.48)	[0.01]	0.33	(0.47)	[0.03]	0.34	(0.48)	[0.02]
Female field (1/0)	0.43	(0.50)	0.64	(0.48)	[0.00]	0.67	(0.47)	[0.00]	0.65	(0.48)	[0.00]
Female presenter (1/0)	0.46	(0.50)	0.75	(0.43)	[0.00]	0.55	(0.50)	[0.13]	0.59	(0.49)	[0.04]
Performance:											
Attention questions score (0 to 12)	8.66	(3.50)	8.87	(3.05)	[0.60]	9.07	(3.09)	[0.31]	9.63	(2.98)	[0.01]
Displayed video rating (0 to 5)	3.82	(0.61)	3.76	(0.67)	[0.40]	3.71	(0.59)	[0.13]	3.80	(0.61)	[0.73]
Total pay (0 to 18)	12.55	(3.40)	13.39	(3.17)	[0.03]	13.46	(3.09)	[0.02]	13.44	(2.92)	[0.02]
Time spent (minutes)	19.86	(11.90)	19.82	(11.15)	[0.98]	19.49	(11.98)	[0.80]	16.83	(9.28)	[0.02]
	N = 141		N = 136			N = 136			N = 138		

* All p-values are for a two-sample t-test comparing mean values with the baseline Male group.

Table A.8: Experiment: Outcomes and performance by the question type

	Male respondents					Female respondents				
	Listening		Content			Listening		Content		
	mean	sd	mean	sd	p-val*	mean	sd	mean	sd	p-val*
Rank 1 choice:										
Field:										
Technology (1/0)	0.37	(0.49)	0.30	(0.46)	[0.34]	0.19	(0.40)	0.17	(0.38)	[0.77]
Business (1/0)	0.17	(0.38)	0.31	(0.47)	[0.05]	0.10	(0.31)	0.23	(0.42)	[0.05]
Health (1/0)	0.21	(0.41)	0.21	(0.41)	[0.97]	0.37	(0.49)	0.26	(0.44)	[0.16]
Environment (1/0)	0.24	(0.43)	0.18	(0.39)	[0.39]	0.34	(0.48)	0.34	(0.48)	[0.95]
Female field (1/0)	0.46	(0.50)	0.39	(0.49)	[0.45]	0.71	(0.46)	0.60	(0.49)	[0.19]
Female presenter (1/0)	0.44	(0.50)	0.48	(0.50)	[0.67]	0.57	(0.50)	0.60	(0.49)	[0.75]
Performance:										
Attention questions score (0 to 12)	8.61	(3.82)	8.70	(3.17)	[0.88]	9.35	(3.13)	9.90	(2.81)	[0.28]
Displayed video rating (0 to 5)	3.79	(0.66)	3.85	(0.56)	[0.57]	3.87	(0.58)	3.73	(0.64)	[0.18]
Total pay (0 to 18)	12.51	(3.66)	12.58	(3.16)	[0.89]	13.25	(3.04)	13.63	(2.81)	[0.45]
Time spent (minutes)	20.70	(13.40)	19.04	(10.24)	[0.41]	16.36	(5.65)	17.28	(11.82)	[0.56]
	N = 70		N = 71			N = 68		N = 70		

* The p-value is for a two-sample t-test comparing mean value for the content-questions group to the mean value of the listening-questions group.

Table A.9: Experiment: Occupational structure among the survey respondents versus among the college-educated labor force in the U.S.

Occupation	Share in the survey	Share in the economy	Diff.
Architecture and engineering occupations	0.029	0.031	-0.002
Arts, design, entertainment, sports, and media occupations	0.047	0.034	0.012
Building and grounds cleaning and maintenance occupations	0.004	0.008	-0.004
Business and financial operations occupations	0.093	0.128	-0.035
Community and social service occupations	0.011	0.037	-0.027
Computer and mathematical occupations	0.140	0.065	0.075
Construction and extraction occupations	0.014	0.009	0.005
Educational instruction and library occupations	0.108	0.126	-0.018
Farming, fishing, and forestry occupations	0.014	0.002	0.013
Food preparation and serving related occupations	0.025	0.029	-0.004
Healthcare practitioners and technical occupations	0.054	0.100	-0.046
Healthcare support occupations	0.047	0.018	0.029
Installation, maintenance, and repair occupations	0.007	0.010	-0.002
Legal occupations	0.018	0.019	-0.001
Life, physical, and social science occupations	0.047	0.020	0.026
Management occupations	0.057	0.118	-0.061
Office and administrative support occupations	0.036	0.088	-0.052
Personal care and service occupations	0.004	0.018	-0.015
Production occupations	0.014	0.015	-0.001
Protective service occupations	0.007	0.018	-0.011
Sales and related occupations	0.075	0.081	-0.005
Transportation and material moving occupations	0.025	0.026	-0.001
Other	0.111	0.000	0.111
Prefer not to say	0.014	0.000	0.014

Note: 'Share in the economy' is the share of the occupation in the U.S. labor force who has a Bachelor's, Master's, or Doctoral/Professional degree, based on authors' own calculations using the U.S. Bureau of Labor Statistics data.

Table A.10: Experiment: Share of female fields and female presenters by employer's gender

	Outcome:	Employer's gender:		Difference
		Men	Women	Men - Women
	Share of female fields S_{FField}	0.426	0.652	-0.226
	st. error	(0.042)	(0.041)	(0.058)
Hyp 1b	P-value (S_{FField} for men < 0.50)	0.038		
Hyp 1b	P-value (S_{FField} for women > 0.50)		0.000	
Hyp 1b	P-value (S_{FField} for men < for women)			0.000
	Share of female presenters $S_{FPresenter}$	0.461	0.587	-0.126
	st. error	(0.042)	(0.042)	(0.059)
Hyp 1a	P-value ($S_{FPresenter}$ for men < 0.50)	0.178		
Hyp 1a	P-value ($S_{FPresenter}$ for women > 0.50)		0.020	
Hyp 1a	P-value ($S_{FPresenter}$ for men < for women)			0.018

Notes: See the list of hypotheses on page 24.

Table A.11: Experiment: Treatment effects

Outcome:		Employer's gender:	
		Men	Women
BY QUESTION TYPE:			
Share of female fields:	Content questions	0.394	0.600
	Listening questions	0.457	0.706
	Difference Content - Listening	-0.063	-0.106
	st.error	(0.084)	(0.081)
Hyp 1c	P-value (Diff. Content - Listening for men < 0)	0.227	
Hyp 1c	P-value (Diff. Content - Listening for women > 0)		0.903
Share of female presenters:	Content questions	0.479	0.600
	Listening questions	0.443	0.574
	Difference Content - Listening	0.036	0.026
	st.error	(0.085)	(0.084)
Hyp 1c	P-value (Diff. Content - Listening for men < 0)	0.665	
Hyp 1c	P-value (Diff. Content - Listening for women > 0)		0.377
BY INCENTIVE:			
Share of female fields:	Baseline	0.426	
	Gender incentive	0.640	
	Field incentive	0.669	
	Difference Gender incentive - baseline	0.214	
	st.error	(0.059)	
Hyp 2b	P-value (Diff. Gender incentive - baseline > 0)	0.000	
	Difference Field incentive - baseline	0.243	
	st.error	(0.058)	
Hyp 2b	P-value (Diff. Field incentive - baseline $\neq$0)	0.000	
Share of female presenters:	Baseline	0.461	
	Gender incentive	0.750	
	Field incentive	0.551	
	Difference Gender incentive - baseline	0.289	
	st.error	(0.056)	
Hyp 2a	P-value (Diff. Gender incentive - baseline > 0)	0.000	
	Difference Field incentive - baseline	0.090	
	st.error	(0.060)	
Hyp 2a	P-value (Diff. Field incentive - baseline $\neq 0$)	0.067	

Notes: See the list of hypotheses on page 24

Figure A.1: Journal rankings

Table 4: Top 60 journals for the *JCR* index

Journal	Rank	Score
AA		
econometrica	1	2.75
quarterly j. of economics	2	3
j. of political economy	3	3.75
j. of finance	4	5
american economic review	5	6
j. of financial economics	6	7.75
review of economic studies	7	7.75
A		
j. of the american statistical asso.	8	8.75
J. OF ECONOMIC LITERATURE	9	12
review of financial studies	10	13
american political science review	11	13
j. of economic theory	12	14.25
j. of monetary economics	13	15
J. OF ECONOMIC PERSPECTIVES	14	15.5
r. of economics and statistics	15	16.25
j. of econometrics	16	17.75
rand j. of economics	17	19.5
economic journal	18	20
international economic review	19	22.75
j. of business and eco. statistics	20	23.75
j. of labor economics	21	24
international orga.	22	26
j. of accounting and economics	23	26.75
j. of inter. economics	24	27.5
j. of public economics	25	29.5
BROOKINGS P. ON ECO. ACTIVITY	26	31.75
european economic review	27	32.25
games and economic behavior	28	33
*j. of business**	29	35.75
j. of accounting research	30	39
B		
demography	31	40
j. of fin. and quanti. analysis	32	40.75
j. of consumer research	33	41.75
j. of health economics	34	45.25
j. of economic growth	35	45.5
j. of law and economics	36	45.5
j. of human resources	37	45.75
j. of money, credit, and banking	38	47.75
accounting review	39	52.5
j. of industrial economics	40	54.75
yale law journal	41	55.5
econometric theory	42	55.75
j. of law, eco., and orga.	43	57
j. of urban economics	44	57.25
j. of the royal statistical society: series a	45	57.5
j. of development economics	46	58.5
j. of applied econometrics	47	60
review of economic dynamics	48	60.5
mathematical finance	49	62.25
population and dev. review	50	62.25
marketing science	51	63
j. of risk and uncertainty	52	63.75
finance and stochastics	53	64
j. of eco. dyna. and control	54	68
industrial and labor relations review	55	68
WORLD BANK ECONOMIC REVIEW	56	70
j. of env. eco. and manag.	57	70.75
j. of eco. and manag. strategy	58	70.75
j. of eco. behavior and orga.	59	71.75
world development	60	72

Journals in **bold** are in the economics category of *JCR*. Survey/commissioning journals are in SMALL CAPS. Other *JCR* journals are in *italic*. *J. of Business* is marked with an * because it stopped being published in 2006.

Figure A.2: Placement rank by gender (for those placed in top-429 Economic research institutions).

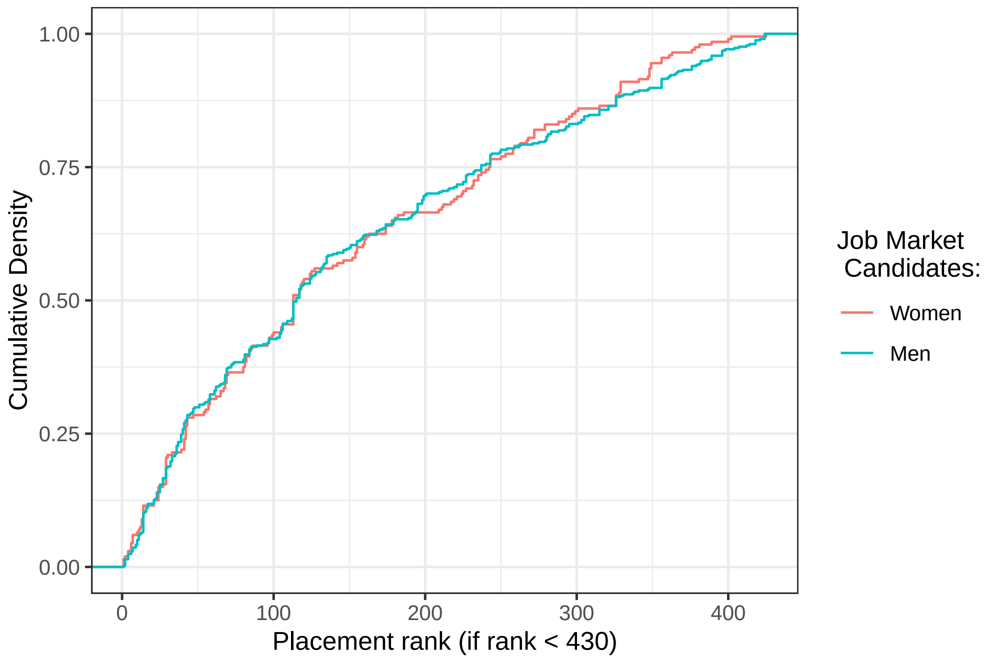
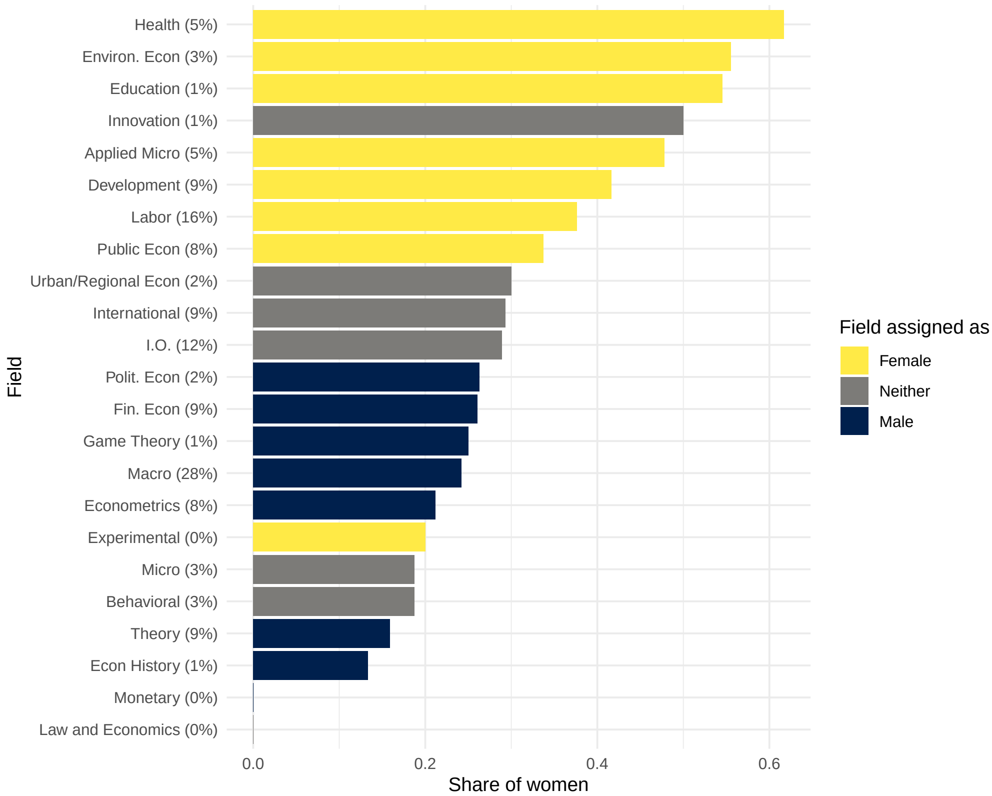


Figure A.3: Fields Mentioned on CV by Share of Women



Note: The parentheses next to the field name report the share of candidates who mention a given field on their CV, e.g., 16% of candidates mention Labor Economics. The share of women on the x-axis is the share of women among all candidates mentioning a given field. The color coding of fields is based on the share of women publishing in the field and hence is based on Figure 1

Figure A.4: Publications and R&Rs by gender and journal category

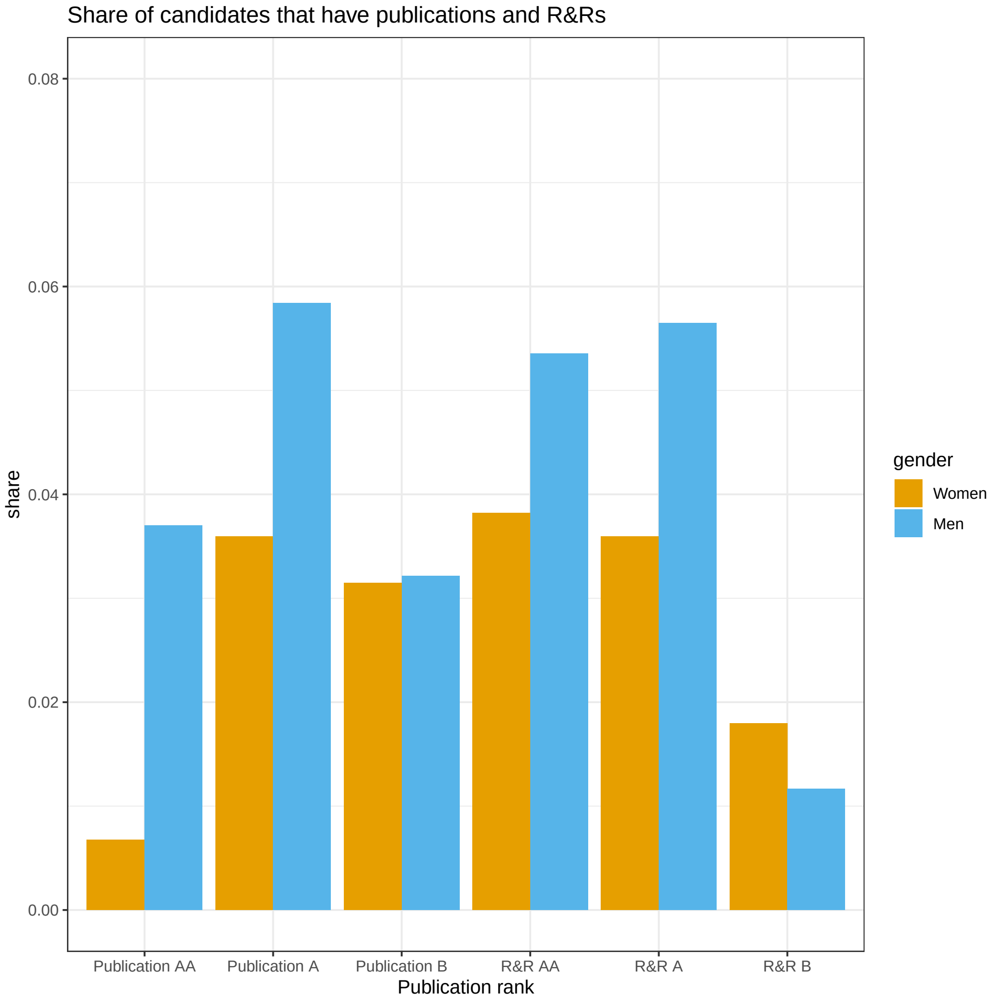
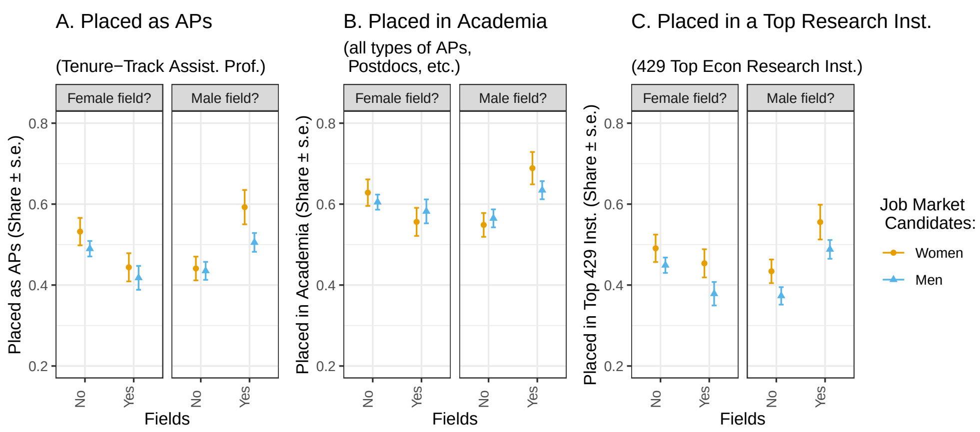
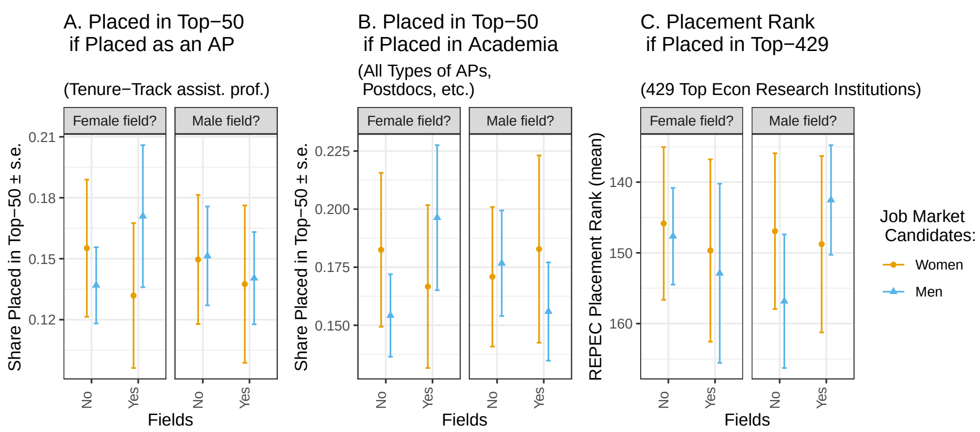


Figure A.5: Placement outcomes by the type of field specialization (Male or Female) and the candidates' gender



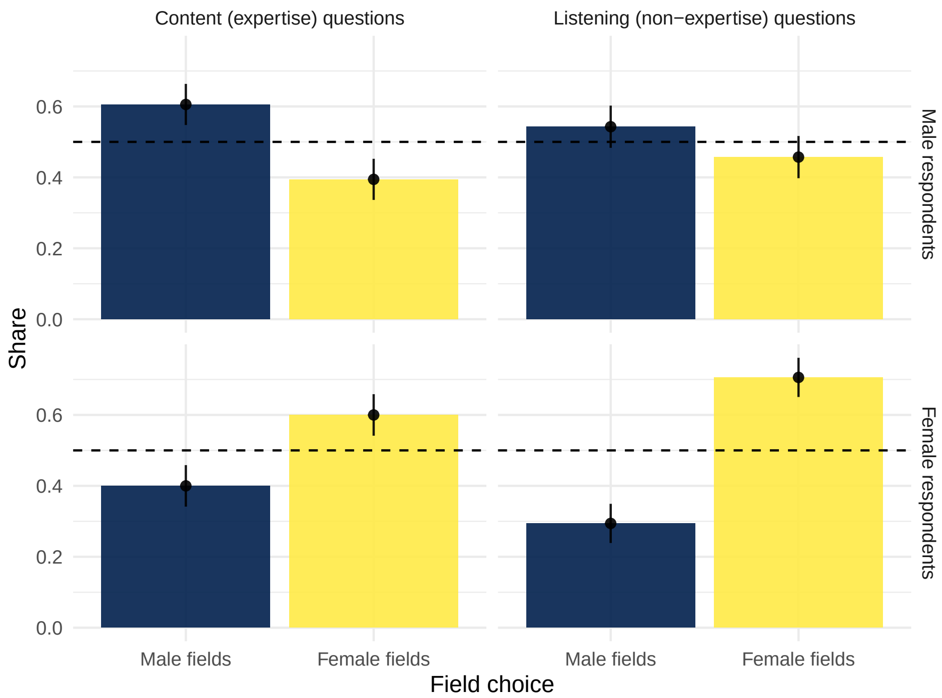
(a) Placement probability (mean $\pm$ 1 std. err.)



(b) Placement rank (mean $\pm$ 1 std. err.)

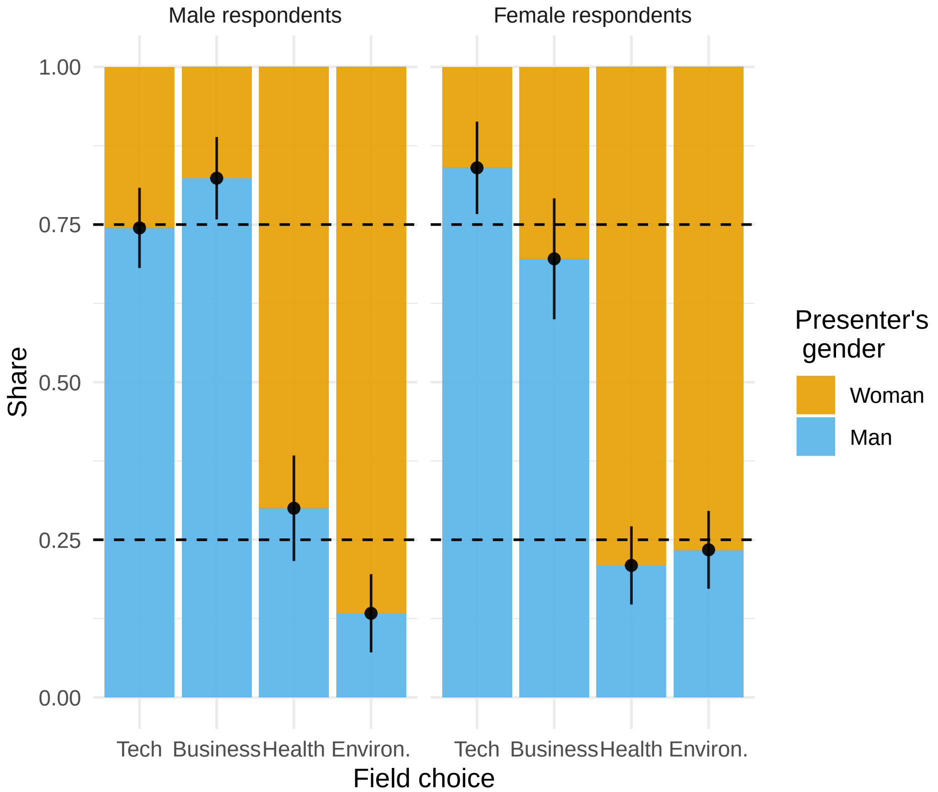
Note: "Placed in Academia" includes both tenure and non-tenure track assistant professorship, as well as visiting, adjunct, and teaching assistant professorship, postdoctoral and other research positions

Figure A.6: Experiment: Field Choices by Treatment



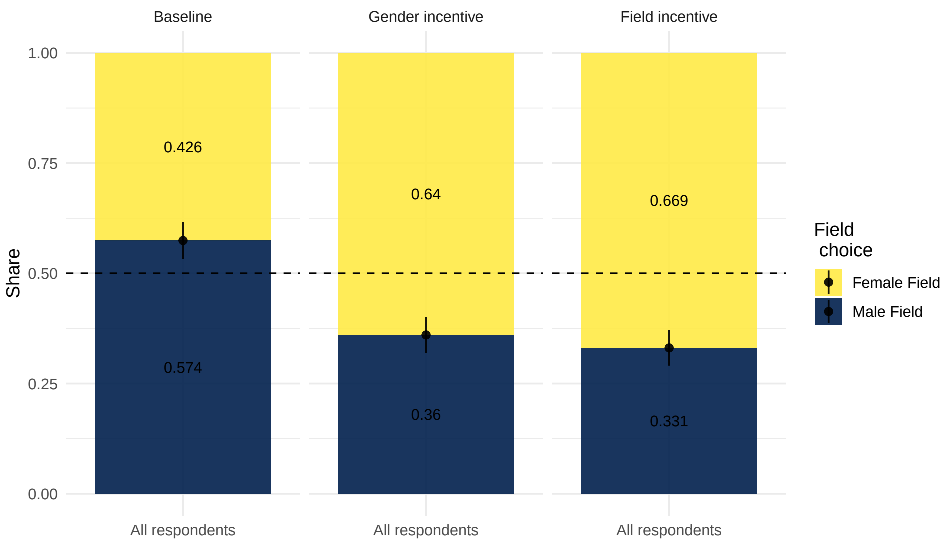
Note:“Content” questions are questions related to the content of the TED talk, and prior expertise in the subject may help answering those correctly. “Listening” questions are of the type “Was this sentence said?”, and prior expertise in the subject would not help much. Sample sizes: 132 male respondents (65 in listening questions group and 67 on content questions group), 126 female respondents (62 in listening questions group and 64 on content questions group).

Figure A.7: Experiment: Gender Choices by Field: Male and Female Respondents



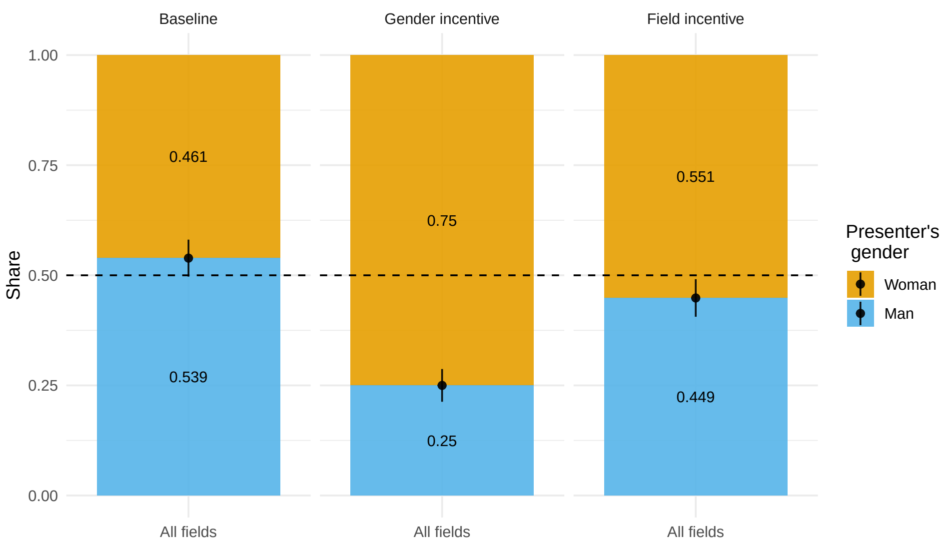
Note: The dashed line at 75% shows the expected share of men in male fields: and the dashed line at 25%, the expected share of men in female fields, if presentations are chosen at random. Sample sizes: 132 male respondents, 126 female respondents.

Figure A.8: Experiment: The Share of Female Fields by Incentive



Note: The dashed line at 50% shows the expected share of male fields, if fields are chosen at random. Sample sizes: 132 respondents in the baseline group, 117 in the gender incentive group, and 126 in the field incentive group. Male respondents only.

Figure A.9: Experiment: The Share of Women by Incentive



Note: The dashed line at 50% shows the expected share of male presenters, if presentations are chosen at random. Sample sizes: 132 respondents in the baseline group, 117 in the gender incentive group, and 126 in the field incentive group. Male respondents only.