Social Media and Job Market Success: A Field Experiment on Twitter[*]

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Abstract

To examine the impact of social media promotion of job market papers on job outcomes, we conduct a field experiment on Twitter (now X). Specifically, we examine how having a prominent economist quote-tweet a job market paper in the field of economics impacts paper visibility and candidate job market outcomes. Our results show that papers assigned to be quote-tweeted in our experiment receive 442% more views and 303% more likes than those assigned to the control condition. We further find that those in the quote-tweet treatment receive one additional flyout and that the women in the treatment group receive 0.9 more job offers. These findings suggest that social media promotion can improve the visibility and success of job market candidates, especially for underrepresented groups in economics such as women.

Keywords: social media, academic job market, field experiment

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1 Introduction

Social media platforms have transformed how people make interaction choices in both their personal and professional lives. Over 5 billion users worldwide engage with these platforms, representing nearly two-thirds of the global population and over 95% of internet users (Tual, 2024). Globally, Internet users spend an average of 2.4 hours daily on social media platforms (Dixon, 2024), reflecting how these platforms have become integrated into daily life. Social media has become a key source of information for users, with information dissemination occurring at unparalleled speed and scope (Aridor et al., 2024). Users derive substantial consumer surplus from social networking sites, become better informed about global events (Allcott et al., 2020), and maintain social ties past graduation that prove beneficial in the labor market (Armona, 2023).

Social media platforms have been especially useful for specialized groups to share information. Among academics, these platforms have become increasingly popular for disseminating their research quickly and widely (Vásárhelyi et al., 2021; Peng et al., 2022). This trend is particularly evident during the academic job market season in fields such as economics, where candidates, along with their advisors and placement officers, routinely use platforms like Twitter (now X) to bring their job market papers to a broader audience.

While job candidates routinely use social media to promote themselves during job search, the effect of doing so on job outcomes is not clear. To add insight to this question, this study explores whether social media promotion has a causal impact on job market outcomes.[1] While there is evidence that social media exposure correlates positively with academic recognition, such as citation counts (Fang et al., 2021; Chan, Zeng and Schäfer, 2022; Chan et al., 2023; Weissburg et al., 2024), the impact of this exposure on career outcomes has not been as well studied. In addition to examining the overall impact of social media promotion on job outcomes, we are also interested in examining whether it can be used to address underrepresentation in academia.

In the field of economics, numerous recent empirical studies find that women are still underrepresented (Lundberg and Stearns, 2019; Fortin, Lemieux and Rehavi, 2021; Jebaraj, Sorto and Kali, 2022; Auriol et al., 2022; Chari, 2023; Ginther, Kahn and Milakhina, 2025). Studies also find that women are likely to face higher standards during the peer review process (Card et al., 2020), publish fewer papers in leading journals (Lundberg and Stearns, 2019; Hengel and Moon, 2020), receive less recognition in co-authored papers (Sarsons et al., 2021), and receive fewer citations (Koffi, 2021). For example, of the total number of academic talks in economics, only 24% are conducted by women (Doleac, Hengel and Pancotti, 2021). While mentoring programs created by the American Economic Association (AEA)

[1] Using data from the top-five PhD programs in the US in the 1990s, Athey et al. (2007) find that student first-year micro and macroeconomics grades and attending elite undergraduate and liberal arts universities are strong predictors of job placement. However, little research has explored how new channels, such as social media promotion, could influence job market outcomes.

and other professional associations have sought to address this issue (Becker, Rouse and Chen, 2016; Carrell and Kurlaender, 2020; Ginther et al., 2020; Guryan et al., 2021), gender disparities continue to exist at almost every stage of the academic career in economics (Ginther, Kahn and Milakhina, 2025), from securing an assistant professorship (Lundberg and Stearns, 2019; Jebaraj, Sorto and Kali, 2022) to achieving tenure (Sarsons et al., 2021; Ginther and Kahn, 2021) to earning a full professorship (Zacchia, 2021).

This lack of diversity in economics extends beyond gender, with even stronger underrepresentation observed for racial and ethnic minorities (Bayer, Hoover and Washington, 2020; Hoover and Washington, 2023). For example, racial and ethnic minority groups comprise only 8.3% of economic faculty (Hoover and Washington, 2023). Furthermore, these groups conduct only 1% of the total number of academic talks in economics (Doleac, Hengel and Pancotti, 2021).[2]

Given the current underrepresentation of women and racial and ethnic minority groups in the economics profession, we are interested in whether social media promotion could be a potential channel to increase representation. To examine the causal impact of social media promotion on job outcomes, we conduct a field experiment on Twitter during the 2022-2023 economics job market.[3] We solicit job market candidates on the American and European job market and then ask these candidates to create a post about their job market paper which we share on a dedicated Twitter account. We then randomly assign a subset of these posts to be quote-tweeted (retweeted with comments) by prominent economists working in the same subfield as the respective candidate. Finally, we measure whether our intervention has an impact on paper visibility on Twitter as well as candidate job market outcomes.

Our results show that our intervention substantially increases job market paper visibility. Posts assigned to be quote-tweeted receive 442% more views and 303% more likes than those in the control group. We further find a positive effect of the intervention on job market outcomes, with candidates in the treatment group receiving one more flyout invitation on average than those in the control group, who receive 5.4 flyout invitations. We also find a positive effect for women, with women in the treatment group receiving 0.9 more job offers than their counterparts in the control group, who receive 3.1 offers. Examining potential mechanisms driving these results, we find that academic reputation drives these effects, with greater effects for quote-tweets from highly-cited scholars, and for quote-tweets for job market candidates from top institutions. Interestingly, we find that quote-tweets from economists who post less frequently actually have a stronger impact on candidates' job market outcomes, suggesting that concentrated attention from academic audiences may be more impactful than broader visibility.

[2]These disparities may affect broader academic outcomes as well as individual careers. For example, studies show that a professor's gender influences female students' performance in a course and likelihood of pursuing a STEM degree (Carrell, Page and West, 2010). Another study finds that students from underrepresented groups show better outcomes in a course when assigned to teaching assistants of similar backgrounds (Oliver et al., 2021). Such findings align with evidence on the positive impact of diversity in leadership (Logan, 2020).

[3]Twitter was acquired by Elon Musk on October 27, 2022, and was rebranded X in July 2023.

Overall, our findings suggest that social media promotion can enhance job market candidates' online visibility and improve their job market outcomes. To our knowledge, this is the first field experiment to establish a causal link between social media promotion and job market outcomes.[4] These results underscore the potential of social media promotion as a low-cost, scalable tool that may be used to support underrepresented groups in academia.

2 Experimental Design

Our field experiment was implemented during the 2022-2023 economics job market season. The study was approved by the University of Michigan IRB (HUM00221663) and pre-registered at the AEA RCT Registry (Chen et al., 2022).[5]

To conduct our experiment, we first constructed a pool of 2,714 job market candidates (JMCs) from the AEA's Job Openings for Economists (JOE), the European Job Market for Economists (EJME), and department websites in September 2022. In October, we created a dedicated Twitter account, Econ Job Market Helper, as the vehicle to post job market papers (JMP) tweets. As academic economists, we then invited our friends and colleagues to follow this account. Throughout the experiment, the account accumulated more than 2,000 followers, placing it well above the 85^{th} percentile of all Twitter users in terms of follower count.[6]

After creating the Twitter account and building its visibility through the development of a follower base, we reached out to a group of academic economists in late October and early November. Specifically, we sent invitations to 251 economists with an established reputation and a Twitter presence with more than 4,000 followers to request their participation in our experiment. Of these economists, 81 agreed to participate (referred to as "influencers" henceforth).[7] These influencers had a median of 13,450 Twitter followers (mean: 20,989) and a median of 8,590 Google Scholar citations (mean: 21,223). Appendix Figure A.1 plots influencers' Google Scholar citations against their Twitter follower counts. The figure reveals a weak positive correlation (ρ = 0.286) between their academic citations and social media visibility. Given that academic economists tend to follow each other on Twitter, tweets from these influencers have the potential to amplify the reach and impact of shared content within this network. With the

[4] For a comprehensive literature review on the economics of social media, see Aridor et al. (2024).

[5] Our pre-registration at the AEA RCT Registry is accessible at https://www.socialscienceregistry.org/trials/10341/history/161067, and included in Appendix F.

[6] According to a market data report on Twitter followers (Gitnux, 2023), "About 15% of Twitter accounts have more than 1,000 followers."

[7] We note that both the influencers in our study as well as economists who were invited to participate in the study may also be on hiring committees or have students entering the job market (see Appendix B for the email invitation template). Since these individuals were apprised of our experimental design, we note that their subsequent hiring-related decisions may or may not have been informed by this knowledge.

participation of these economists secured, we proceeded to conduct our experiment in three phases.

Phase 1: Pre-market survey. In early November 2022, we distributed a pre-market survey to all 2,714 JMCs in our pool, collecting information on their academic background, job preferences, demographics, and Twitter handles. We also provided them with empirically-grounded guidance on what drives attention on social media (Qiu and Golman, 2024) and asked them to compose a tweet about their JMPs. Appendix B contains the informed consent, the pre-market survey, response statistics, and tweet instructions.

To encourage JMCs to complete the pre-market survey, we offered two perks: the opportunity to join a virtual workshop on job market preparation[8] and the assurance that their JMP tweet would be posted on our dedicated Twitter account. Of the 849 JMCs who completed the pre-market survey, 590 also submitted a JMP tweet.

We posted these 590 JMP tweets on our Twitter account between November 9 and December 1, 2022. This limited timeframe for posting ensures a similar audience for each candidate's tweet, thereby reducing inequalities that could arise from differences in the JMCs' own Twitter posts and follower bases. To obtain our final participant group, we identify those from the 590 who submitted a tweet and also posted their JMP online before the intervention period.[9] This yields a final sample of 519 participants. Note that this number falls short of our pre-registered target of 800 participants (400 per condition) needed to detect a minimum effect size of 0.2 standard deviations ($\delta = 0.2\sigma$) with 80% power and a significance level of 5% (Chen et al., 2022).

Phase 2: Intervention. Phase 2 consists of assigning participants to either the treatment or control group and implementing our intervention for those in the treatment group. Below we describe our stratified randomization process, the algorithm used to match each JMC in the treatment group with an influencer, the intervention process, and the data collection process for intermediate outcomes.

Randomization: From our pool of 519 JMCs, we categorize participants into one of two groups: Underrepresented Groups (URG, including women, racial and ethnic minorities, and LGBTQ+ individuals) and non-Underrepresented Groups (non-URG).[10] JMCs are further stratified based on whether their academic institution ranks among the top 30 in the US (Appendix Table C.1) or the top 30 outside the US (Appendix Table C.2).[11] Within each stratum, JMCs are sorted according to their primary advisors'

[8] We thank Frank Schilbach for suggesting this idea. We also thank Ellen Muir, Kathleen Ngangoue, and Frank Schilbach for generously taking the time to serve as panelists at the virtual workshop, which took place on November 19, 2022.

[9] We remove three participants from our analysis who each completed the pre-market survey twice using different email addresses and who ended up being assigned to both the treatment and control conditions.

[10] Our definition of racial and ethnic minorities is consistent with the AEA Committee on the Status of Minority Groups in the Economics Profession (see https://www.aeaweb.org/about-aea/committees/csmgep/market). Non-URGs in our sample include Asian and white men who identify as heterosexual.

[11] We rely on the 2022 ranking of Economics Departments from *US News and World Report* for the US and the 2022 RePEc

Google Scholar citations in such a way as to form triplets. In our experiment, we implement a matched-triplet design, an extension of the efficient matched-pair design (Bai, 2022), assigning URG (non-URG) candidates to the treatment group with a probability of $\frac{2}{3}$ ($\frac{1}{3}$). The higher probability of URGs being assigned to the treatment group reflects our aim to provide support to underrepresented candidates.

Matching: After the randomization process, we match the JMCs in the treatment group with influencers in their respective fields. For each JMP, we calculate the *cosine similarity* between its abstract and the abstracts of each influencer's top 20 most cited papers on Google Scholar. We match each JMP with the influencer whose work produced the highest cosine similarity score.[12] Cosine similarity is widely used in natural language processing and text analysis to measure semantic similarity (Singhal et al., 2001). It has also been applied in economic research to quantify similarities between texts (Chen et al., 2024). We describe the computation method and provide pseudocode for our experiment in Appendix D. After the algorithmic matching process, we manually review the matches and adjust 49 of 247 JMPs to ensure closer alignments in research topics.

Intervention process: Between November 28 and December 8, 2022, we email each of our 81 influencers, informing them of their assigned JMPs, and asking them to quote-tweet the relevant JMP tweets posted on our dedicated Twitter account, using either a modifiable template we provide or their own message construction. Our templates are constructed to be neutral (see Appendix Figure A.2 for an example). On average, each influencer is tasked with quote-tweeting three JMPs. To ensure a more organic spread of the tweets, we time the emails to avoid a bunching of quote-tweets within a small timeframe. The compliance rate is high, with 88% of assigned tweets quote-tweeted by the influencers.

Data collection: In January 2023, we collected JMP tweets data from our dedicated Twitter account from Twitter Analytics. In April 2023, after the completion of the job market season, we collect data from Twitter API and Twitter Analytics to examine whether influencer quote-tweets affect the visibility of JMP tweets relative to the control group. We measure visibility through the number of views for the JMP tweets (which naturally include views of the quote-tweets). We also examine whether influencer quote-tweets impact people's responses to JMP tweets. We measure this user engagement through the number of likes received by the JMP tweets and the influencer quote-tweets. Views indicate the reach of the tweets, reflecting how widely the JMP tweets were exposed, while likes reflect endorsements or quality signals of the JMP tweets' content. We note that 98% of the Twitter activity related to the JMP tweets and influencer quote-tweets occurrs in December 2022, around the time of our intervention.[13]

Top 100 Economics Department ranking for institutions outside the US. See Appendix C for details.

[12] We used abstracts to reduce computation time, possibly resulting in a noisy measure of the true match quality.

[13] For example, the total number of likes for all tweets from our dedicated Twitter account was 3,090 by December 12, 2022, and 3,157 by March 29, 2023. We collected data on Twitter metrics for the JMP tweets on January 6, 2023, and for the influencers' quote-tweets on April 27, 2023.

Phase 3: Post-market survey. In the final phase of our experiment, we conduct a post-market survey in May 2023 to collect data on job market outcomes, including the number of interviews, flyouts, and job offers, as well as the salary ranges and level of satisfaction with job placement for those with an offer. A copy of the post-market survey is provided in Appendix E.

To encourage participants to complete the post-market survey, we offer each JMC an unconditional $10 Amazon gift card.[14] We send non-respondents an email reminder up to six times. To ensure response accuracy, we follow up on any participants reporting outliers, including those reporting a pre-tax salary below $25K or above $600K as well as those who report more than 50 interviews. Most participants either confirm or revise their responses upon contact.[15] To validate the accuracy of the self-reported salary information, we manually collected salary data for those who accepted job offers at public universities in the US. Among the 50 participants who provided salary information and accepted positions at US public universities, we were able to find official salary information for 31 of them. Among these 31 participants, the Pearson correlation between publicly available salary information in 2023 or 2024 and self-reported salary in 2023 was 0.77.

Figure 1 summarizes our experimental design and the number of participants in each phase of the experiment. Of the 519 participants who posted their JMP online before the intervention and were thus assigned to either the treatment or control group, 417 (80%) completed the post-market survey (henceforth, 'pre-market' and 'post-market' samples).[16] Appendix Table A.1 shows that the treatment group had a 4 percentage points higher likelihood of completing the post-market survey compared to the control group, but the difference is not statistically significant ($p > 0.257$). We further find that US citizens and those with an existing Twitter account were significantly more likely to complete the post-market survey ($p = 0.005$ and 0.048, column 2). However, as shown in Appendix Table A.2, the treatment and control groups remain balanced across the observed characteristics in the post-market sample, except for age and parental income class ($p = 0.018$ and 0.010, respectively), which we control for in our regression analysis.

Descriptive statistics for the pre-market and post-market samples are presented in Appendix Table A.2. Among the pre-market sample, the average participant is 31.6 years old and from a middle class background (mean = 2.2 on a 0-4 scale).[17] Underrepresented groups comprise 43% of the participant sample, including women (29.7%), Black (2.3%), Hispanic (13.1%), American Indian or Alaskan Native

[14] All monetary figures are in US dollars.

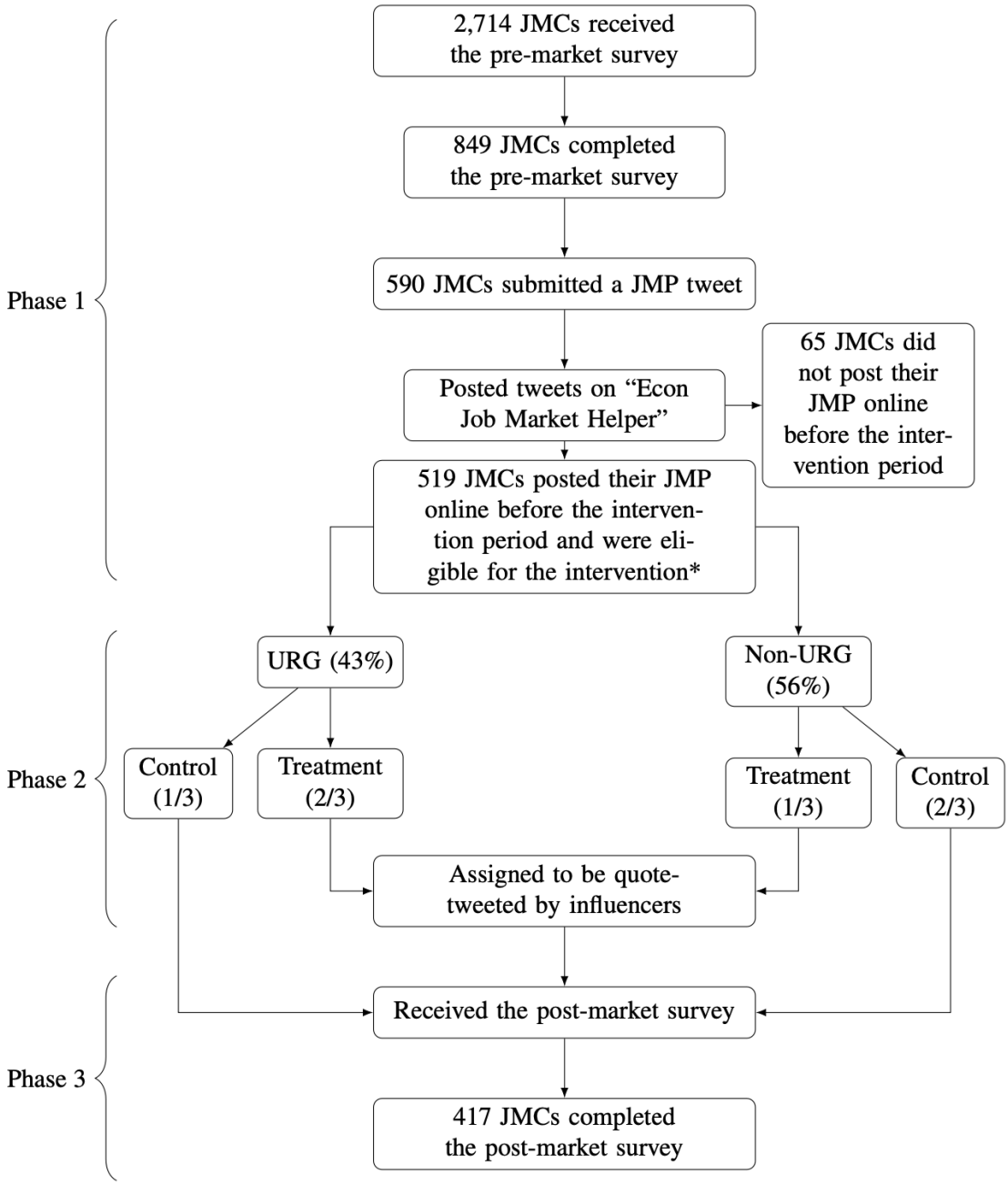
[15] Four out of five participants with salaries above $600,000 revised their salary, while one confirmed it. Among six participants with salaries below $25,000, one confirmed, three revised, one did not respond (coded as "non-disclosed"), and one was not contacted because their job position and the exchange rate suggested a low salary. Seven out of 11 participants with more than 50 interviews confirmed their number, while four made revisions. We conjecture that the virtual interview format may have contributed to the high number of interviews for some participants.

[16] This includes five participants who emailed us their job market outcomes instead of completing the post-market survey.

[17] We coded parental income class as follows: 4 for "High income / wealthy," 3 for "Upper middle class," 2 for "Middle class," 1 for "Low income," and 0 for "In poverty."

(0.4%), LGBTQ+ (5.3%), non-binary (0.4%), and transgender (0.4%) individuals.[18] Finally, in our pre-market sample, 18% are US citizens, and 70% have a Twitter account, with 81.3% of women and 68.2% of men owning one.

Figure 1: Experiment Design



These statistics resemble those of the AEA survey of economists on the job market in 2022-23,

[18] Note that there are overlaps between identities, e.g., a participant can be both a woman and Hispanic.

conducted in May 2023 ($n = 623$), with a few exceptions (Appendix Table A.5).[19] For example, our sample has fewer US citizens (18% vs. 34%, $p < 0.001$), likely due to our drawing of participants from both the AEA JOE and the European Job Market. In addition, the AEA survey sample has some missing data related to underrepresented group categories and US citizenship, which may also explain some differences between our descriptive statistics and the AEA survey.[20]

Regarding academic background, we find that 46% of our participants either have obtained or would obtain their PhD degree from a university ranked in the top 30 in the US or top 30 outside the US, 87% are on the job market for the first time, 18% have predoctoral research experience, and 15% have postdoctoral experience. We further find that 59% of our participants have at least one article published or under revision at the time of entering the job market, compared to 28% in McFall et al. (2015)'s sample. Finally, most of our participants apply for "101-150 jobs," followed by "201 or more jobs"[21] and 76% use the AEA signaling mechanism to send two signals to express their interest in specific employers (Coles et al., 2010). In our post-market sample, we find that two-thirds of participants report the salary of their accepted job, and the average pre-tax annual salary is $107,969 (see Appendix Figure A.3 for the full distribution).[22]

Prediction studies. To compare our results with expert predictions, we conduct two prediction studies, pre-registered in the AEA RCT Registry (Chen et al., 2023) on May 11, 2023. Following the methodology of DellaVigna and Pope (2018), we incorporate design features such as benchmarks and accuracy incentives. On December 11, 2023, we distributed the prediction survey through the Social Science Prediction Platform (SSPP) to 73 primarily early-career economists. A few days later, we extended the survey to our 81 influencers and received predictions from 31 of them. The survey outlined our experimental design and provided the average and standard deviation of the job market outcomes of the control group, along with the sample size. SSPP experts and influencers were then asked to predict the expected increase in these outcomes for the treated participants using a 0 to 100% slider scale.[23] The three most accurate predictors within each group received an Amazon gift card of $100. Appendix G presents the prediction survey that SSPP experts and our influencers received.

[19] We thank John Cawley for sharing the summary demographics statistics of the AEA survey with us.

[20] Specifically, the AEA survey sample has 9.2% missing data on gender identity, sexual orientation, and transgender identity, 8.8% missing data on race and Hispanic identity, and 8.2% missing data on US citizenship.

[21] We asked participants to select a range from multiple choice options, as it may be difficult for them to keep track of the specific number of applications submitted.

[22] While we ask participants to report their pre-tax annual salaries in thousands of US dollars, we conjecture that 148 participants potentially report in dollars rather than thousands. Thus, we divided salaries above $9,900 by 1,000 to reconcile this inconsistency.

[23] The survey design excluded options for predicting negative treatment effects, potentially skewing predicted outcomes upward.

Ethics considerations. After the release of our working paper on the Social Science Research Network (SSRN) on May 20, 2024, a vigorous discussion arose on both social and mainstream media, particularly on Twitter, about the ethics of our experiment and of field experiments more generally (e.g., Keynes, 2024). The main concern suggested that job markets are essentially constant sum, so that randomly promoting some candidates through having their job market papers quote-tweeted by influencers would necessarily (and unethically) disadvantage both those who were in the control condition of the experiment and those who did not participate in the experiment.

We understand the importance of considering the ethical implications of any experiment and that ethicality is connected to the underlying economics of the job market. In this latter respect, given the information friction and congestion in the interview process, job markets may not be constant sum. Aside from the possibility of welfare gains from improved match quality, we note that, typically in matching markets, many employers fail to fill all their positions while at the same time qualified candidates fail to find one, so that welfare can also be improved by filling more positions.[24] In the field of economics, the job market often has unfilled positions by the end of February, leading to a scramble round each year starting in March. Similarly, the annual National Resident Matching Program (NRMP) for new physicians in the US also leads to some positions being unfilled, despite having far more applicants than available positions. For example, in 2024, 38,494 positions were offered to 44,853 active applicants and 2,510 positions were unfilled (6.5%), at the end of both the main match (a deferred acceptance algorithm, see Roth and Peranson, 1999) and a centralized post-match scramble called the Supplemental Offer and Acceptance Program (National Residency Matching Program, 2024).[25]

The phenomenon of unfilled positions in a thick labor market may reflect congestion in the interview process. In such a market, since many positions receive more applications than the number of candidates who can feasibly be interviewed, the matching of interviews to jobs may be imperfect in the sense that an employer can find that none of the people interviewed can be successfully hired, but could have filled the position if more appropriate interviewees had been chosen. To mitigate this issue, signaling mechanisms have been introduced in both the economics and medical markets to facilitate a better matching of interviewees and employers (Coles et al., 2010; Rosenblatt et al., 2023). In our context, the quote-tweeting of job market papers may similarly serve to help employers find better matches with their selection of interviewees who can be hired.

We also propose that highlighting suitable candidates from underrepresented groups for a position

[24] In the 2022-23 job market, the total number of jobs listed on JOE was 3,608, including 933 (1,083) full-time academic jobs in (outside) the US and 718 full-time nonacademic jobs (any location). On the supply side, 1,386 Ph.D. students and postdocs applied to at least one job through JOE from August to December 2022 (Cawley, 2023).

[25] Similarly, in the matching of approximately 90,000 high school students to places in New York City, before a centralized clearinghouse was introduced, approximately 30,000 applicants were not matched through the decentralized admissions process, and had to be administratively assigned to places to which they had not applied. After a centralized (deferred acceptance) clearinghouse was introduced, the number of unmatched students who needed to be so assigned was still approximately 3,000 (Abdulkadiroğlu, Pathak and Roth (2005, 2009)).

could potentially expand the overall number of job openings. A notable example is the President's Postdoctoral Fellowship Program, implemented across multiple institutions including the University of Michigan and the University of California system. This program seeks to recruit future faculty members "with the potential to bring to their research and undergraduate teaching the critical perspective that comes from their non-traditional educational background or understanding of the experiences of groups historically underrepresented in higher education."[26]

Finally, we consider trends in the broader context of job search in evaluating the ethical considerations related to our study. Social media has become a common channel for academics to advertise the job market papers of their students. Thus, we are not introducing a new channel for candidate promotion nor are we excluding others outside of our experiment from availing themselves of this channel. Our goal is to understand the extent to which this channel may create visibility or improve outcomes for job candidates, especially since not all candidates may have equal access. Our paper belongs to the class of *natural field experiments* (Harrison and List, 2004), a class that has seen a growing number of studies in which field experiments are used to assess the effects of market interventions.[27] These studies are widely accepted and even recognized, with the 2019 Nobel Prize for experiments in development economics. If it is ethical for economists to use experiments to evaluate interventions in other markets, it should also be ethical for economists to study the market for economists.

3 Results

In this section, we first report the results from our pre-registered analysis in Section 3.1. In Section 3.2, we explore the potential mechanisms which might drive our observed treatment effects. Finally, in Section 3.3, we present an exploratory analysis that examines the correlations between candidate characteristics and job market outcomes.

3.1 Main Results

This section reports the impact of our intervention on Twitter metrics (views and likes), job market outcomes (interviews, flyouts, job offers, and future salary), and satisfaction with job placement. Our pre-analysis plan (see Appendix F) specified the Twitter metrics as intermediate outcomes, interviews, flyouts, and job offers as primary outcomes, and satisfaction with job placement as a secondary out-

[26] See, e.g., https://presidentspostdoc.umich.edu/, retrieved on December 18, 2024.

[27] A *natural field experiment* is one "where the subjects do not know that they are in an experiment" (Harrison and List, 2004). In our context, participants were told only that we would arrange for their job market papers to be tweeted, but not that there would be a quote-tweet treatment.

come. To correct for multiple hypothesis testing, we report the false discovery rate adjusted q-values in square brackets (Benjamini and Hochberg, 1995; Anderson, 2008) for our pre-registered main outcomes in Table 1. To claim statistical significance, we use a 5% (10%) cutoff for our p-values (q-values) (Efron, 2012).[28] Given the high compliance rate among our influencers (88%), the local average treatment effects (LATE) are similar to the intent-to-treat (ITT) effects. We therefore focus on the ITT effects in the main text and present the LATE analysis in Appendix A.

To estimate the ITT effects, we use an ordinary least squares (OLS) approach and estimate the following regression:

$$Y_i = \alpha + \beta_1 \text{ Treatment group}_i + \beta_2 \text{URG}_i + \boldsymbol{\gamma_1'} \mathbf{X}_i + \boldsymbol{\gamma_2'} \mathbf{Z}_i + \epsilon_i \,, \tag{1}$$

where Y_i is an outcome of interest for individual i, Treatment group$_i$ is an indicator for being assigned to the treatment group, and URG$_i$ is an indicator for underrepresented groups, which we include to account for the different treatment assignment probabilities between URG ($\frac{2}{3}$) and non-URG ($\frac{1}{3}$) participants. We also control for personal and academic background characteristics, $\mathbf{X}_i$ and $\mathbf{Z}_i$, respectively. The parameter β_1 measures the ITT effect.

We first examine the impact of our intervention on the visibility of JMP tweets and the subsequent engagement of Twitter users with the quote-tweets. We use the number of views as a proxy for the visibility of JMP tweets and the number of likes as a proxy for engagement, interpreting likes as a signal of endorsement or perceived quality of the paper (or candidate).

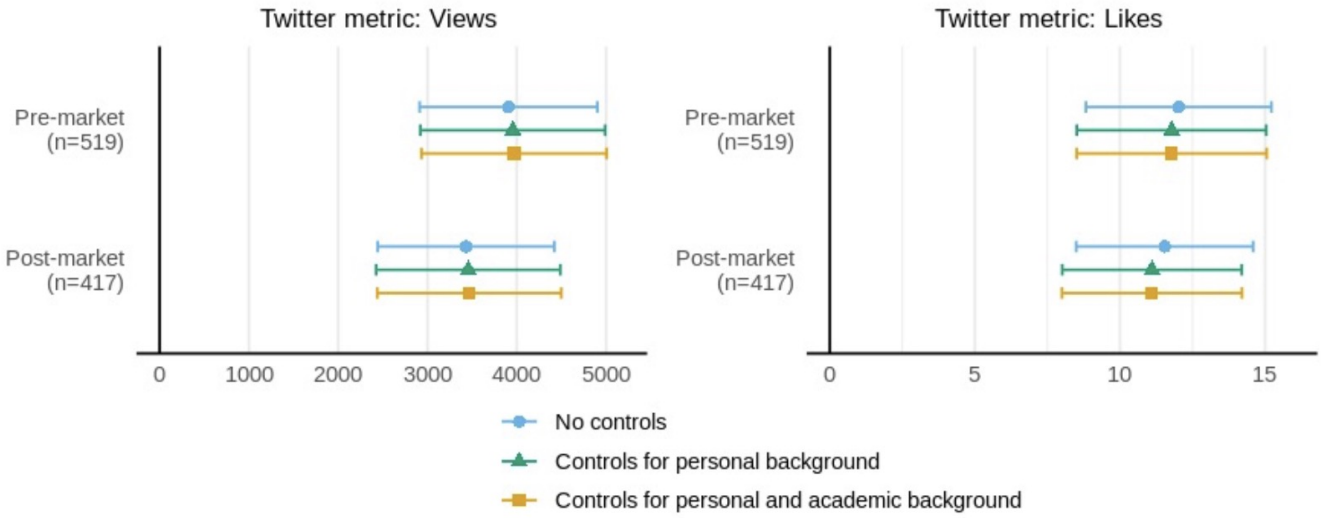
Figure 2 summarizes the ITT estimates based on Equation (1), with and without controls. The left panel reports the results for the number of views, while the right panel presents the results for the number of likes. To facilitate a comparison between Twitter metrics and job market outcomes, we report the results for views and likes for both the pre- and post-market samples.

Our results show that tweets from the control group garner 899 views on average. In contrast, tweets from the treatment group receive an additional 3,970 views compared to the control group ($p < 0.001$, column 1 in Table 1), representing a 442% increase. Restricting the sample to post-market survey participants, we find that the treatment group receives 3,468 more views than the control group ($p < 0.001$, column 6 in Appendix Table A.6).

The results for likes follow a similar pattern as those for views. Tweets from the control group receive an average of 3.9 likes. In comparison, tweets from the treatment group receive 11.8 more likes than the control group ($p < 0.001$, column 2 in Table 1), corresponding to a 303% increase. The results are again similar for the post-market sample (column 6 in Appendix Table A.6). Interestingly, tweets of

[28] False discovery rate adjusted q-values are provided only for the pre-registered main outcomes: number of views, likes, job interviews, flyouts, and job offers.

Figure 2: Intent-to-treat Effects of Social Media Promotion on Twitter Visibility and Engagement



Notes: OLS estimates are provided with 95% confidence intervals. "Views" represents the number of views received by JMP tweets (including views of quote-tweets), and "Likes" represents the sum of likes received by the JMP tweets and the influencer quote-tweets. All specifications include a dummy variable for underrepresented group (URG) status to account for the varying probability of treatment assignment for URG and non-URG participant. "Personal background" controls for participants' personal background characteristics such as age, parental income class, US citizenship status, and Twitter account ownership. "Academic background" controls for graduating from a top 30 PhD institution (in or outside the US), first-time job market presence, and predoctoral and postdoctoral experience. The pre-market sample comprises 519 participants, while the post-market sample includes 417 participants. See Appendix Tables A.6 and A.7 for detailed regression results.

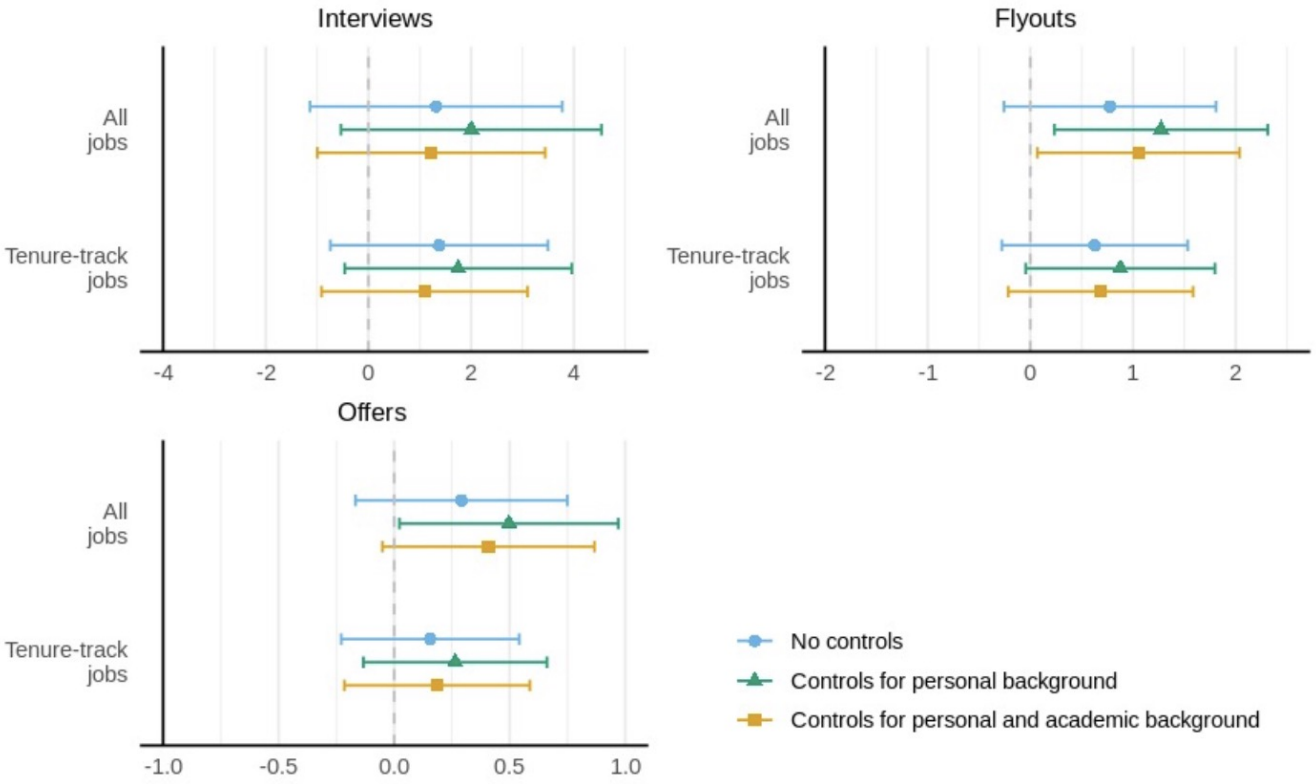
JMPs by URG participants receive slightly more views and likes than non-URG participants, although the differences are not statistically significant ($p > 0.372$, columns 1 and 2 in Table 1). Overall, our intervention increases the visibility of and engagement with JMP tweets.

Result 1 (Visibility and Engagement)**.** *JMP tweets of the treatment group received 3,970 more views (+442%) and 11.8 more likes (+303%) on Twitter than those of the control group.*

We next explore whether this increase in visibility and engagement on Twitter translates into better job market outcomes. Figure 3 presents the ITT effects for interviews, flyouts, and job offers, showing the results for all job types and tenure-track positions.

In the field of economics, the job search season begins with securing interviews at the Allied Social Science Associations (ASSA) or the European Economic Association (EEA) meetings held in January and December, respectively. Due to the COVID-19 pandemic, both the AEA and EEA recommended that interviews be conducted online via Zoom for the 2022-23 job market season. JMCs in the control group secure an average of 16.6 interviews, of which 10.8 are for tenure-track positions. Those in the treatment group secure an additional 1.2 interviews across all job types (column 3 in Table 1) and 1.1 interviews

Figure 3: Intent-to-treat Effects of Social Media Promotion on Job Market Outcomes



Notes: OLS estimates are provided with 95% confidence intervals. "Interviews," "Flyouts," and "Offers" represent the additional number of each job market outcome received by the treatment group. All specifications include a dummy variable for underrepresented group (URG) status to account for the varying probability of treatment assignment for URG and non-URG participants. Here, "academic background" controls also include whether participants have at least one publication or paper under revision, the number of applications submitted (in ranges), and whether two AEA signals are sent, in addition to the controls used for the Twitter metrics analysis. "All jobs" refer to all job types, while "Tenure-track jobs" comprise only tenure-track positions. See Appendix Tables A.10, A.11, and A.12 for detailed regression results.

specifically for tenure-track positions (column 6 in Appendix Table A.10), representing a 7% and 10% increase, respectively. However, these effects are not statistically significant ($p > 0.281$).[29]

Result 2 (Interviews)**.** *The number of interviews received by the participants in the treatment group does not differ significantly from that in the control group.*

The lack of a statistically significant treatment effect at the interview stage could be due to the timing of our intervention. Based on the interview data reported on econjobmarket.org, 199 (2,931) cumulative interview invitations were issued by November 28 (December 8), the start (end) date of our intervention.

[29]For clarity, we present the Twitter visibility, engagement and all job outcome variables with full controls in a single table, Table 1, in the main text. For detailed regression results across different specifications, please refer to Appendix Tables A.6, A.7, A.10, A.11, and A.12.

We also note that interview invitations for the 2022-23 job market in particular were issued earlier than those for the previous two cycles.[30] Thus, our intervention period, which was based on historical invitation cycles, might have occurred too late in the job process to have an effect on interview invitation decisions.

We next examine the impact of our intervention on flyout invitations. Following the interview phase, the next step in the job market process is to receive invitations to visit university campuses and give job talks, also known as flyouts. In the economics job market, flyouts typically take place between January and March. On average, the control group receives 5.4 flyouts, of which 3.3 are for tenure-track positions. The treatment group receives one additional flyout for all job types (column 4 in Table 1) and 0.7 additional flyouts for tenure-track positions (column 6 in Appendix Table A.11), resulting in a 19% and 21% increase, respectively ($p = 0.037$ and 0.137).

Result 3 (Flyouts)**.** *Participants in the treatment group receive one more flyout than those in the control group, who receive an average of 5.4 flyouts.*

We next examine whether our intervention impacts the number of job offers received. Column 5 in Table 1 shows that the control group receives an average of 3 offers, of which 1.5 are for tenure-track positions (column 6 in Appendix Table A.12). The treatment group receives 0.4 more offers for all job types, representing a 13% marginally significant increase ($p = 0.082$, column 5 in Table 1) , and 0.2 more offers for tenure-track positions, which is not statistically significant ($p = 0.137$, column 6 in Appendix Table A.12).[31]

Result 4 (Job Offers)**.** *Participants in the treatment group receive 0.4 marginally more job offers than those in the control group, who receive an average of 3 offers.*

In addition to examining the effect of our intervention on job market outcomes, we explore heterogeneous treatment effects with respect to URG by estimating models that include an interaction term between URG and the treatment group indicator. In the control group, we find that URG participants receive slightly more interviews and flyouts but slightly fewer job offers compared to non-URG participants. However, these differences are not statistically significant ($p > 0.414$; columns 3 in Appendix Tables A.14, A.15, and A.16). We further find that URG participants tend to benefit less from the treatment in terms of flyouts, but more in terms of interviews and job offers. However, these differences are again not statistically significant ($p > 0.243$, columns 3 in Appendix Tables A.15, A.16, and A.16).

[30] See https://econjobmarket.org/marketState/interviews for the cumulative number of interview invitations issued on EconJobMarket between 2018-2024.

[31] Appendix Table A.1 shows that the treatment group is 4 percentage points more likely to complete the post-market survey than the control group, although this difference is not statistically significant ($p = 0.257$). To address the possibility that attrition is endogenous to treatment, we estimate Lee bounds for the treatment effects in Appendix Table A.13. The bounds include zero for interviews and flyouts, consistent with our relatively modest treatment effect estimates in the main analysis.

Table 1: Intent-to-treat Effects of Social Media Promotion on Twitter Visibility, Engagement and Job Market Outcomes

Dependent variable:	Views	Likes	Interviews	Flyouts	Job Offers
	(1)	(2)	(3)	(4)	(5)
Treatment group	3969.650***	11.782***	1.222	1.052**	0.408*
	(524.201)	(1.723)	(1.132)	(0.502)	(0.234)
	[0.001]	[0.001]	[0.115]	[0.039]	[0.066]
URG	463.512	1.255	0.776	0.355	0.067
	(519.259)	(1.844)	(1.138)	(0.536)	(0.235)
Age	-110.429**	-0.470**	-0.268**	-0.125**	-0.100***
	(53.845)	(0.203)	(0.130)	(0.059)	(0.028)
Parental income class	245.115	-0.186	-0.529	0.479	0.128
	(248.966)	(0.923)	(0.699)	(0.324)	(0.148)
US citizen	-788.243*	-2.760*	1.544	0.425	-0.444*
	(429.099)	(1.458)	(1.308)	(0.622)	(0.257)
Twitter account	852.422**	2.463	2.863**	0.621	0.241
	(433.291)	(1.526)	(1.117)	(0.540)	(0.261)
Top 30 PhD institution	130.520	1.933	5.819***	2.239***	0.812***
	(502.443)	(1.698)	(1.133)	(0.498)	(0.231)
First-time JMC	-1233.218	-2.197	2.512**	1.853***	0.766***
	(870.146)	(1.846)	(1.168)	(0.497)	(0.277)
Predoc	-742.502	-0.928	0.429	0.579	0.253
	(506.940)	(1.797)	(1.318)	(0.622)	(0.341)
Postdoc	-459.400	-2.397	-4.238***	-0.955**	-0.492*
	(617.476)	(1.641)	(1.043)	(0.471)	(0.268)
Publication or R&R (1+)			3.420***	0.973**	0.604**
			(1.123)	(0.490)	(0.246)
# applications (51-100)			5.898***	2.139***	1.158***
			(1.484)	(0.648)	(0.317)
# applications (101-150)			7.319***	3.223***	1.233***
			(1.416)	(0.682)	(0.337)
# applications (151-200)			9.921***	3.015***	1.187***
			(1.788)	(0.738)	(0.395)
# applications (200+)			13.863***	2.815***	1.184***
			(1.685)	(0.663)	(0.326)
AEA signals (2)			2.728**	0.519	0.473*
			(1.148)	(0.511)	(0.253)
Constant	4460.413**	19.099***	6.969	1.466	2.943**
	(1914.762)	(6.987)	(5.328)	(2.429)	(1.175)
Observations	500	500	394	394	394
Sample	Pre-market	Pre-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect of being quote-tweeted by established economists on Twitter. Column 1 shows the effect on the number of views received by JMP tweets (which naturally include views of quote-tweets). Column 2 presents the effect on the number of likes received by both the JMP tweets and the influencer quote-tweets. Columns 3-5 show the effects on the number of interviews, flyouts, and job offers received by job market candidates for all types of jobs. The q-values are included in brackets []. All specifications include a dummy variable indicating whether an individual is classified as belonging to an underrepresented group (URG) to account for the varying probability of treatment assignment for URG and non-URG participants. All columns control for participants' personal background characteristics, including age, parental income class (on a 0-4 scale, coded as follows: 4 for "High income/wealthy," 3 for "Upper middle class," 2 for "Middle class," 1 for "Low income," and 0 for "In poverty"), US citizenship status, and Twitter account ownership. Columns 3-5 additionally control for participants' academic background, including graduation from a top 30 PhD institution (in or outside the US), being on the job market for the first time, predoctoral and postdoctoral experience, having at least one publication or paper under revision, the number of applications submitted (in ranges), and whether two AEA signals are sent. OLS estimates are provided with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In addition to examining the effects for underrepresented groups, we explore any differences in our treatment effect by gender, as women account for 71% of the URG participants in our sample. While we do not find heterogeneous treatment effects for the URG group as a whole, we do find that women in the treatment group receive 0.9 more job offers than women in the control group ($p = 0.024$, column 3 of Appendix Table A.19), who receive an average of 3.1 job offers. In contrast, non-female participants in the treatment group do not receive significantly more offers than their counterparts in the control group ($p = 0.615$, column 3).[32] Overall, the positive ITT effect for women on job offers suggests that our intervention has the potential to help improve women's job prospects in the economics job market.

Result 5 (Gender)**.** *Women in the treatment group receive 0.9 more job offers compared to women in the control group, who receive an average of 3.1 offers.*

While the ITT estimates represent a conservative measure of the treatment effect by considering all participants regardless of whether their JMP tweet has been quote-tweeted, we next examine the results using our LATE analysis. To derive our LATE estimates, we employ two-stage least-squares (2SLS) regressions, using the treatment assignment as an instrument for the actual treatment received.

Our LATE results suggest that, overall, treated JMCs experience improved job market outcomes, although not all improvements are statistically significant. Specifically, treated JMCs receive 1.4 more interviews, a non-significant 8% increase compared to the control group ($p = 0.270$, column 3 in Appendix Table A.20). However, we also find that they secure 1.2 more flyouts, a significant 22% increase ($p = 0.033$, column 3 in Appendix Table A.21). Treated JMCs further receive 0.5 more job offers, a 17% increase, although this effect is only marginally significant ($p = 0.075$, column 3 in Appendix Table A.22).

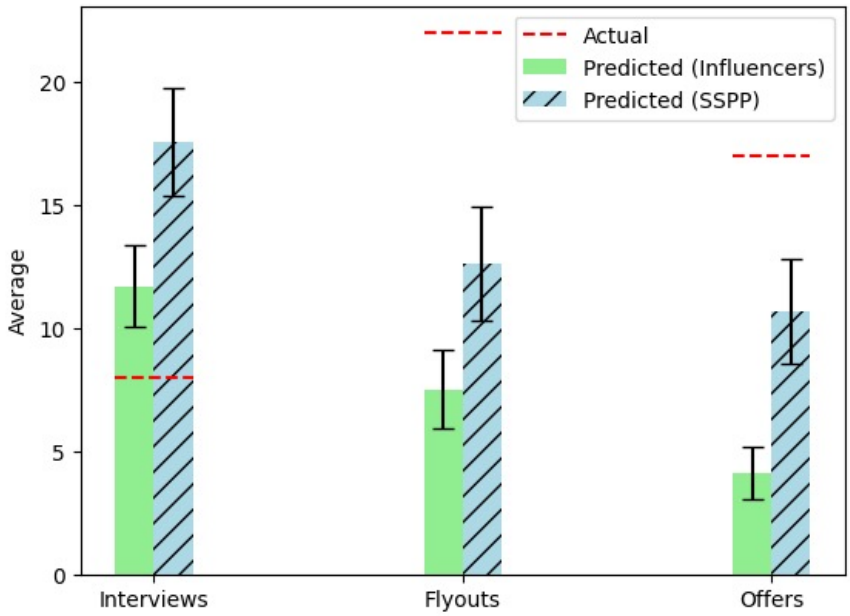
We are interested in how the actual results compare to the predictions made by our influencers and SSPP experts, who were asked to guess the treatment effects (LATE) as percentage increases relative to the control group.

Figure 4 presents the predictions of each group compared to the actual results (red dotted line). While both influencers and SSPP experts predict a monotonic decline in effect size from interviews to job offers, our influencers consistently provide more conservative estimates compared to SSPP experts. Interestingly, both groups overestimate the positive impact of quote-tweeting on interviews and underestimate the positive impact on flyouts and job offers. As discussed above, our smaller observed effect on interviews could be due to the timing of our intervention.

We next examine the treatment effects on salaries for accepted jobs and job placement satisfaction. JMCs in the treatment group report an average salary that is $4,680 higher than those in the control group;

[32] The non-female group mainly consists of male participants, but also includes some participants who did not disclose their gender, or participants who are non-binary.

Figure 4: Predictions by Economist Influencers and SSPP Experts



Notes: This figure presents predictions made by our influencers from the field experiment and experts from the Social Science Prediction Platform (SSPP) regarding the effects of social media promotion on the percentage increase in interviews, flyouts, and job offers. "Actual" lines represent LATE estimates from models with personal and academic background controls, as percentage changes relative to the control group. Error bars indicate the standard error of the mean.

however, this difference is not statistically significant ($p = 0.515$, column 3 of Appendix Table A.23). Regarding job placement satisfaction, two-thirds of all participants in our study report being satisfied or very satisfied with their job placement (rated 6 or 7 on a 1-7 Likert scale). Figure A.4 presents the results of ordered probit regressions (with and without controls) comparing placement satisfaction levels between the treatment and control groups. Although the treatment group is about 6 percentage points less likely to report being fully satisfied (rating of 7), this difference is again not statistically significant ($p = 0.152$).

Turning to job preferences and aggregate outcomes, our pre-market survey indicates that 81% of our JMCs strongly prefer tenure-track jobs (rating of 7 on a 1-7 Likert scale). Among those who complete the post-market survey, 92% in both the treatment and control groups have secured a job at the time of the post-market survey. Conditional on accepting an offer, the share of JMCs who accept a tenure-track position is also similar between the treatment (51%) and control groups (50%). Among JMCs who accept a tenure-track job, our results show that those in the treatment group are more likely to secure a position at a top 30 institution in the US or a top 30 institution outside the US compared to those in the control group (19% vs. 11%), but this difference is not statistically significant ($p = 0.141$).

3.2 Potential Mechanisms

To better understand our findings, we explore potential mechanisms driving the positive effects of social media promotion on academic job market outcomes. While our results generally show improvements across outcomes, some effects do not reach statistical significance, possibly due to sample size limitations. We examine three potential channels through which our intervention might operate. First, social media promotion may help JMCs stand out in the highly competitive economics job market, where typically hundreds of candidates compete for the same positions (**attention mechanism**). Second, quote-tweets from established scholars may be perceived as endorsements of JMCs, lending credibility to candidates through public recognition from respected figures in their fields (**endorsement mechanism**). Third, receiving attention from established scholars may boost JMCs' confidence during interviews and job talks, potentially improving their performance in these critical evaluation stages (**confidence mechanism**).

We first examine the increased attention mechanism. Recall that the quote-tweets from the influencers significantly increased the JMP tweets' reach, generating 3 times more views and 4.4 times more likes. Examining these results further, we see that these effects are generally larger for JMCs assigned to high-reach influencers (those with above-median follower counts relative to all influencers in our sample, median: 13,450 followers). Specifically, the ITT effect on views is almost three times as large for JMCs assigned to high-reach influencers as for those assigned to low-reach influencers ($p < 0.001$, column 3 in Appendix Table A.24). The effect on likes is also larger for JMCs assigned to high-reach influencers, although this difference is not statistically significant (12.7 vs. 9.1, $p = 0.166$, column 6 in Appendix Table A.24). While these results are consistent with the explanation that quote-tweets increase candidate visibility, we acknowledge that it is likely that the pool of Twitter followers for high-reach influencers includes many followers with no influence on hiring decisions. In fact, we find that JMCs assigned to *low-reach* influencers achieve significantly better *job market* outcomes, securing 3.6 more interviews ($p = 0.012$, column 6 in Appendix Table A.25), 1.4 more flyouts ($p = 0.024$, column 6 in Appendix Table A.26), and 0.6 marginally more job offers for tenure-track positions ($p = 0.065$, column 6 in Appendix Table A.27) compared to those assigned to high-reach influencers. This finding points to a nuanced relationship between the attention of the academic audience and the attention of a broader, less specialized follower base: we find that low-reach influencers also tweet less frequently during the intervention period (2.3 vs. 6.4 tweets per day, $p = 0.002$).[33] Thus, it is possible that each tweet captures greater attention from the academic audience, which could explain their stronger impact on job market

[33] Due to the new data restriction on X (see https://developer.twitter.com/docs/twitter-api/tweets/timelines), which only allows retrieval of the 3,200 most recent tweets per user, we were unable to access eight influencers' posting data from our intervention period when collecting data in April 2024. These eight influencers had posted more than 3,200 tweets between our intervention period and the data collection date, which pushed their intervention-period tweets beyond the API's historical reach. For these eight influencers, we top-code their daily posting activity at 19.2 tweets per day, which represents the top 1% of daily posting frequency among our influencers.

outcomes.

We next examine the endorsement mechanism. Although our quote-tweet templates are designed to be neutral with respect to endorsing a candidate, our influencers are able to modify the text of the quote-tweet. To examine heterogeneity in treatment effects by tweet language, we ask three raters (one human research assistant and two large language models – ChatGPT-4 and Claude-3) to evaluate the quote-tweets on a 1-5 scale for specificity and endorsement.[34] Analysis of the ratings reveals relatively low scores for both specificity (mean = 1.9, std = 0.88, median = 2) and endorsement (mean = 1.7, std = 0.86, median = 1), suggesting most quote-tweets maintain neutral language. The generally low levels of specificity and endorsement could explain the limited effects of text characteristics on job market outcomes. While JMCs promoted with above-median specificity quote-tweets secure 2.6 more flyouts (p = 0.010, column 3 in Appendix Table A.29), the level of specificity does not significantly affect the number of interviews or job offers (see Appendix Tables A.28 and A.30). Similarly, the level of endorsement in the quote-tweets does not significantly influence job market outcomes (see Appendix Table A.31, A.32, and A.33). By contrast, while tweet language shows little impact on job market outcomes, we find that the academic reputation of both the influencers and the JMCs strongly affects the effectiveness of the quote-tweets in achieving better job market outcomes. Specifically, JMCs assigned to influencers with above-median Google Scholar citations (median: 8,590) in our sample secure 2.9 marginally more interviews (p = 0.051 column 3 in Appendix Table A.34), 2.1 more flyouts (p = 0.002, column 3 in Appendix Table A.35), and 0.5 marginally more tenure-track offers (p = 0.096, column 6 in Appendix Table A.36) compared to those assigned to below-median cited influencers.[35] Similarly, JMCs from the top 30 PhD institutions (in or outside the US) secure 4.3 more interviews (p = 0.023, column 3 in Appendix Table A.37) and 2.1 more flyouts (p = 0.004, column 3 in Appendix Table A.38) compared to other treated candidates, though the difference in the effect size on offers (0.2 more) is not statistically significant (p = 0.175, column 3 in Appendix Table A.39).

Finally, we examine whether being quote-tweeted by an established scholar boosts candidate confidence during the interviews and flyout visits leading to an increase in flyouts and job offers. Since applications were submitted before our intervention, any confidence effects would be manifested in candidates' interview and job talk performance rather than in their ability to secure more interviews. Thus, if increased confidence is the mechanism behind our findings, we should observe larger effects for flyouts and offers compared to the number of interviews. Our analysis shows greater effects (in relative terms) on the number of flyouts and offers for our sample compared to the number of interviews. However,

[34] The level of agreement between human and AI raters was moderate to substantial, with Cohen's kappa values of 0.626 for specificity and 0.587 for endorsement. We use the median score across raters. See Appendix H for details on the rating instructions and procedure.

[35] The relatively low Pearson correlation (0.286) between influencers' follower count and citation count indicates that academic reputation captures a dimension of influence different from that related to social media visibility (see Appendix Figure A.1).

we are also cognizant of the fact that interview invitations were sent earlier during our sample period, which could explain the lower effect sizes for interviews relative to flyouts and offers. Thus, we conduct an additional analysis to examine whether increased candidate confidence can explain our results, using a difference-in-differences approach to compare changes in tweet volume between the treatment and control groups before and after our intervention. If JMCs experience greater confidence due to the intervention, they might feel more empowered to tweet about their work or other topics related to their academic fields. However, we find no significant differences in either overall tweeting or economics-specific content (see Appendix Table A.40), suggesting that increased candidate confidence is unlikely to be a primary mechanism driving our results.

Overall, our analysis of potential mechanisms suggests that increased attention from relevant audiences and association with academic reputation both play a role in our findings. We find that quote-tweets appear most effective when coming from highly-cited scholars or when promoting candidates from top institutions. Our analysis further reveals that influencers with fewer followers have a stronger impact on candidates' job market outcomes. Since these influencers also tweet less frequently, it suggests that their more selective posting may attract more focused attention from academic audiences compared to the broader but less concentrated visibility achieved by frequent posters.

3.3 Correlates of Job Market Outcomes

In our final analysis, we explore how candidates' personal and academic characteristics are associated with job market outcomes. Columns 3 to 5 of Table 1 present the regression coefficients for key background variables, focusing on outcomes for any type of job. The results for tenure-track jobs are included in the appendix.

Two notable patterns emerge regarding candidate personal characteristics. First, we find that age is negatively associated with job market success, with older candidates receiving fewer interviews, flyouts, and offers. Specifically, each additional year of age corresponds to 0.3 fewer interviews (p = 0.040), 0.1 fewer flyouts (p = 0.037), and 0.1 fewer offers (p = 0.0004). Second, there is a negative association between holding US citizenship and securing a tenure-track position, as US citizens receive 1.1 fewer flyouts for tenure-track jobs (p = 0.021) and 0.9 fewer offers ($p < 0.001$) for tenure-track jobs compared to non-US-citizens. Other personal characteristics, such as parental income class, show no significant relationship with job market outcomes. Finally, having a Twitter account is associated with receiving 2.8 more interviews (p = 0.011), though this effect does not extend to flyouts and offers.

Regarding professional characteristics, we find better job market outcomes for candidates from top universities as well as those with more publications. Institutional prestige and research output emerge as strong predictors, alongside prior job market experience. Our results show that candidates from top

30 institutions (in or outside the US) receive 5.8 more interviews ($p < 0.001$), 2.2 more flyouts ($p < 0.001$), and 0.8 more offers (p = 0.001) compared to their peers from lower-ranked institutions. Similarly, candidates with at least one published or revise-and-resubmit paper receive 3.4 more interviews (p = 0.003), one additional flyout (p = 0.048), and 0.6 more offers (p = 0.015). Candidates on the job market for the first time also fare better than those who had previously been on the market, receiving 2.5 more interviews (p = 0.033), 1.9 more flyouts ($p < 0.001$), and 0.8 more offers (p = 0.006).

While predoctoral research positions have become an increasingly common pathway to economics PhD programs, their impact on job market outcomes remains unclear. We find positive but statistically insignificant effects of predoctoral experience on interviews (+0.4), flyouts (+0.6), and offers (+0.3).In contrast, we find that postdoctoral experience is negatively associated with job market success, even after controlling for age and being on the job market for the first time. Postdocs received 4.2 fewer interviews ($p < 0.001$), one fewer flyout (p = 0.044), and 0.5 fewer offers (p = 0.068).

Finally, we examine the role of application volume in job market outcomes. Our results show that submitting more job applications is positively associated with success across all stages of the job market, but with diminishing returns at higher volumes. Compared to candidates applying to 1-50 jobs, those submitting 51-100 applications receive 5.9 more interviews ($p < 0.001$), while those applying to 101-150, 151- 200, and over 200 jobs secure 7.3 ($p < 0.001$), 9.9 ($p < 0.001$), and 13.9 ($p < 0.001$) more interviews, respectively. However, the marginal gains decline with each additional 50 applications, from 5.9 for the first increase to 4.0 for the highest category. Similarly, higher application volumes correlate with better job market outcomes in later stages. Candidates submitting over 50 applications received between 2.1 and 3.2 more flyouts ($p \leq 0.002$) and approximately 1.2 more offers ($p \leq 0.003$) compared to those applying to 1-50 jobs. Moreover, the use of the AEA signaling mechanism is associated with 2.7 more interviews (p = 0.018), highlighting the potential benefits of strategic signaling in the job market.

4 Discussion

Our study examines whether the promotion of job market papers by established economists on Twitter increases the visibility of these papers and improves the candidates' job market outcomes, focusing on the impact for underrepresented groups in the economics profession. Our findings suggest that social media promotion significantly increases visibility and engagement of these papers, leading to 442% more views and 303% more likes than papers in the control condition.

Regarding job market outcomes, we find that participants in the treatment group receive one additional flyout compared to those in the control group, who receive an average of 5.4 flyouts. Moreover, women in the treatment group obtain 0.9 more job offers than their counterparts in the control group, who average 3.1 job offers. These findings suggest that social media promotion can be an effective

and scalable tool for improving job market outcomes, especially for women who have historically been underrepresented in economics.

Finally, we acknowledge that our conclusions should be considered in the context of potential study limitations. First, our sample size was limited by the number of candidates willing to participate in our study during an intense period of job search, possibly affecting our ability to obtain precise estimates of the impact of our interventions. Second, since our data were collected within one year of the 2022-2023 job market, we cannot assess the long-term career impacts of our intervention. Other studies suggest that social media promotion can have extended effects. For example, a recent Twitter experiment in biological sciences finds that research papers promoted by science communicators receive 12% more citations over three years, but sample size constraints similarly led to statistically insignificant results (Branch et al., 2024).[36] In economics, an observational study finds that papers with VoxEU columns receive 16-25% more citations over nine years when their columns receive at least one tweet, compared to columns without any Twitter mentions (Chan et al., 2023).[37] While these studies suggest that there are sustained benefits from online visibility, more research is needed to establish the long-term effects of social media promotion on academic careers, especially for scholars from underrepresented groups.

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Online Appendix for

Social Media and Job Market Success: A Field Experiment on Twitter

Jingyi Qiu Yan Chen Alain Cohn Alvin Roth

March 18, 2025

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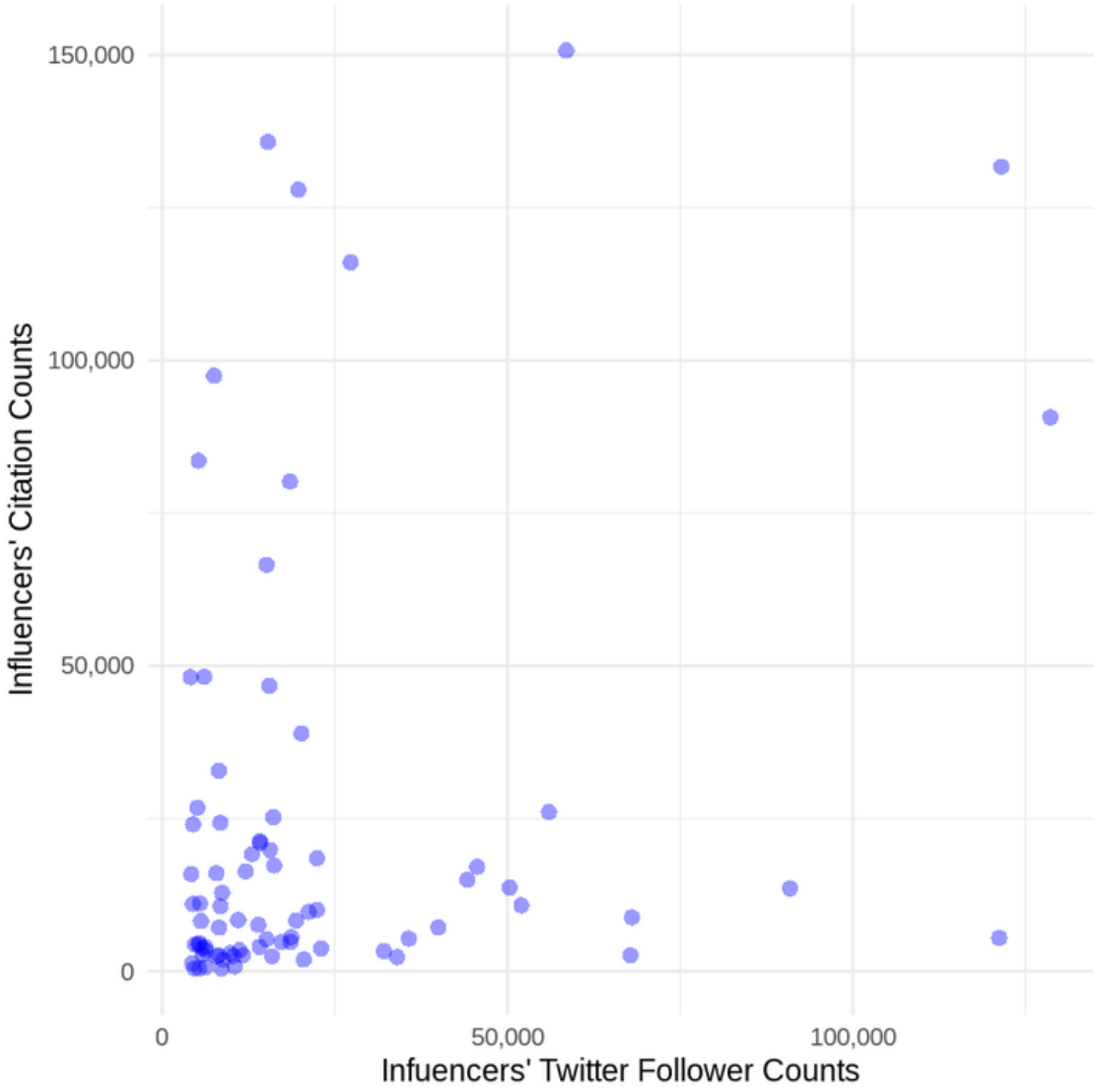
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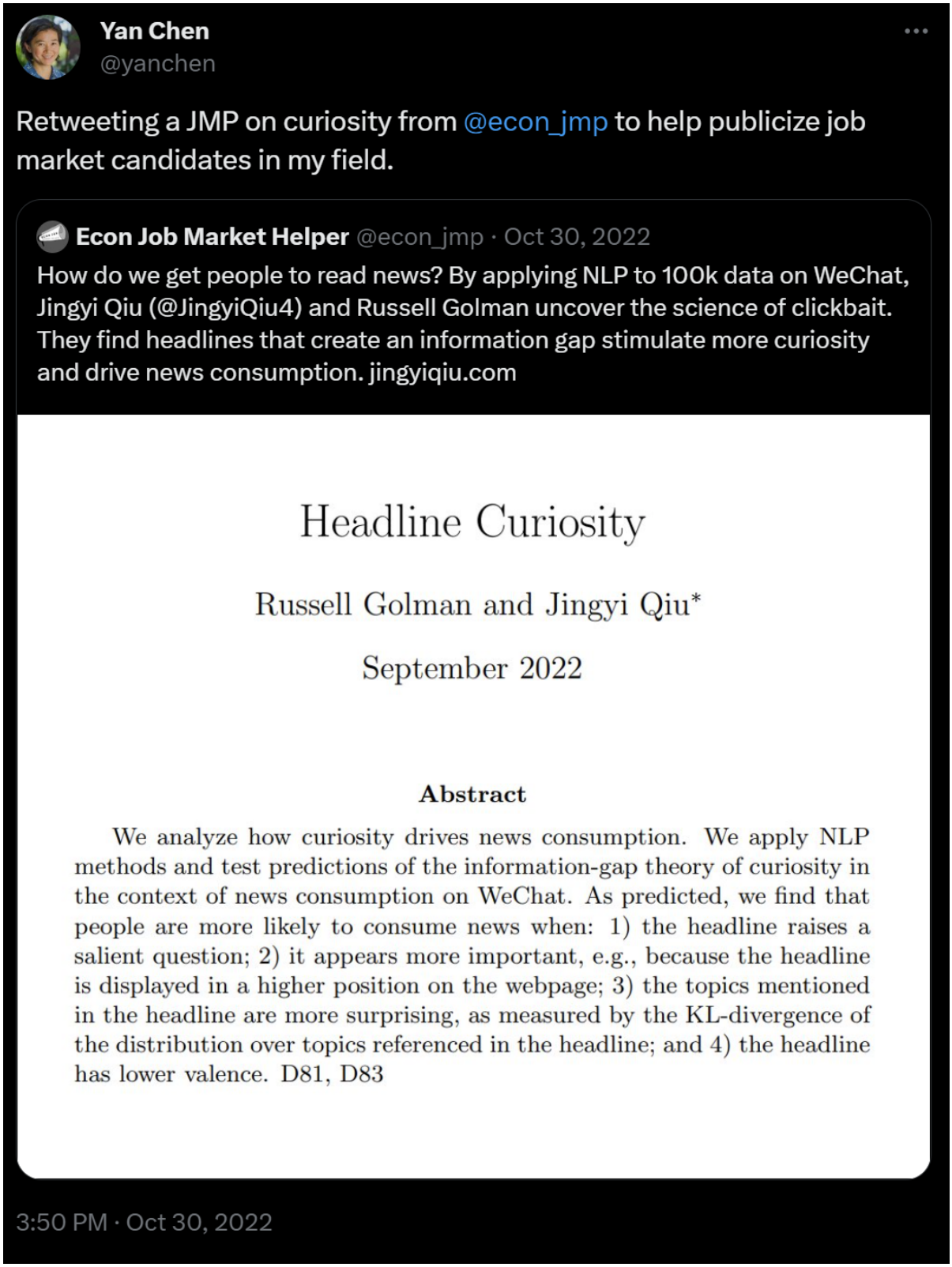
A Figures and Tables

Figure A.1: Influencers' Twitter Follower Counts vs. Citation Counts



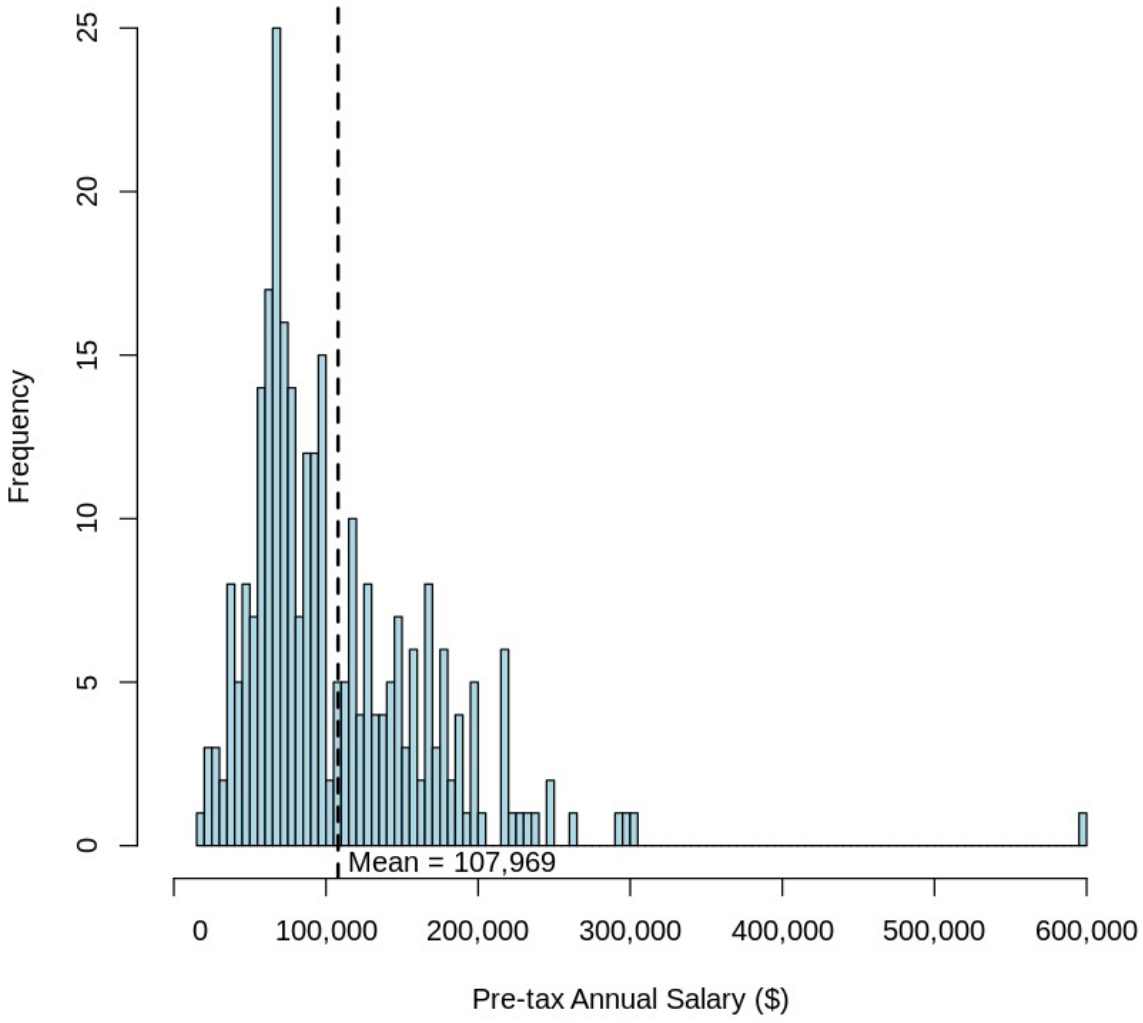
Notes: The Pearson correlation between influencers' Twitter follower counts and citation counts is 0.286.

Figure A.2: A Made-up Quote-tweet Example



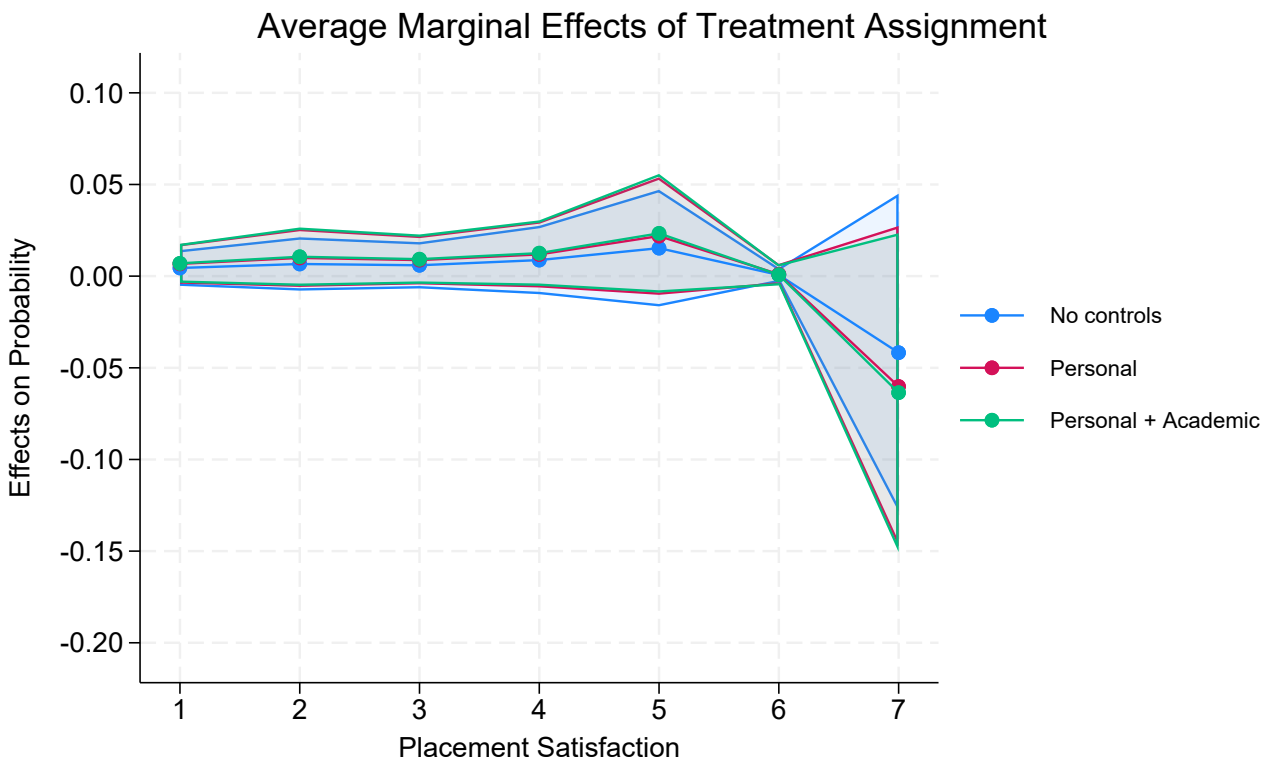
Notes: To preserve the anonymity of the participants, we present a made-up quote-tweet example. Yan Chen was not an economist influencer in the study and Jingyi Qiu was not a job market candidate in 2022-23.

Figure A.3: Distribution of Self-reported Pre-tax Annual Salary (in USD) (n = 281)



Notes: We asked participants to report their pre-tax annual salaries in thousands of US dollars, but 148 participants potentially reported in dollars rather than thousands. We divided salaries above 9,900 by 1,000 to reconcile the inconsistency.

Figure A.4: Placement Satisfaction (ITT)



Notes: Ordered Probit estimates of intent-to-treat (ITT) effects on placement satisfaction. Placement satisfaction is measured on a 7-point Likert scale from '1' (Not satisfied at all) to '7' (Very satisfied). Sample size: n=378.

Table A.1: Post-Market Survey Completion

Dependent variable:	**Completed Post-Market Survey (=1)**	
	(1)	(2)
Treatment group	0.043	0.042
	(0.038)	(0.038)
URG	0.058	0.065*
	(0.038)	(0.039)
Age		-0.008
		(0.005)
Parental income class		-0.010
		(0.022)
US citizen		0.113***
		(0.040)
Twitter account		0.083**
		(0.042)
Top 30 PhD institution		0.011
		(0.037)
First-time JMC		0.009
		(0.068)
Predoc		0.052
		(0.043)
Postdoc		0.004
		(0.060)
Constant	0.758***	0.923***
	(0.028)	(0.200)
Observations	519	500
Sample	Pre-market	Pre-market

Notes: This table presents the post-market survey completion rates across the treatment and control groups. Both specifications include a dummy variable indicating whether an individual is classified as belonging to underrepresented groups (URG) to account for the varying probability of treatment assignment. Column 2 controls for participants' personal and academic background characteristics. Personal background characteristics include age, parental income class (on a 0-4 scale, coded as follows: 4 for "High income / wealthy", 3 for "Upper middle class", 2 for "Middle class", 1 for "Low income", and 0 for "In poverty"), US citizenship status, and Twitter account ownership, while academic background characteristics include graduating from a top 30 PhD institution (in or outside the US), being on the job market for the first time, as well as predoctoral and postdoctoral experience. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Descriptive Statistics and Balance Checks

Pre-market Sample				
	Control (n=275)	Treatment (n=244)	Total (n=519)	p-values
URG	78 (28%)	147 (60%)	225 (43%)	
Age	31.3 (3.5)	31.9 (4.2)	31.6 (3.8)	0.084
Parental income class	2.2 (0.8)	2.1 (0.9)	2.2 (0.8)	0.071
US citizen	58 (21%)	36 (15%)	94 (18%)	0.061
Twitter account	188 (68%)	174 (71%)	362 (70%)	0.466
Top 30 PhD institution	127 (46%)	110 (45%)	237 (46%)	0.802
First-time JMC	236 (86%)	213 (87%)	449 (87%)	0.623
Predoc	47 (17%)	45 (18%)	92 (18%)	0.687
Postdoc	39 (14%)	38 (16%)	77 (15%)	0.656
Post-market Sample				
	Control (n=213)	Treatment (n=204)	Total (n=417)	p-values
URG	61 (29%)	129 (63%)	190 (46%)	
Age	31.0 (3.3)	31.9 (4.2)	31.5 (3.8)	0.018
Parental income class	2.3 (0.8)	2.1 (0.9)	2.2 (0.8)	0.010
US citizen	50 (23%)	34 (17%)	84 (20%)	0.083
Twitter account	151 (71%)	151 (74%)	302 (72%)	0.475
Top 30 PhD institution	101 (47%)	92 (45%)	193 (46%)	0.635
First-time JMC	185 (87%)	179 (88%)	364 (87%)	0.785
Predoc	40 (19%)	39 (19%)	79 (19%)	0.930
Postdoc	29 (14%)	31 (15%)	60 (14%)	0.646
Publication or R&R (1+)	124 (60%)	118 (59%)	242 (59%)	0.899
# applications (1-50)	29 (14%)	22 (11%)	51 (12%)	0.378
# applications (51-100)	38 (18%)	33 (16%)	71 (17%)	0.652
# applications (101-150)	56 (27%)	55 (27%)	111 (27%)	0.875
# applications (151-200)	43 (20%)	38 (19%)	81 (20%)	0.688
# applications (201+)	45 (21%)	54 (27%)	99 (24%)	0.198
AEA signals (2)	159 (75%)	156 (77%)	315 (76%)	0.655

Notes: The table presents descriptive statistics and balance checks for control variables in the pre-market and post-market samples. For continuous variables, means and standard deviations are reported; for binary variables, counts and percentages are provided. The last column reports p-values from t-tests (continuous variables) and Pearson χ^2 tests (binary variables). In the pre-market sample, there are 6 missing observations for "Age" and 16 for "Parental Income Status". The post-market sample has the following missing observations: 4 for "Age", 11 for "Parental income class", 9 for "Publication or R&R (1+)", 4 for "# applications", and 4 for "AEA signals (2)".

Table A.3: Descriptive Statistics for URG

Variable	Control	Treatment	Total	p-value
Pre-market Sample				
US citizen	9 (11.5%)	19 (12.9%)	28 (12.4%)	0.930
Twitter account	59 (75.6%)	111 (75.5%)	170 (75.6%)	1.000
Top 30 PhD institution	32 (41%)	63 (42.9%)	95 (42.2%)	0.902
First-time JMC	69 (88.5%)	130 (88.4%)	199 (88.4%)	1.000
Predoc	18 (23.1%)	28 (19%)	46 (20.4%)	0.590
Publication or R&R (1+)	34 (56.7%)	76 (59.8%)	110 (58.8%)	0.800
Age	31.69 (4.22)	31.96 (4.4)	31.87 (4.33)	0.654
Parental income class	2.2 (0.76)	2.09 (0.84)	2.13 (0.81)	0.318
Post-market Sample				
US citizen	6 (14.3%)	14 (13.7%)	20 (13.9%)	1.000
Twitter account	33 (78.6%)	79 (77.5%)	112 (77.8%)	1.000
Top 30 PhD institution	20 (47.6%)	48 (47.1%)	68 (47.2%)	1.000
Rookie	40 (95.2%)	91 (89.2%)	131 (91%)	0.347
Predoc	12 (28.6%)	20 (19.6%)	32 (22.2%)	0.339
Postdoc	2 (4.8%)	13 (12.7%)	15 (10.4%)	0.231
# applications (1-50)	2 (4.8%)	10 (9.9%)	12 (8.4%)	0.509
# applications (51-100)	7 (16.7%)	15 (14.9%)	22 (15.4%)	0.984
# applications (101-150)	11 (26.2%)	20 (19.8%)	31 (21.7%)	0.534
# applications (151-200)	13 (31%)	24 (23.8%)	37 (25.9%)	0.494
# applications (200+)	9 (21.4%)	32 (31.7%)	41 (28.7%)	0.302
AEA signal sent: 2	37 (88.1%)	84 (83.2%)	121 (84.6%)	0.625
Publication/R&R (1+)	24 (58.5%)	61 (61%)	85 (60.3%)	0.935
Age	30.6 (2.74)	31.45 (4.19)	31.2 (3.84)	0.155
Parental income class	2.17 (0.78)	2.15 (0.77)	2.16 (0.77)	0.864

Table A.4: Descriptive Statistics for Non-URG

Variable	Control	Treatment	Total	P-value
Pre-market Sample				
US citizen	49 (24.9%)	17 (17.5%)	66 (22.4%)	0.204
Twitter account	129 (65.5%)	63 (64.9%)	192 (65.3%)	1.000
Top 30 PhD institution	95 (48.2%)	47 (48.5%)	142 (48.3%)	1.000
First-time JMC	167 (84.8%)	83 (85.6%)	250 (85%)	0.995
Predoc	29 (14.7%)	17 (17.5%)	46 (15.6%)	0.651
Postdoc	32 (16.2%)	17 (17.5%)	49 (16.7%)	0.912
Age	31.2 (3.19)	31.87 (3.77)	31.42 (3.4)	0.136
Parental income class	2.26 (0.8)	2.14 (0.89)	2.22 (0.83)	0.276
Post-market Sample				
US citizen	32 (26%)	14 (22.2%)	46 (24.7%)	0.698
Twitter account	82 (66.7%)	41 (65.1%)	123 (66.1%)	0.958
Top 30 PhD institution	66 (53.7%)	33 (52.4%)	99 (53.2%)	0.992
First-time JMC	109 (88.6%)	56 (88.9%)	165 (88.7%)	1.000
Predoc	17 (13.8%)	12 (19%)	29 (15.6%)	0.474
Postdoc	17 (13.8%)	10 (15.9%)	27 (14.5%)	0.876
# applications (1-50)	14 (11.6%)	4 (6.5%)	18 (9.8%)	0.402
# applications (51-100)	20 (16.5%)	11 (17.7%)	31 (16.9%)	1.000
# applications (101-150)	38 (31.4%)	22 (35.5%)	60 (32.8%)	0.697
# applications (151-200)	23 (19%)	9 (14.5%)	32 (17.5%)	0.581
# applications (200+)	26 (21.5%)	16 (25.8%)	42 (23%)	0.637
AEA signal sent: 2	91 (75.2%)	49 (79%)	140 (76.5%)	0.694
Publication or R&R (1+)	68 (57.1%)	35 (57.4%)	103 (57.2%)	1.000
Age	30.83 (3)	31.69 (3.54)	31.12 (3.21)	0.102
Parental income class	2.34 (0.8)	2.11 (0.88)	2.27 (0.83)	0.094

Table A.5: Comparison Between Our Sample and AEA Sample

Characteristics	Our Sample (in %) n = 519	AEA Sample (in %) n = 623	p-values
Gender Identity - Female	29.7	28.1	0.557
Gender Identity - Male	67.8	59.9	0.005
Gender Identity - Non-Binary / Agender / Something else	0.4	0.6	0.561
Gender Identity - Prefer not to say	2.1	2.3	0.881
Gender Identity - Missing data	0	9.2	<0.001
Sexual Orientation - Heterosexual / Straight	84.6	75.4	<0.001
Sexual Orientation - Bisexual	1.4	4.8	0.001
Sexual Orientation - Gay / Lesbian	2.9	4.0	0.305
Sexual Orientation - Something else / Unsure	1.0	1.0	1.0
Sexual Orientation - Prefer not to say	10.2	5.6	0.004
Sexual Orientation - Missing data	0	9.2	<0.001
Transgender - No	92.3	87.5	0.008
Transgender - Don't know / Not sure	1.5	0.6	0.137
Transgender - Yes, Transgender, gender nonconforming	0.4	0.2	0.451
Transgender - Prefer not to say	5.8	2.6	0.006
Transgender - Missing data	0	9.2	<0.001
Hispanic - Yes	13.1	13.6	0.790
Hispanic - No	84.0	75.0	<0.001
Hispanic - Prefer not to say	2.9	2.6	0.740
Hispanic - Missing data	0	8.8	<0.001
US Citizenship - Yes	18.1	33.6	<0.001
US Citizenship - No	81.9	58.3	<0.001
US Citizenship - Missing data	0	8.2	<0.001
Race - White	49.7	51.0	0.654
Race - Asian	36.4	27.0	0.001
Race - Black or African American	2.3	2.7	0.653
Race - Other	5.6	2.6	0.009
Race - Mixed race		2.6	
Race - Prefer not to say	6.0	5.3	0.624
Race - Missing data	0	8.8	<0.001
Age - Mean (Std Dev)	31.6 (3.8)	33.1 (5.1)	
Age - Missing data (in %)	1.2	20.4	

Notes: This table compares the percentages of participants with different demographic characteristics between the AEA sample and our sample. The p-values are calculated using z-tests for the difference in proportions. In our sample, the sum exceeding 100% in the "Sexual Orientation" category is attributed to the rounding of decimal figures to the nearest tenth. Specifically, "Sexual Orientation - Bisexual" was reported as 1.35% but rounded to 1.4%, and "Sexual Orientation - Something else / Unsure" was reported as 0.96% but rounded to 1.0%. When these rounded figures are added together with the other categories, the total exceeds 100% by a slight margin. In our sample, 19.65% of participants chose the option "I do not consider myself either transgender or cisgender" in response to the question about their transgender identity, likely due to a lack of understanding of the terminology. Thus, we merged this category with "No, I am cisgender" for analysis purposes. Notably, the AEA survey does not include the option "I do not consider myself either transgender or cisgender." For the question about race, since the AEA survey does not provide the option "American Indian or Alaska Native," we combined responses from this category with those from the "Other" category in this table.

Table A.6: Number of Views (ITT)

Dependent variable:	**Number of Views**					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	3907.186***	3955.413***	3969.650***	3431.105***	3456.410***	3467.637***
	(501.988)	(518.344)	(524.201)	(421.077)	(434.121)	(432.829)
URG	492.052	390.809	463.512	511.997	410.163	512.531
	(513.045)	(512.387)	(519.259)	(448.593)	(429.776)	(440.544)
Age		-85.556*	-110.429**		-1.477	-40.850
		(50.110)	(53.845)		(52.635)	(57.038)
Parental income class		219.921	245.115		224.662	235.522
		(239.199)	(248.966)		(241.974)	(252.678)
US citizen		-725.687*	-788.243*		-396.101	-529.516
		(431.458)	(429.099)		(410.886)	(415.916)
Twitter account		773.924*	852.422**		772.451**	924.491**
		(429.406)	(433.291)		(373.152)	(394.673)
Top 30 PhD institution			130.520			302.909
			(502.443)			(480.727)
First-time JMC			-1233.218			-1912.072*
			(870.146)			(1105.566)
Predoc			-742.502			-191.900
			(506.940)			(536.762)
Postdoc			-459.400			-735.878
			(617.476)			(745.602)
Constant	734.320***	2602.795	4460.413**	756.921***	-117.956	2631.277
	(192.211)	(1713.432)	(1914.762)	(202.949)	(1937.674)	(2033.670)
Observations	519	500	500	417	403	403
Sample	Pre-market	Pre-market	Pre-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect of being quote-tweeted by established economists on Twitter on the number of views received by job market paper tweets (which naturally include views of quote-tweets). Columns 1-3 present the results for the pre-market sample, which comprises 519 participants who completed our pre-market survey. Columns 4-6 present the results for the post-market sample, which includes 417 participants who reported their job market outcomes. All specifications include a dummy variable indicating whether an individual is classified as belonging to underrepresented groups (URG) to account for the varying probability of treatment assignment. Columns 2 and 5 control for participants' personal background characteristics, including age, parental income class (on a 0-4 scale, coded as follows: 4 for "High income / wealthy", 3 for "Upper middle class", 2 for "Middle class", 1 for "Low income", and 0 for "In poverty"), US citizenship status, and Twitter account ownership. Columns 3 and 6 additionally control for participants' academic background, including graduating from a top 30 PhD institution (in or outside the US), being on the job market for the first time, as well as predoctoral and postdoctoral experience. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Number of Likes (ITT)

Dependent variable:	**Number of Likes**					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	12.021***	11.777***	11.782***	11.540***	11.103***	11.101***
	(1.746)	(1.725)	(1.723)	(1.574)	(1.516)	(1.520)
URG	1.274	1.160	1.255	0.191	0.043	0.076
	(1.776)	(1.788)	(1.844)	(1.580)	(1.594)	(1.646)
Age		-0.466**	-0.470**		-0.168	-0.175
		(0.203)	(0.203)		(0.177)	(0.165)
Parental income class		-0.016	-0.186		-0.302	-0.526
		(0.889)	(0.923)		(0.982)	(0.997)
US citizen		-2.590*	-2.760*		-1.871	-2.077
		(1.471)	(1.458)		(1.420)	(1.393)
Twitter account		2.173	2.463		1.831	2.182
		(1.513)	(1.526)		(1.505)	(1.501)
Top 30 PhD institution			1.933			1.633
			(1.698)			(1.566)
First-time JMC			-2.197			-2.304
			(1.846)			(2.285)
Predoc			-0.928			1.029
			(1.797)			(1.887)
Postdoc			-2.397			-2.536
			(1.641)			(1.947)
Constant	3.388***	17.290**	19.099***	3.795***	9.022	10.930*
	(0.759)	(6.728)	(6.987)	(0.850)	(6.656)	(6.285)
Observations	519	500	500	417	403	403
Sample	Pre-market	Pre-market	Pre-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect of being quote-tweeted by established economists on Twitter on the sum of likes received by the job market paper tweets and the influencer quote-tweets. For a description of the variables, see the table notes in Appendix Table A.6. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Number of Views (LATE)

Dependent variable:	**Number of Views**					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	4413.850***	4455.248***	4475.910***	3858.257***	3868.918***	3885.121***
	(557.561)	(572.556)	(577.769)	(459.890)	(471.130)	(467.649)
URG	605.038	542.157	595.322	589.348	528.609	610.101
	(503.354)	(498.572)	(504.803)	(438.432)	(417.512)	(428.118)
Age		-84.734*	-108.369**		-2.673	-40.550
		(49.398)	(53.357)		(52.231)	(56.679)
Parental income class		220.585	237.950		212.500	214.277
		(228.331)	(236.585)		(231.433)	(240.174)
US citizen		-722.525*	-783.374*		-370.700	-498.805
		(422.838)	(419.052)		(399.046)	(401.442)
Twitter account		632.238	702.840*		653.474*	798.136**
		(413.040)	(414.268)		(352.257)	(372.440)
Top 30 PhD institution			61.266			260.602
			(490.978)			(464.334)
First-time JMC			-1199.114			-1827.406*
			(846.822)			(1077.143)
Predoc			-579.908			-34.599
			(477.031)			(504.338)
Postdoc			-545.118			-728.134
			(611.704)			(730.106)
Constant	702.273***	2630.258	4463.132**	734.769***	-8.308	2640.532
	(190.896)	(1678.280)	(1899.506)	(201.503)	(1913.501)	(2017.632)
First stage instrument:						
Treatment assignment	0.885	0.888	0.887	0.885	0.888	0.893
Standard error	0.021	0.021	0.021	0.021	0.021	0.023
F-statistics	1789.836	1826.429	1789.442	1505.779	1584.249	1544.164
Observations	519	500	500	417	403	403
Sample	Pre-market	Pre-market	Pre-market	Post-market	Post-market	Post-market

Notes: This table presents the local average treatment effect (LATE) of being quote-tweeted by established economists on Twitter on the number of views received by job market paper tweets (which naturally include views of quote-tweets). For a description of the variables, see the table notes in Appendix Table A.6. 2SLS estimates with Robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Number of Likes (LATE)

Dependent variable:	**Number of Likes**					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	13.429***	13.112***	13.135***	12.771***	12.219***	12.226***
	(1.940)	(1.906)	(1.899)	(1.742)	(1.671)	(1.664)
URG	1.943	1.868	1.898	0.870	0.786	0.784
	(1.716)	(1.710)	(1.760)	(1.541)	(1.545)	(1.594)
Age		-0.507**	-0.504**		-0.236	-0.233
		(0.198)	(0.197)		(0.176)	(0.163)
Parental income class		-0.247	-0.441		-0.663	-0.916
		(0.867)	(0.895)		(0.962)	(0.971)
US citizen		-2.627*	-2.799**		-1.868	-2.074
		(1.427)	(1.406)		(1.375)	(1.337)
Twitter account		1.882	2.164		1.631	1.998
		(1.463)	(1.463)		(1.446)	(1.434)
Top 30 PhD institution			2.005			1.933
			(1.632)			(1.522)
First-time JMC			-2.229			-2.210
			(1.806)			(2.234)
Predoc			-0.569			1.297
			(1.695)			(1.791)
Postdoc			-2.729*			-2.642
			(1.635)			(1.900)
Constant	3.334***	19.226***	20.851***	3.782***	12.040*	13.448**
	(0.758)	(6.600)	(6.817)	(0.849)	(6.693)	(6.265)
First stage instrument:						
Treatment assignment	0.883	0.885	0.885	0.883	0.885	0.893
Standard error	0.021	0.021	0.021	0.021	0.021	0.023
F-statistics	1774.466	1806.236	1774.707	1522.059	1596.866	1561.949
Observations	523	504	504	420	406	406
Sample	Pre-market	Pre-market	Pre-market	Post-market	Post-market	Post-market

Notes: This table presents the local average treatment effect (LATE) of being quote-tweeted by established economists on Twitter on the sum of likes received by the job market paper tweets and the influencer quote-tweets. For a description of the variables, see the table notes in Appendix Table A.6. 2SLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Number of Interviews (ITT)

Dependent variable:	**Number of Interviews**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	1.317	2.002	1.222	1.377	1.747	1.091
	(1.253)	(1.295)	(1.132)	(1.081)	(1.128)	(1.024)
URG	1.101	1.104	0.776	0.315	0.150	0.129
	(1.271)	(1.285)	(1.138)	(1.084)	(1.118)	(1.038)
Age		-0.669***	-0.268**		-0.428***	-0.168
		(0.139)	(0.130)		(0.128)	(0.123)
Parental income class		0.201	-0.529		-0.379	-0.838
		(0.754)	(0.699)		(0.637)	(0.598)
US citizen		2.069	1.544		-0.535	-0.983
		(1.479)	(1.308)		(1.208)	(1.136)
Twitter account		2.934**	2.863**		1.731	1.889*
		(1.241)	(1.117)		(1.068)	(0.974)
Top 30 PhD institution			5.819***			6.022***
			(1.133)			(1.025)
First-time JMC			2.512**			2.039*
			(1.168)			(1.165)
Predoc			0.429			-0.153
			(1.318)			(1.147)
Postdoc			-4.238***			-2.207**
			(1.043)			(1.024)
Publication or R&R (1+)			3.420***			3.852***
			(1.123)			(1.001)
# applications (51-100)			5.898***			4.473***
			(1.484)			(1.416)
# applications (101-150)			7.319***			6.040***
			(1.416)			(1.331)
# applications (151-200)			9.921***			7.044***
			(1.788)			(1.615)
# applications (201+)			13.863***			10.300***
			(1.685)			(1.443)
AEA signals (2)			2.728**			1.293
			(1.148)			(1.061)
Constant	16.384***	33.952***	6.969	10.924***	23.749***	3.205
	(0.802)	(4.957)	(5.328)	(0.732)	(4.530)	(4.968)
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect of being quote-tweeted by established economists on Twitter on the number of interviews received by job market candidates. Columns 1-3 show the effect for all jobs, while columns 4-6 focus on tenure-track positions. All specifications include a dummy variable indicating whether an individual is classified as belonging to underrepresented groups (URG) to account for the varying probability of treatment assignment. Columns 2 and 5 control for participants' personal background characteristics, including age, parental income class (on a 0-4 scale, coded as follows: 4 for "High income / wealthy", 3 for "Upper middle class", 2 for "Middle class", 1 for "Low income", and 0 for "In poverty"), US citizenship status, and Twitter account ownership. Columns 3 and 6 additionally control for participants' academic background, including graduating from a top 30 PhD institution (in or outside the US), being on the job market for the first time, predoctoral and postdoctoral experience, whether participants have at least one publication or paper under revision, the number of applications submitted (in ranges), and whether two AEA signals were sent. The post-market sample includes 417 participants who reported their job market outcomes. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Number of Flyouts (ITT)

Dependent variable:	**Number of Flyouts**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	0.775	1.272**	1.052**	0.627	0.876*	0.684
	(0.527)	(0.531)	(0.502)	(0.462)	(0.470)	(0.460)
URG	0.440	0.363	0.355	0.369	0.173	0.267
	(0.533)	(0.543)	(0.536)	(0.462)	(0.469)	(0.475)
Age		-0.264***	-0.125**		-0.169***	-0.095*
		(0.058)	(0.059)		(0.051)	(0.051)
Parental income class		0.726**	0.479		0.176	0.059
		(0.315)	(0.324)		(0.265)	(0.273)
US citizen		0.535	0.425		-0.881*	-1.054**
		(0.647)	(0.622)		(0.453)	(0.454)
Twitter account		0.596	0.621		0.437	0.554
		(0.561)	(0.540)		(0.439)	(0.428)
Top 30 PhD institution			2.239***			2.124***
			(0.498)			(0.429)
First-time JMC			1.853***			1.034**
			(0.497)			(0.451)
Predoc			0.579			0.029
			(0.622)			(0.492)
Postdoc			-0.955**			-0.290
			(0.471)			(0.429)
Publication or R&R (1+)			0.973**			1.098***
			(0.490)			(0.414)
# applications (51-100)			2.139***			1.557***
			(0.648)			(0.600)
# applications (101-150)			3.223***			2.330***
			(0.682)			(0.625)
# applications (151-200)			3.015***			1.921***
			(0.738)			(0.652)
# applications (201+)			2.815***			1.570***
			(0.663)			(0.544)
AEA signals (2)			0.519			0.470
			(0.511)			(0.459)
Constant	5.334***	11.262***	1.466	3.322***	8.024***	1.475
	(0.330)	(2.137)	(2.429)	(0.275)	(1.865)	(2.026)
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect of being quote-tweeted by established economists on Twitter on the number of flyouts received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Number of Offers (ITT)

Dependent variable:	**Number of Offers**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	0.291	0.497**	0.408*	0.156	0.264	0.186
	(0.234)	(0.242)	(0.234)	(0.196)	(0.203)	(0.205)
URG	0.162	0.121	0.067	0.299	0.216	0.245
	(0.236)	(0.241)	(0.235)	(0.200)	(0.203)	(0.201)
Age		-0.156***	-0.100***		-0.088***	-0.066***
		(0.025)	(0.028)		(0.022)	(0.022)
Parental income class		0.209	0.128		-0.072	-0.094
		(0.159)	(0.148)		(0.147)	(0.137)
US citizen		-0.329	-0.444*		-0.746***	-0.866***
		(0.261)	(0.257)		(0.188)	(0.194)
Twitter account		0.209	0.241		-0.031	0.029
		(0.263)	(0.261)		(0.218)	(0.225)
Top 30 PhD institution			0.812***			0.811***
			(0.231)			(0.206)
First-time JMC			0.766***			0.258
			(0.277)			(0.247)
Predoc			0.253			-0.118
			(0.341)			(0.254)
Postdoc			-0.492*			-0.117
			(0.268)			(0.237)
Publication or R&R (1+)			0.604**			0.617***
			(0.246)			(0.214)
# applications (51-100)			1.158***			0.694**
			(0.317)			(0.293)
# applications (101-150)			1.233***			0.813***
			(0.337)			(0.307)
# applications (151-200)			1.187***			0.678*
			(0.395)			(0.355)
# applications (201+)			1.184***			0.632**
			(0.326)			(0.284)
AEA signals (2)			0.473*			0.353
			(0.253)			(0.224)
Constant	2.930***	7.215***	2.943**	1.468***	4.540***	2.104**
	(0.175)	(1.012)	(1.175)	(0.142)	(0.905)	(0.962)
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect of being quote-tweeted by established economists on Twitter on the number of offers received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Lee Bounds on Treatment Effects for Interviews, Flyouts, and Job Offers (ITT)

Dependent variable:	**Number of Interviews, Flyouts, Job Offers**					
	Interviews		Flyouts		Job Offers	
	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	1.657	-1.021	1.289**	-0.061	0.569**	0.030
	(1.155)	(0.951)	(0.514)	(0.394)	(0.239)	(0.209)
URG	0.964	0.517	0.220	0.477	-0.023	-0.125
	(1.169)	(0.977)	(0.553)	(0.418)	(0.237)	(0.219)
Age	-0.301*	-0.157	-0.150**	-0.091*	-0.107***	-0.076***
	(0.158)	(0.115)	(0.073)	(0.054)	(0.032)	(0.025)
Parental income class	-0.746	-1.125**	0.401	0.170	0.090	0.110
	(0.728)	(0.518)	(0.326)	(0.242)	(0.152)	(0.117)
US citizen	1.560	1.239	0.309	0.352	-0.463*	-0.321
	(1.326)	(1.112)	(0.628)	(0.505)	(0.258)	(0.235)
Twitter account	2.452**	2.291**	0.486	0.775*	0.211	0.265
	(1.152)	(1.036)	(0.563)	(0.449)	(0.270)	(0.235)
Top 30 PhD institution	5.902***	5.461***	2.064***	2.292***	0.705***	0.726***
	(1.144)	(0.987)	(0.499)	(0.425)	(0.234)	(0.208)
First-time JMC	2.502**	2.696**	2.093***	1.785***	0.727**	0.806***
	(1.221)	(1.108)	(0.519)	(0.463)	(0.289)	(0.271)
Predoc	0.104	-0.203	0.599	0.570	0.263	0.016
	(1.332)	(1.114)	(0.636)	(0.544)	(0.349)	(0.293)
Postdoc	-4.727***	-3.803***	-0.758	-0.745*	-0.499*	-0.310
	(1.106)	(1.007)	(0.475)	(0.447)	(0.281)	(0.256)
Publication or R&R (1+)	3.530***	3.717***	1.024**	1.270***	0.668***	0.353
	(1.134)	(0.947)	(0.497)	(0.410)	(0.246)	(0.218)
# applications (51-100)	5.038***	6.497***	2.038***	2.259***	0.997***	1.172***
	(1.500)	(1.394)	(0.650)	(0.591)	(0.322)	(0.307)
# applications (101-150)	6.465***	8.029***	3.075***	3.183***	1.103***	1.158***
	(1.467)	(1.339)	(0.698)	(0.625)	(0.349)	(0.320)
# applications (151-200)	9.407***	9.807***	2.887***	2.782***	1.102***	0.915***
	(1.777)	(1.643)	(0.739)	(0.632)	(0.398)	(0.336)
# applications (201+)	12.893***	11.427***	2.684***	2.406***	1.042***	1.037***
	(1.708)	(1.468)	(0.683)	(0.557)	(0.341)	(0.301)
AEA signals (2)	2.891**	2.257**	0.734	0.294	0.463*	0.320
	(1.204)	(1.086)	(0.542)	(0.459)	(0.262)	(0.241)
Constant	9.322	5.976	2.375	1.120	3.467***	2.632**
	(5.962)	(4.691)	(2.779)	(2.217)	(1.284)	(1.042)
Observations	380	380	380	380	380	380

OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: Number of Interviews (ITT) — Heterogenous Effects by URG

Dependent variable:	**Number of Interviews**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	1.325	1.896	1.175	1.087	1.263	0.761
	(1.664)	(1.719)	(1.515)	(1.524)	(1.578)	(1.439)
URG	1.110	0.982	0.720	-0.020	-0.406	-0.255
	(1.672)	(1.690)	(1.584)	(1.403)	(1.443)	(1.408)
Treatment group × URG	-0.018	0.232	0.104	0.642	1.060	0.720
	(2.530)	(2.502)	(2.231)	(2.154)	(2.167)	(1.972)
Age		-0.669***	-0.268**		-0.429***	-0.167
		(0.139)	(0.130)		(0.128)	(0.124)
Parental income class		0.199	-0.530		-0.387	-0.844
		(0.756)	(0.702)		(0.638)	(0.600)
US citizen		2.063	1.541		-0.561	-1.003
		(1.481)	(1.310)		(1.213)	(1.138)
Twitter account		2.936**	2.864**		1.741	1.899*
		(1.241)	(1.117)		(1.068)	(0.972)
Top 30 PhD institution			5.817***			6.014***
			(1.132)			(1.025)
First-time JMC			2.514**			2.052*
			(1.172)			(1.167)
Predoc			0.432			-0.129
			(1.327)			(1.156)
Postdoc			-4.240***			-2.223**
			(1.046)			(1.022)
Publication or R&R (1+)			3.419***			3.845***
			(1.125)			(1.000)
# applications (51-100)			5.902***			4.496***
			(1.495)			(1.420)
# applications (101-150)			7.321***			6.054***
			(1.418)			(1.332)
# applications (151-200)			9.926***			7.077***
			(1.802)			(1.622)
# applications (201+)			13.862***			10.291***
			(1.690)			(1.441)
AEA signals (2)			2.729**			1.302
			(1.149)			(1.062)
Constant	16.382***	33.996***	6.979	11.020***	23.951***	3.277
	(0.847)	(4.977)	(5.331)	(0.787)	(4.563)	(4.962)
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the heterogeneous intent-to-treat (ITT) effect, by the URG group, of being quote-tweeted by established economists on Twitter on the number of interviews received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15: Number of Flyouts (ITT) — Heterogenoues Effects by URG

Dependent variable:	**Number of Flyouts**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	1.130	1.521**	1.213*	0.923	1.047	0.815
	(0.713)	(0.741)	(0.720)	(0.649)	(0.676)	(0.671)
URG	0.848	0.649	0.542	0.711	0.370	0.419
	(0.697)	(0.668)	(0.663)	(0.612)	(0.594)	(0.607)
Treatment group × URG	-0.784	-0.544	-0.352	-0.656	-0.375	-0.286
	(1.059)	(1.016)	(0.951)	(0.920)	(0.903)	(0.871)
Age		-0.264***	-0.125**		-0.169***	-0.095*
		(0.058)	(0.059)		(0.051)	(0.051)
Parental income class		0.730**	0.482		0.179	0.061
		(0.316)	(0.325)		(0.266)	(0.275)
US citizen		0.548	0.435		-0.872*	-1.046**
		(0.645)	(0.621)		(0.452)	(0.452)
Twitter account		0.591	0.616		0.434	0.550
		(0.562)	(0.540)		(0.440)	(0.428)
Top 30 PhD institution			2.242***			2.127***
			(0.498)			(0.429)
First-time JMC			1.847***			1.029**
			(0.503)			(0.456)
Predoc			0.568			0.020
			(0.625)			(0.494)
Postdoc			-0.947**			-0.284
			(0.474)			(0.432)
Publication or R&R (1+)			0.976**			1.100***
			(0.489)			(0.412)
# applications (51-100)			2.128***			1.548**
			(0.656)			(0.607)
# applications (101-150)			3.216***			2.324***
			(0.682)			(0.624)
# applications (151-200)			2.999***			1.908***
			(0.737)			(0.656)
# applications (201+)			2.819***			1.574***
			(0.665)			(0.547)
AEA signals (2)			0.515			0.466
			(0.511)			(0.457)
Constant	5.217***	11.158***	1.431	3.224***	7.953***	1.446
	(0.346)	(2.133)	(2.427)	(0.284)	(1.862)	(2.022)
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the heterogeneous intent-to-treat (ITT) effect, by the URG group, of being quote-tweeted by established economists on Twitter on the number of flyouts received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Number of Offers (ITT) — Heterogenous Effects by URG

Dependent variable:	**Number of Offers**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	0.180	0.307	0.161	0.020	0.065	-0.035
	(0.312)	(0.325)	(0.316)	(0.257)	(0.263)	(0.265)
URG	0.033	-0.098	-0.220	0.143	-0.014	-0.012
	(0.326)	(0.332)	(0.335)	(0.268)	(0.272)	(0.283)
Treatment group × URG	0.247	0.416	0.540	0.301	0.437	0.482
	(0.472)	(0.471)	(0.462)	(0.397)	(0.398)	(0.403)
Age		-0.156***	-0.099***		-0.088***	-0.065***
		(0.026)	(0.027)		(0.022)	(0.022)
Parental income class		0.206	0.124		-0.075	-0.097
		(0.159)	(0.148)		(0.147)	(0.137)
US citizen		-0.339	-0.459*		-0.757***	-0.880***
		(0.261)	(0.257)		(0.188)	(0.194)
Twitter account		0.213	0.248		-0.027	0.035
		(0.264)	(0.261)		(0.219)	(0.226)
Top 30 PhD institution			0.806***			0.805***
			(0.231)			(0.206)
First-time JMC			0.776***			0.266
			(0.277)			(0.248)
Predoc			0.271			-0.103
			(0.345)			(0.256)
Postdoc			-0.504*			-0.127
			(0.269)			(0.238)
Publication or R&R (1+)			0.599**			0.613***
			(0.246)			(0.214)
# applications (51-100)			1.175***			0.709**
			(0.314)			(0.290)
# applications (101-150)			1.243***			0.823***
			(0.337)			(0.308)
# applications (151-200)			1.212***			0.700*
			(0.396)			(0.357)
# applications (201+)			1.178***			0.626**
			(0.325)			(0.283)
AEA signals (2)			0.480*			0.360
			(0.254)			(0.227)
Constant	2.967***	7.294***	2.997**	1.513***	4.623***	2.153**
	(0.191)	(1.021)	(1.170)	(0.154)	(0.921)	(0.959)
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the heterogeneous intent-to-treat (ITT) effect, by the URG group, of being quote-tweeted by established economists on Twitter on the number of offers received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Number of Interviews (ITT) — Heterogenous Effects by Female

Dependent variable:	**Number of Interviews**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	0.480	0.979	1.262	0.696	0.833	1.082
	(1.515)	(1.570)	(1.378)	(1.315)	(1.371)	(1.233)
URG	-1.129	-0.188	-1.731	-1.461	-1.064	-2.040
	(1.901)	(1.855)	(1.610)	(1.457)	(1.468)	(1.271)
Female	1.794	0.205	3.866*	1.405	0.274	3.274*
	(2.530)	(2.467)	(2.102)	(2.055)	(2.034)	(1.837)
Treatment group × female	2.623	3.092	-0.363	2.134	2.757	-0.182
	(2.702)	(2.657)	(2.233)	(2.313)	(2.323)	(2.044)
Age		-0.666***	-0.248*		-0.425***	-0.150
		(0.140)	(0.131)		(0.129)	(0.124)
Parental income class		0.081	-0.652		-0.489	-0.947
		(0.742)	(0.693)		(0.630)	(0.595)
US citizen		1.989	1.523		-0.607	-1.003
		(1.478)	(1.282)		(1.202)	(1.112)
Twitter account		2.874**	2.636**		1.672	1.695*
		(1.241)	(1.113)		(1.059)	(0.968)
Top 30 PhD institution			5.913***			6.101***
			(1.136)			(1.026)
First-time JMC			2.527**			2.054*
			(1.191)			(1.176)
Predoc			0.202			-0.349
			(1.326)			(1.151)
Postdoc			-4.378***			-2.331**
			(1.096)			(1.062)
Publication or R&R (1+)			3.433***			3.858***
			(1.112)			(0.986)
# applications (51-100)			5.940***			4.507***
			(1.494)			(1.424)
# applications (101-150)			7.703***			6.375***
			(1.419)			(1.332)
# applications (151-200)			10.265***			7.340***
			(1.789)			(1.610)
# applications (201+)			14.183***			10.569***
			(1.679)			(1.456)
AEA signals (2)			2.572**			1.155
			(1.131)			(1.054)
Constant	16.661***	34.522***	6.615	11.149***	24.261***	2.921
	(0.832)	(4.971)	(5.338)	(0.758)	(4.560)	(4.975)
Treatment × female + Treatment = 0 (p-values from *t*-tests)	0.166	0.064	0.620	0.138	0.061	0.594
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: Number of Flyouts (ITT) — Heterogenous Effects by Female

Dependent variable:	**Number of Flyouts**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	0.891	1.275**	1.231**	0.773	0.903	0.861
	(0.609)	(0.634)	(0.599)	(0.552)	(0.578)	(0.563)
URG	-1.294*	-0.864	-1.279**	-0.691	-0.580	-0.757
	(0.671)	(0.669)	(0.587)	(0.583)	(0.584)	(0.549)
Female	2.649**	1.801*	2.776***	1.743*	1.147	1.847**
	(1.026)	(0.959)	(0.845)	(0.910)	(0.863)	(0.801)
Treatment group × female	-0.367	-0.087	-0.719	-0.462	-0.132	-0.652
	(1.172)	(1.099)	(0.991)	(1.001)	(0.972)	(0.899)
Age		-0.259***	-0.112*		-0.166***	-0.087*
		(0.058)	(0.059)		(0.051)	(0.051)
Parental income class		0.669**	0.405		0.143	0.015
		(0.310)	(0.317)		(0.266)	(0.274)
US citizen		0.513	0.419		-0.893**	-1.055**
		(0.634)	(0.602)		(0.446)	(0.444)
Twitter account		0.503	0.467		0.379	0.454
		(0.564)	(0.538)		(0.443)	(0.430)
Top 30 PhD institution			2.311***			2.174***
			(0.496)			(0.429)
First-time JMC			1.855***			1.032**
			(0.507)			(0.456)
Predoc			0.430			-0.065
			(0.625)			(0.491)
Postdoc			-1.033**			-0.335
			(0.482)			(0.437)
Publication or R&R (1+)			0.997**			1.120***
			(0.480)			(0.406)
# applications (51-100)			2.174***			1.582***
			(0.652)			(0.606)
# applications (101-150)			3.469***			2.482***
			(0.678)			(0.622)
# applications (151-200)			3.243***			2.065***
			(0.744)			(0.657)
# applications (201+)			3.051***			1.730***
			(0.667)			(0.557)
AEA signals (2)			0.426			0.415
			(0.498)			(0.453)
Constant	5.296***	11.310***	1.154	3.273***	8.041***	1.245
	(0.333)	(2.124)	(2.429)	(0.275)	(1.864)	(2.018)
Treatment × female + Treatment = 0 (p-values from *t*-tests)	0.601	0.197	0.531	0.709	0.330	0.774
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.19: Number of Offers (ITT) — Heterogenous Effects by Female

Dependent variable:	**Number of Offers**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	0.033	0.156	0.138	-0.024	0.013	-0.003
	(0.279)	(0.287)	(0.273)	(0.219)	(0.225)	(0.224)
URG	-0.591*	-0.487	-0.673**	-0.262	-0.302	-0.362
	(0.335)	(0.326)	(0.304)	(0.226)	(0.229)	(0.224)
Female	0.646	0.328	0.671	0.501	0.345	0.605*
	(0.464)	(0.464)	(0.434)	(0.365)	(0.364)	(0.356)
Treatment group × female	0.809	1.018**	0.777	0.564	0.745	0.535
	(0.506)	(0.504)	(0.477)	(0.452)	(0.454)	(0.447)
Age		-0.154***	-0.094***		-0.086***	-0.061***
		(0.025)	(0.027)		(0.021)	(0.021)
Parental income class		0.161	0.079		-0.110	-0.132
		(0.152)	(0.141)		(0.144)	(0.135)
US citizen		-0.359	-0.464*		-0.769***	-0.881***
		(0.254)	(0.248)		(0.184)	(0.190)
Twitter account		0.175	0.187		-0.061	-0.017
		(0.264)	(0.259)		(0.218)	(0.223)
Top 30 PhD institution			0.820***			0.819***
			(0.230)			(0.206)
First-time JMC			0.784***			0.271
			(0.283)			(0.251)
Predoc			0.188			-0.172
			(0.346)			(0.251)
Postdoc			-0.556**			-0.166
			(0.273)			(0.241)
Publication or R&R (1+)			0.577**			0.598***
			(0.240)			(0.209)
# applications (51-100)			1.156***			0.694**
			(0.314)			(0.291)
# applications (101-150)			1.356***			0.913***
			(0.335)			(0.307)
# applications (151-200)			1.282***			0.757**
			(0.391)			(0.352)
# applications (201+)			1.227***			0.673**
			(0.329)			(0.289)
AEA signals (2)			0.411*			0.304
			(0.248)			(0.223)
Constant	3.016***	7.412***	2.988**	1.528***	4.688***	2.124**
	(0.184)	(0.997)	(1.165)	(0.146)	(0.904)	(0.952)
Treatment × female + Treatment = 0 (p-values from *t*-tests)	0.047	0.006	0.024	0.172	0.058	0.179
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the heterogeneous intent-to-treat (ITT) effect, by gender, of being quote-tweeted by established economists on Twitter on the number of offers received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.20: Number of Interviews (LATE)

Dependent variable:	**Number of Interviews**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	1.481	2.241	1.376	1.548	1.955	1.228
	(1.403)	(1.437)	(1.248)	(1.210)	(1.252)	(1.128)
URG	1.130	1.172	0.812	0.346	0.210	0.161
	(1.258)	(1.267)	(1.106)	(1.071)	(1.099)	(1.006)
Age		-0.670***	-0.269**		-0.428***	-0.169
		(0.138)	(0.128)		(0.127)	(0.121)
Parental income class		0.194	-0.539		-0.385	-0.848
		(0.751)	(0.684)		(0.633)	(0.584)
US citizen		2.084	1.553		-0.522	-0.974
		(1.478)	(1.289)		(1.206)	(1.118)
Twitter account		2.865**	2.813**		1.671	1.845*
		(1.238)	(1.094)		(1.058)	(0.949)
Top 30 PhD institution			5.805***			6.010***
			(1.111)			(1.004)
First-time JMC			2.556**			2.078*
			(1.139)			(1.134)
Predoc			0.485			-0.103
			(1.292)			(1.126)
Postdoc			-4.246***			-2.214**
			(1.019)			(1.001)
Publication or R&R (1+)			3.433***			3.863***
			(1.097)			(0.977)
# applications (51-100)			5.798***			4.384***
			(1.474)			(1.406)
# applications (101-150)			7.228***			5.959***
			(1.408)			(1.318)
# applications (151-200)			9.796***			6.933***
			(1.760)			(1.588)
# applications (201+)			13.767***			10.215***
			(1.657)			(1.415)
AEA signals (2)			2.758**			1.319
			(1.126)			(1.041)
Constant	16.376***	34.015***	7.081	10.915***	23.805***	3.305
	(0.803)	(4.916)	(5.233)	(0.732)	(4.490)	(4.878)
First stage instrument:						
Treatment assignment	0.889	0.893	0.888	0.889	0.893	0.888
Standard error	0.023	0.022	0.024	0.023	0.022	0.024
F-statistics	1505.779	1584.249	1414.141	1505.779	1584.249	1414.141
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the local average treatment effect (LATE) of being quote-tweeted by established economists on Twitter on the number of interviews received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. 2SLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.21: Number of Flyouts (LATE)

Dependent variable:	**Number of Flyouts**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.872	1.424**	1.184**	0.705	0.981*	0.770
	(0.590)	(0.590)	(0.554)	(0.516)	(0.521)	(0.506)
URG	0.457	0.407	0.386	0.383	0.203	0.287
	(0.526)	(0.535)	(0.522)	(0.455)	(0.457)	(0.457)
Age		-0.264***	-0.126**		-0.170***	-0.096*
		(0.057)	(0.058)		(0.051)	(0.050)
Parental income class		0.722**	0.470		0.173	0.053
		(0.313)	(0.317)		(0.262)	(0.267)
US citizen		0.544	0.433		-0.875*	-1.049**
		(0.651)	(0.619)		(0.452)	(0.447)
Twitter account		0.552	0.578		0.407	0.526
		(0.565)	(0.535)		(0.436)	(0.418)
Top 30 PhD institution			2.226***			2.116***
			(0.488)			(0.420)
First-time JMC			1.890***			1.058**
			(0.483)			(0.438)
Predoc			0.628			0.061
			(0.611)			(0.482)
Postdoc			-0.962**			-0.295
			(0.459)			(0.417)
Publication or R&R (1+)			0.983**			1.105***
			(0.479)			(0.403)
# applications (51-100)			2.052***			1.501**
			(0.639)			(0.593)
# applications (101-150)			3.145***			2.279***
			(0.673)			(0.616)
# applications (151-200)			2.908***			1.851***
			(0.725)			(0.640)
# applications (201+)			2.732***			1.516***
			(0.652)			(0.534)
AEA signals (2)			0.545			0.486
			(0.503)			(0.451)
Constant	5.329***	11.302***	1.563	3.318***	8.052***	1.538
	(0.330)	(2.116)	(2.385)	(0.275)	(1.847)	(1.989)
First stage instrument:						
Treatment assignment	0.889	0.893	0.888	0.889	0.893	0.888
Standard error	0.023	0.022	0.024	0.023	0.022	0.024
F-statistics	1505.779	1584.249	1414.141	1505.779	1584.249	1414.141
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the local average treatment effect (LATE) of being quote-tweeted by established economists on Twitter on the number of flyouts received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. 2SLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.22: Number of Offers (LATE)

Dependent variable:	**Number of Offers**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.327	0.556**	0.460*	0.176	0.296	0.209
	(0.262)	(0.269)	(0.258)	(0.220)	(0.225)	(0.226)
URG	0.168	0.138	0.080	0.303	0.225	0.250
	(0.235)	(0.239)	(0.229)	(0.198)	(0.201)	(0.196)
Age		-0.156***	-0.100***		-0.088***	-0.066***
		(0.025)	(0.027)		(0.021)	(0.021)
Parental income class		0.207	0.124		-0.073	-0.095
		(0.158)	(0.145)		(0.146)	(0.134)
US citizen		-0.325	-0.441*		-0.744***	-0.865***
		(0.262)	(0.254)		(0.188)	(0.191)
Twitter account		0.192	0.225		-0.040	0.021
		(0.263)	(0.256)		(0.216)	(0.220)
Top 30 PhD institution			0.808***			0.808***
			(0.227)			(0.202)
First-time JMC			0.781***			0.265
			(0.269)			(0.240)
Predoc			0.272			-0.110
			(0.335)			(0.251)
Postdoc			-0.495*			-0.118
			(0.261)			(0.231)
Publication or R&R (1+)			0.608**			0.619***
			(0.240)			(0.209)
# applications (51-100)			1.124***			0.678**
			(0.311)			(0.287)
# applications (101-150)			1.202***			0.799***
			(0.333)			(0.301)
# applications (151-200)			1.146***			0.659*
			(0.386)			(0.344)
# applications (201+)			1.152***			0.617**
			(0.323)			(0.279)
AEA signals (2)			0.483*			0.358
			(0.248)			(0.219)
Constant	2.928***	7.231***	2.980***	1.467***	4.548***	2.121**
	(0.175)	(1.001)	(1.153)	(0.142)	(0.895)	(0.941)
First stage instrument:						
Treatment assignment	0.889	0.893	0.888	0.889	0.893	0.888
Standard error	0.023	0.022	0.024	0.023	0.022	0.024
F-statistics	1505.779	1584.249	1414.141	1505.779	1584.249	1414.141
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the local average treatment effect (LATE) of being quote-tweeted by established economists on Twitter on the number of offers received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. 2SLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.23: Annual Pre-tax Salary (ITT and LATE)

Dependent variable:	**Salary (in USD 1,000)**					
	ITT			LATE		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment				8.041	9.802	5.233
				(8.460)	(8.414)	(7.769)
Treatment group	7.282	8.872	4.680			
	(7.706)	(7.716)	(7.180)			
URG	-6.334	-2.596	-1.629	-6.065	-2.236	-1.463
	(7.873)	(7.755)	(8.182)	(7.754)	(7.575)	(7.845)
Age		-0.060	0.216		-0.038	0.220
		(1.077)	(0.957)		(1.056)	(0.925)
Parental income class		4.206	0.880		4.157	0.846
		(5.313)	(4.598)		(5.236)	(4.450)
US citizen		24.721***	19.825***		24.788***	19.881***
		(7.751)	(7.278)		(7.643)	(7.061)
Twitter account		-0.465	7.302		-0.744	7.165
		(7.941)	(8.399)		(7.822)	(8.109)
Top 30 PhD institution			47.925***			47.996***
			(9.250)			(8.961)
First-time JMC			-8.491			-8.658
			(10.662)			(10.333)
Predoc			4.439			4.391
			(8.563)			(8.277)
Postdoc			-21.968**			-22.095**
			(9.430)			(9.135)
Publication or R&R (1+)			10.511			10.523
			(8.005)			(7.744)
# applications (51-100)			36.941**			36.359**
			(15.846)			(15.331)
# applications (101-150)			16.047*			15.569*
			(9.203)			(9.055)
# applications (151-200)			20.840**			20.399**
			(10.371)			(10.080)
# applications (201+)			21.140**			20.747**
			(9.461)			(9.208)
AEA signals (2)			3.814			3.764
			(10.401)			(10.080)
Constant	107.320***	91.198**	45.769	107.248***	90.729**	46.320
	(4.767)	(39.918)	(40.193)	(4.774)	(39.258)	(39.068)
First stage instrument:						
Treatment				0.906	0.905	0.894
Standard error				0.026	0.025	0.028
F-statistics				1249.737	1266.604	1011.473
Observations	281	276	276	281	276	276
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect and the local average treatment effect (LATE) of being quote-tweeted by established economists on Twitter on the pre-tax annual salary self-reported by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS and 2SLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.24: Number of Views and Likes (ITT) — Median Split by Influencers' Twitter Followers

Dependent variable:	**Number of Views and Likes**					
	Views			Likes		
	(1)	(2)	(3)	(4)	(5)	(6)
Above-median follower influencer	4782.751***	4816.752***	4831.574***	13.125***	12.632***	12.692***
	(708.507)	(718.606)	(702.408)	(1.858)	(1.759)	(1.729)
Below-median follower influencer	1712.509***	1729.808***	1738.810***	9.525***	9.162***	9.084***
	(384.664)	(394.218)	(397.883)	(2.268)	(2.270)	(2.302)
URG	607.305	517.771	612.296	0.303	0.164	0.192
	(454.568)	(439.549)	(451.127)	(1.597)	(1.624)	(1.684)
Age		-11.800	-53.174		-0.180	-0.190
		(53.344)	(57.463)		(0.176)	(0.163)
Parental income class		202.281	202.631		-0.327	-0.565
		(235.869)	(241.836)		(0.981)	(0.990)
US citizen		-432.925	-571.222		-1.913	-2.125
		(409.602)	(410.666)		(1.419)	(1.387)
Twitter account		506.809	663.323*		1.533	1.877
		(334.391)	(356.453)		(1.505)	(1.502)
Top 30 PhD institution			364.825			1.705
			(469.524)			(1.576)
First-time JMC			-1901.851*			-2.292
			(1047.848)			(2.225)
Predoc			-9.562			1.242
			(511.718)			(1.863)
Postdoc			-642.025			-2.427
			(696.293)			(1.900)
Constant	729.626***	421.452	3171.883	3.763***	9.628	11.561*
	(204.303)	(1911.320)	(2016.190)	(0.853)	(6.594)	(6.143)
Above-median = Below-median (*p*-values from *t*-tests)	<0.001	<0.001	<0.001	0.172	0.184	0.166
Observations	417	403	403	417	403	403
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect, by influencers' Twitter followers (median split), of being quote-tweeted by established economists on Twitter on the number of views and likes. 'Views' represents the number of views received by job market paper tweets (which naturally include views of quote-tweets), and 'Likes' is the sum of likes received by the job market paper tweets and the influencer quote-tweets. For a description of the variables, see the table notes in Appendix Table A.6. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.25: Number of Interviews (ITT) — Median Split by Influencers' Twitter Followers

Dependent variable:	**Number of Interviews**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Above-median follower influencer	-0.529	0.048	-0.277	-0.318	-0.063	-0.491
	(1.330)	(1.347)	(1.114)	(1.149)	(1.153)	(1.000)
Below-median follower influencer	3.663**	4.481**	3.090*	3.532**	4.043**	3.061**
	(1.848)	(1.870)	(1.658)	(1.543)	(1.611)	(1.464)
URG	0.970	0.949	0.669	0.195	0.007	0.017
	(1.266)	(1.272)	(1.136)	(1.080)	(1.110)	(1.037)
Age		-0.654***	-0.261**		-0.414***	-0.160
		(0.135)	(0.130)		(0.124)	(0.124)
Parental income class		0.233	-0.492		-0.349	-0.799
		(0.741)	(0.691)		(0.625)	(0.588)
US citizen		2.122	1.646		-0.486	-0.875
		(1.453)	(1.291)		(1.181)	(1.113)
Twitter account		3.316***	3.194***		2.085*	2.238**
		(1.272)	(1.144)		(1.091)	(0.989)
Top 30 PhD institution			5.790***			5.992***
			(1.128)			(1.017)
First-time JMC			2.476**			2.002*
			(1.210)			(1.196)
Predoc			0.266			-0.325
			(1.322)			(1.144)
Postdoc			-4.415***			-2.394**
			(1.092)			(1.062)
Publication or R&R (1+)			3.546***			3.984***
			(1.100)			(0.982)
# applications (51-100)			5.680***			4.243***
			(1.497)			(1.423)
# applications (101-150)			7.246***			5.964***
			(1.417)			(1.325)
# applications (151-200)			9.790***			6.906***
			(1.793)			(1.630)
# applications (201+)			13.768***			10.200***
			(1.681)			(1.441)
AEA signals (2)			2.366**			0.911
			(1.141)			(1.069)
Constant	16.422***	33.177***	6.836	10.958***	23.032***	3.064
	(0.802)	(4.842)	(5.316)	(0.733)	(4.415)	(4.945)
Above-median = Below-median (*p*-values from *t*-tests)	0.032	0.022	0.038	0.017	0.012	0.012
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect, by influencers' Twitter followers (median split), of being quote-tweeted by established economists on Twitter on the number of interviews received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.26: Number of Flyouts (ITT) — Median Split by Influencers' Twitter Followers

Dependent variable:	**Number of Flyouts**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Above-median follower influencer	0.137	0.619	0.552	-0.031	0.204	0.082
	(0.561)	(0.559)	(0.507)	(0.471)	(0.474)	(0.449)
Below-median follower influencer	1.587**	2.102***	1.674**	1.462**	1.730***	1.434**
	(0.765)	(0.758)	(0.724)	(0.655)	(0.663)	(0.642)
URG	0.395	0.311	0.319	0.322	0.120	0.224
	(0.532)	(0.538)	(0.534)	(0.462)	(0.467)	(0.475)
Age		-0.259***	-0.122**		-0.164***	-0.092*
		(0.058)	(0.060)		(0.051)	(0.051)
Parental income class		0.737**	0.492		0.187	0.074
		(0.310)	(0.320)		(0.258)	(0.267)
US citizen		0.552	0.459		-0.863*	-1.013**
		(0.642)	(0.620)		(0.449)	(0.448)
Twitter account		0.724	0.731		0.569	0.686
		(0.563)	(0.541)		(0.445)	(0.433)
Top 30 PhD institution			2.229***			2.112***
			(0.495)			(0.425)
First-time JMC			1.841***			1.020**
			(0.501)			(0.452)
Predoc			0.525			-0.036
			(0.622)			(0.491)
Postdoc			-1.014**			-0.362
			(0.484)			(0.436)
Publication or R&R (1+)			1.014**			1.148***
			(0.483)			(0.406)
# applications (51-100)			2.066***			1.469**
			(0.653)			(0.601)
# applications (101-150)			3.199***			2.301***
			(0.686)			(0.622)
# applications (151-200)			2.972***			1.868***
			(0.746)			(0.656)
# applications (201+)			2.783***			1.532***
			(0.667)			(0.544)
AEA signals (2)			0.399			0.324
			(0.512)			(0.457)
Constant	5.347***	11.002***	1.422	3.335***	7.758***	1.422
	(0.330)	(2.123)	(2.440)	(0.275)	(1.842)	(2.031)
Above median = Below median (*p*-values from *t*-tests)	0.070	0.059	0.115	0.021	0.019	0.024
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect, by influencers' Twitter followers (median split), of being quote-tweeted by established economists on Twitter on the number of flyouts received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.27: Number of Offers (ITT) — Median Split by Influencers' Twitter Followers

Dependent variable:	**Number of Offers**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Above-median follower influencer	0.031	0.231	0.221	-0.126	-0.014	-0.065
	(0.262)	(0.268)	(0.254)	(0.226)	(0.229)	(0.228)
Below-median follower influencer	0.622*	0.834**	0.642**	0.515*	0.617**	0.498*
	(0.329)	(0.333)	(0.323)	(0.276)	(0.285)	(0.284)
URG	0.143	0.100	0.054	0.280	0.194	0.227
	(0.235)	(0.239)	(0.235)	(0.197)	(0.201)	(0.200)
Age		-0.154***	-0.099***		-0.086***	-0.065***
		(0.026)	(0.028)		(0.022)	(0.022)
Parental income class		0.214	0.132		-0.067	-0.087
		(0.157)	(0.147)		(0.145)	(0.136)
US citizen		-0.322	-0.432*		-0.739***	-0.849***
		(0.259)	(0.255)		(0.186)	(0.192)
Twitter account		0.261	0.283		0.023	0.084
		(0.266)	(0.264)		(0.219)	(0.226)
Top 30 PhD institution			0.809***			0.806***
			(0.231)			(0.205)
First-time JMC			0.762***			0.252
			(0.283)			(0.252)
Predoc			0.233			-0.146
			(0.339)			(0.254)
Postdoc			-0.514*			-0.146
			(0.276)			(0.247)
Publication or R&R (1+)			0.620**			0.638***
			(0.247)			(0.215)
# applications (51-100)			1.130***			0.657**
			(0.318)			(0.295)
# applications (101-150)			1.224***			0.801***
			(0.337)			(0.305)
# applications (151-200)			1.171***			0.657*
			(0.390)			(0.350)
# applications (201+)			1.172***			0.616**
			(0.324)			(0.281)
AEA signals (2)			0.428*			0.293
			(0.256)			(0.225)
Constant	2.936***	7.110***	2.926**	1.474***	4.430***	2.082**
	(0.175)	(1.018)	(1.184)	(0.141)	(0.906)	(0.972)
Above median = Below median (*p*-values from *t*-tests)	0.097	0.089	0.208	0.038	0.046	0.065
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect, by influencers' Twitter followers (median split), of being quote-tweeted by established economists on Twitter on the number of offers received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.28: Number of Interviews (ITT) — Median Split by Quote-tweet Specificity

Dependent variable:	**Number of Interviews**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet above median specificity	3.597	4.732*	3.922	2.969	3.427	2.975
	(2.551)	(2.421)	(2.493)	(2.107)	(2.092)	(2.196)
Tweet below median specificity	0.817	1.401	0.666	1.028	1.377	0.703
	(1.306)	(1.339)	(1.120)	(1.117)	(1.153)	(1.002)
URG	1.166	1.206	0.874	0.360	0.214	0.197
	(1.267)	(1.277)	(1.125)	(1.077)	(1.107)	(1.022)
Age		-0.667***	-0.269**		-0.427***	-0.168
		(0.140)	(0.128)		(0.128)	(0.123)
Parental income class		0.273	-0.451		-0.335	-0.784
		(0.757)	(0.700)		(0.643)	(0.609)
US citizen		2.203	1.658		-0.452	-0.903
		(1.468)	(1.301)		(1.203)	(1.130)
Twitter account		2.934**	2.862**		1.731	1.889*
		(1.249)	(1.131)		(1.073)	(0.983)
Top 30 PhD institution			5.851***			6.045***
			(1.125)			(1.019)
First-time JMC			2.455**			2.000*
			(1.179)			(1.174)
Predoc			0.425			-0.156
			(1.328)			(1.153)
Postdoc			-4.375***			-2.303**
			(1.060)			(1.026)
Publication or R&R (1+)			3.418***			3.850***
			(1.116)			(0.996)
# applications (51-100)			5.896***			4.472***
			(1.460)			(1.399)
# applications (101-150)			7.172***			5.938***
			(1.402)			(1.322)
# applications (151-200)			9.701***			6.890***
			(1.765)			(1.620)
# applications (200+)			13.744***			10.217***
			(1.672)			(1.432)
AEA signals (2)			2.682**			1.261
			(1.134)			(1.052)
Constant	16.366***	33.391***	7.418	10.911***	23.907***	3.987
	(0.803)	(5.372)	(5.632)	(0.732)	(4.855)	(5.201)
Above median = Below median (p-values of t-test)	0.287	0.199	0.154	0.385	0.359	0.260
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

OLS estimate with robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.29: Number of Flyouts (ITT) — Median Split by Quote-tweet Specificity

Dependent variable:	**Number of Flyouts**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet above median specificity	2.430**	3.164***	3.166***	2.339**	2.612**	2.661**
	(1.103)	(1.039)	(1.019)	(1.048)	(1.032)	(1.070)
Tweet below median specificity	0.413	0.856	0.616	0.251	0.494	0.277
	(0.539)	(0.540)	(0.504)	(0.453)	(0.457)	(0.436)
URG	0.487	0.434	0.432	0.418	0.238	0.339
	(0.528)	(0.538)	(0.529)	(0.456)	(0.462)	(0.464)
Age		-0.263***	-0.125**		-0.168***	-0.096*
		(0.058)	(0.058)		(0.052)	(0.051)
Parental income class		0.776**	0.540*		0.222	0.116
		(0.314)	(0.322)		(0.263)	(0.273)
US citizen		0.628	0.514		-0.796*	-0.970**
		(0.640)	(0.618)		(0.445)	(0.447)
Twitter account		0.596	0.620		0.437	0.553
		(0.564)	(0.543)		(0.441)	(0.428)
Top 30 PhD institution			2.264***			2.148***
			(0.491)			(0.423)
First-time JMC			1.808***			0.992**
			(0.494)			(0.446)
Predoc			0.576			0.026
			(0.617)			(0.485)
Postdoc			-1.063**			-0.391
			(0.463)			(0.428)
Publication or R&R (1+)			0.971**			1.096***
			(0.481)			(0.405)
# applications (51-100)			2.137***			1.555***
			(0.631)			(0.578)
# applications (101-150)			3.108***			2.222***
			(0.666)			(0.611)
# applications (151-200)			2.843***			1.759***
			(0.746)			(0.658)
# applications (200+)			2.721***			1.482***
			(0.657)			(0.533)
AEA signals (2)			0.484			0.436
			(0.505)			(0.449)
Constant	5.321***	10.286***	0.924	3.308***	7.619***	1.358
	(0.329)	(2.336)	(2.578)	(0.274)	(2.017)	(2.129)
Above median = Below median (p-values of t-test)	0.060	0.028	0.010	0.018	0.015	0.004
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

OLS estimate with robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.30: Number of Offers (ITT) — Median Split by Quote-tweet Specificity

Dependent variable:	**Number of Offers**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet above median specificity	0.518	0.722*	0.721*	0.586	0.604	0.632
	(0.418)	(0.408)	(0.416)	(0.391)	(0.380)	(0.415)
Tweet below median specificity	0.241	0.447*	0.344	0.062	0.189	0.094
	(0.251)	(0.258)	(0.248)	(0.208)	(0.215)	(0.213)
URG	0.168	0.129	0.079	0.312	0.229	0.261
	(0.237)	(0.243)	(0.236)	(0.199)	(0.204)	(0.201)
Age		-0.156***	-0.100***		-0.088***	-0.066***
		(0.026)	(0.027)		(0.022)	(0.022)
Parental income class		0.215	0.137		-0.063	-0.081
		(0.158)	(0.147)		(0.146)	(0.135)
US citizen		-0.318	-0.431*		-0.730***	-0.847***
		(0.263)	(0.259)		(0.190)	(0.196)
Twitter account		0.209	0.241		-0.031	0.029
		(0.264)	(0.262)		(0.219)	(0.227)
Top 30 PhD institution			0.816***			0.816***
			(0.231)			(0.205)
First-time JMC			0.760***			0.249
			(0.278)			(0.247)
Predoc			0.253			-0.119
			(0.342)			(0.256)
Postdoc			-0.508*			-0.139
			(0.269)			(0.239)
Publication or R&R (1+)			0.604**			0.616***
			(0.245)			(0.213)
# applications (51-100)			1.158***			0.693**
			(0.314)			(0.287)
# applications (101-150)			1.216***			0.789***
			(0.336)			(0.304)
# applications (151-200)			1.162***			0.642*
			(0.394)			(0.351)
# applications (200+)			1.170***			0.612**
			(0.325)			(0.281)
AEA signals (2)			0.468*			0.346
			(0.252)			(0.221)
Constant	2.928***	6.976***	2.806**	1.465***	4.567***	2.185**
	(0.175)	(1.116)	(1.266)	(0.142)	(1.003)	(1.048)
Above median = Below median (p-values of t-test)	0.588	0.588	0.445	0.226	0.339	0.211
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

OLS estimate with robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.31: Number of Interviews (ITT) — Median Split by Quote-tweet Endorsement

Dependent variable:	**formula_str**					
	All			TT		
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet above median endorsement	0.755	1.168	1.121	1.503	1.738	1.634
	(1.653)	(1.647)	(1.559)	(1.414)	(1.445)	(1.394)
Tweet below median endorsement	1.532	1.739	0.484	1.521	1.631	0.624
	(1.612)	(1.586)	(1.282)	(1.351)	(1.362)	(1.121)
URG	1.220	1.384	0.988	0.365	0.297	0.208
	(1.282)	(1.295)	(1.137)	(1.064)	(1.100)	(1.017)
Age		-0.653***	-0.257**		-0.414***	-0.159
		(0.138)	(0.128)		(0.127)	(0.122)
Parental income class		0.136	-0.551		-0.401	-0.832
		(0.762)	(0.707)		(0.642)	(0.605)
US citizen		2.071	1.538		-0.521	-0.980
		(1.493)	(1.312)		(1.215)	(1.138)
Twitter account		2.911**	2.816**		1.685	1.829*
		(1.244)	(1.117)		(1.069)	(0.974)
Top 30 PhD institution			5.823***			6.013***
			(1.135)			(1.024)
First-time JMC			2.549**			2.072*
			(1.163)			(1.165)
Predoc			0.426			-0.145
			(1.333)			(1.163)
Postdoc			-4.267***			-2.273**
			(1.042)			(1.024)
Publication or R&R (1+)			3.460***			3.920***
			(1.105)			(0.984)
# applications (51-100)			5.887***			4.390***
			(1.484)			(1.420)
# applications (101-150)			7.274***			5.893***
			(1.424)			(1.338)
# applications (151-200)			9.865***			6.927***
			(1.795)			(1.625)
# applications (200+)			13.913***			10.294***
			(1.690)			(1.440)
AEA signal sent: 2			2.760**			1.338
			(1.154)			(1.067)
Constant	16.477***	33.831***	6.824	10.932***	23.475***	2.995
	(0.796)	(5.018)	(5.319)	(0.725)	(4.561)	(4.953)
Above median = Below median (p-values of t-test)	0.725	0.794	0.740	0.992	0.955	0.550
Observations	417	403	394	417	403	394

OLS estimate with robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.32: Number of Flyouts (ITT) — Median Split by Quote-tweet Endorsement

Dependent variable:	**formula_str**					
	All			TT		
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet above median endorsement	0.807	1.166	0.969	1.038	1.207*	1.009
	(0.739)	(0.713)	(0.704)	(0.652)	(0.649)	(0.664)
Tweet below median endorsement	0.666	0.854	0.662	0.652	0.732	0.569
	(0.627)	(0.618)	(0.569)	(0.505)	(0.501)	(0.460)
URG	0.503	0.532	0.499	0.355	0.222	0.292
	(0.540)	(0.555)	(0.545)	(0.442)	(0.449)	(0.455)
Age		-0.254***	-0.116**		-0.163***	-0.090*
		(0.057)	(0.059)		(0.050)	(0.050)
Parental income class		0.707**	0.459		0.182	0.061
		(0.318)	(0.327)		(0.266)	(0.276)
US citizen		0.539	0.426		-0.871*	-1.048**
		(0.650)	(0.625)		(0.453)	(0.455)
Twitter account		0.562	0.584		0.401	0.519
		(0.568)	(0.547)		(0.441)	(0.430)
Top 30 PhD institution			2.237***			2.115***
			(0.499)			(0.429)
First-time JMC			1.886***			1.055**
			(0.491)			(0.452)
Predoc			0.590			0.044
			(0.625)			(0.494)
Postdoc			-0.982**			-0.332
			(0.473)			(0.433)
Publication or R&R (1+)			0.997**			1.132***
			(0.487)			(0.408)
# applications (51-100)			2.108***			1.491**
			(0.642)			(0.601)
# applications (101-150)			3.182***			2.239***
			(0.679)			(0.629)
# applications (151-200)			2.956***			1.841***
			(0.746)			(0.660)
# applications (200+)			2.823***			1.542***
			(0.673)			(0.546)
AEA signal sent: 2			0.542			0.494
			(0.515)			(0.465)
Constant	5.374***	11.129***	1.336	3.282***	7.828***	1.342
	(0.326)	(2.142)	(2.414)	(0.269)	(1.861)	(2.011)
Above median = Below median (p-values of t-test)	0.876	0.726	0.715	0.603	0.519	0.533
Observations	417	403	394	417	403	394

OLS estimate with robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.33: Number of Offers (ITT) — Median Split by Quote-tweet Endorsement

Dependent variable:	**formula_str**					
	All			TT		
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet above median endorsement	0.275	0.366	0.333	0.326	0.346	0.295
	(0.313)	(0.304)	(0.307)	(0.291)	(0.279)	(0.291)
Tweet below median endorsement	0.289	0.399	0.285	0.158	0.215	0.116
	(0.292)	(0.294)	(0.279)	(0.237)	(0.247)	(0.243)
URG	0.183	0.187	0.125	0.289	0.234	0.255
	(0.237)	(0.242)	(0.235)	(0.194)	(0.200)	(0.197)
Age		-0.152***	-0.096***		-0.086***	-0.065***
		(0.026)	(0.028)		(0.022)	(0.022)
Parental income class		0.197	0.118		-0.071	-0.092
		(0.156)	(0.145)		(0.144)	(0.133)
US citizen		-0.328	-0.443*		-0.743***	-0.866***
		(0.263)	(0.258)		(0.189)	(0.195)
Twitter account		0.200	0.229		-0.041	0.018
		(0.266)	(0.263)		(0.219)	(0.227)
Top 30 PhD institution			0.812***			0.809***
			(0.232)			(0.206)
First-time JMC			0.779***			0.264
			(0.276)			(0.248)
Predoc			0.259			-0.116
			(0.344)			(0.260)
Postdoc			-0.500*			-0.129
			(0.270)			(0.240)
Publication or R&R (1+)			0.610**			0.629***
			(0.244)			(0.211)
# applications (51-100)			1.147***			0.677**
			(0.316)			(0.292)
# applications (101-150)			1.223***			0.785**
			(0.338)			(0.312)
# applications (151-200)			1.167***			0.656*
			(0.395)			(0.354)
# applications (200+)			1.185***			0.629**
			(0.325)			(0.283)
AEA signal sent: 2			0.480*			0.361
			(0.255)			(0.226)
Constant	2.943***	7.173***	2.897**	1.450***	4.485***	2.066**
	(0.171)	(1.023)	(1.179)	(0.138)	(0.906)	(0.962)
Above median = Below median (p-values of t-test)	0.974	0.939	0.909	0.645	0.720	0.620
Observations	417	403	394	417	403	394

OLS estimate with robust standard errors in parenthesis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.34: Number of Interviews (ITT) — Median Split by Influencers' Google Scholar Citations

Dependent variable:	**Number of Interviews**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Above-median citation influencer	1.429	2.694	2.831**	1.690	2.337	2.410*
	(1.673)	(1.731)	(1.423)	(1.426)	(1.492)	(1.299)
Below-median citation influencer	1.226	1.465	-0.117	1.126	1.289	-0.007
	(1.484)	(1.474)	(1.284)	(1.259)	(1.275)	(1.137)
URG	1.106	1.143	0.886	0.329	0.184	0.219
	(1.268)	(1.277)	(1.116)	(1.080)	(1.110)	(1.020)
Age		-0.674***	-0.275**		-0.432***	-0.173
		(0.141)	(0.129)		(0.129)	(0.123)
Parental income class		0.252	-0.416		-0.335	-0.746
		(0.758)	(0.697)		(0.641)	(0.602)
US citizen		2.097	1.603		-0.511	-0.934
		(1.480)	(1.313)		(1.211)	(1.149)
Twitter account		2.932**	2.828**		1.729	1.861*
		(1.240)	(1.116)		(1.068)	(0.976)
Top 30 PhD institution			5.915***			6.101***
			(1.119)			(1.016)
First-time JMC			2.704**			2.197*
			(1.143)			(1.147)
Predoc			0.580			-0.029
			(1.322)			(1.147)
Postdoc			-4.019***			-2.028**
			(0.999)			(0.989)
Publication or R&R (1+)			3.352***			3.796***
			(1.125)			(1.004)
# applications (51-100)			6.156***			4.685***
			(1.503)			(1.434)
# applications (101-150)			7.377***			6.088***
			(1.435)			(1.343)
# applications (151-200)			9.885***			7.015***
			(1.808)			(1.639)
# applications (201+)			14.049***			10.452***
			(1.710)			(1.467)
AEA signals (2)			2.942**			1.468
			(1.156)			(1.070)
Constant	16.383***	33.972***	6.423	10.920***	23.767***	2.757
	(0.803)	(4.977)	(5.319)	(0.733)	(4.546)	(4.938)
Above-median = Below-median (*p*-values from *t*-tests)	0.906	0.511	0.051	0.722	0.509	0.070
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect, by influencers' Google Scholar citations (median split), of being quote-tweeted by established economists on Twitter on the number of interviews received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.35: Number of Flyouts (ITT) — Median Split by Influencers' Google Scholar Citations

Dependent variable:	**Number of Flyouts**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Above-median citation influencer	1.324*	2.140***	2.184***	1.277*	1.683**	1.698***
	(0.734)	(0.742)	(0.665)	(0.670)	(0.684)	(0.650)
Below-median citation influencer	0.335	0.600	0.109	0.105	0.251	-0.159
	(0.577)	(0.559)	(0.526)	(0.451)	(0.449)	(0.429)
URG	0.464	0.413	0.432	0.398	0.219	0.336
	(0.524)	(0.529)	(0.514)	(0.454)	(0.456)	(0.456)
Age		-0.270***	-0.130**		-0.175***	-0.100**
		(0.058)	(0.059)		(0.052)	(0.051)
Parental income class		0.791**	0.559*		0.236	0.130
		(0.315)	(0.321)		(0.265)	(0.272)
US citizen		0.570	0.467		-0.849*	-1.016**
		(0.653)	(0.629)		(0.458)	(0.463)
Twitter account		0.593	0.596		0.434	0.532
		(0.557)	(0.533)		(0.436)	(0.423)
Top 30 PhD institution			2.306***			2.185***
			(0.493)			(0.423)
First-time JMC			1.988***			1.155**
			(0.499)			(0.460)
Predoc			0.686			0.124
			(0.620)			(0.487)
Postdoc			-0.801*			-0.153
			(0.463)			(0.420)
Publication or R&R (1+)			0.925*			1.055**
			(0.486)			(0.412)
# applications (51-100)			2.320***			1.719***
			(0.662)			(0.613)
# applications (101-150)			3.264***			2.367***
			(0.689)			(0.634)
# applications (151-200)			2.990***			1.898***
			(0.745)			(0.671)
# applications (201+)			2.945***			1.687***
			(0.671)			(0.563)
AEA signals (2)			0.670			0.604
			(0.508)			(0.461)
Constant	5.327***	11.287***	1.082	3.313***	8.048***	1.131
	(0.329)	(2.132)	(2.420)	(0.274)	(1.861)	(2.004)
Above-median = Below-median (*p*-values from *t*-tests)	0.208	0.043	0.002	0.073	0.028	0.002
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect, by influencers' Google Scholar citations (median split), of being quote-tweeted by established economists on Twitter on the number of flyouts received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.36: Number of Offers (ITT) — Median Split by Influencers' Google Scholar Citations

Dependent variable:	**Number of Offers**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Above-median citation influencer	0.286	0.571*	0.595**	0.347	0.459*	0.460*
	(0.304)	(0.307)	(0.279)	(0.273)	(0.276)	(0.268)
Below-median citation influencer	0.295	0.439	0.253	0.003	0.113	-0.043
	(0.280)	(0.284)	(0.285)	(0.227)	(0.233)	(0.239)
URG	0.161	0.125	0.080	0.308	0.227	0.264
	(0.236)	(0.241)	(0.234)	(0.198)	(0.202)	(0.198)
Age		-0.156***	-0.101***		-0.089***	-0.067***
		(0.026)	(0.027)		(0.022)	(0.021)
Parental income class		0.215	0.141		-0.057	-0.074
		(0.158)	(0.147)		(0.147)	(0.137)
US citizen		-0.326	-0.437*		-0.738***	-0.856***
		(0.262)	(0.259)		(0.190)	(0.198)
Twitter account		0.208	0.237		-0.032	0.023
		(0.264)	(0.261)		(0.218)	(0.226)
Top 30 PhD institution			0.823***			0.827***
			(0.231)			(0.205)
First-time JMC			0.789***			0.291
			(0.278)			(0.248)
Predoc			0.271			-0.093
			(0.340)			(0.254)
Postdoc			-0.467*			-0.079
			(0.267)			(0.232)
Publication or R&R (1+)			0.596**			0.605***
			(0.246)			(0.215)
# applications (51-100)			1.188***			0.738**
			(0.322)			(0.299)
# applications (101-150)			1.239***			0.823***
			(0.341)			(0.310)
# applications (151-200)			1.183***			0.672*
			(0.399)			(0.362)
# applications (201+)			1.206***			0.663**
			(0.331)			(0.292)
AEA signals (2)			0.498**			0.390*
			(0.253)			(0.223)
Constant	2.930***	7.217***	2.879**	1.466***	4.545***	2.011**
	(0.175)	(1.012)	(1.178)	(0.142)	(0.903)	(0.959)
Above-median = Below-median (*p*-values from *t*-tests)	0.981	0.696	0.281	0.265	0.259	0.096
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the intent-to-treat (ITT) effect, by influencers' Google Scholar citations (median split), of being quote-tweeted by established economists on Twitter on the number of offers received by job market candidates. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.37: Number of Interviews (ITT) — Heterogenous Effects by Top 30 Institution

Dependent variable:	**Number of Interviews**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	-0.938	-0.201	-0.766	-0.271	0.062	-0.353
	(1.620)	(1.675)	(1.522)	(1.293)	(1.356)	(1.290)
Top 30 PhD institution	5.071***	5.104***	3.730***	5.145***	5.286***	4.506***
	(1.425)	(1.447)	(1.419)	(1.276)	(1.286)	(1.296)
Treatment group × Top 30 PhD institution	4.746**	4.237*	4.328**	3.445*	3.145	3.143*
	(2.291)	(2.295)	(2.089)	(1.958)	(1.978)	(1.837)
URG	1.770	1.671	0.804	0.931	0.686	0.149
	(1.248)	(1.266)	(1.143)	(1.056)	(1.094)	(1.039)
Age		-0.605***	-0.255**		-0.370***	-0.159
		(0.135)	(0.128)		(0.122)	(0.122)
Parental income class		-0.259	-0.511		-0.812	-0.825
		(0.734)	(0.698)		(0.612)	(0.598)
US citizen		1.801	1.535		-0.786	-0.989
		(1.456)	(1.302)		(1.192)	(1.132)
Twitter account		3.658***	2.974***		2.402**	1.970**
		(1.216)	(1.122)		(1.059)	(0.985)
First-time JMC			2.486**			2.020*
			(1.179)			(1.173)
Predoc			0.336			-0.220
			(1.289)			(1.127)
Postdoc			-4.355***			-2.292**
			(1.092)			(1.065)
Publication or R&R (1+)			3.304***			3.767***
			(1.113)			(0.995)
# applications (51-100)			5.833***			4.426***
			(1.498)			(1.428)
# applications (101-150)			7.463***			6.145***
			(1.440)			(1.352)
# applications (151-200)			9.752***			6.921***
			(1.826)			(1.639)
# applications (200+)			13.960***			10.370***
			(1.701)			(1.463)
AEA signal sent: 2			2.580**			1.185
			(1.152)			(1.070)
Constant	13.788***	30.022***	7.651	8.308***	19.885***	3.700
	(1.087)	(4.803)	(5.261)	(0.928)	(4.318)	(4.911)
Treatment × Top 30 + Treatment = 0 (p-values from *t*-tests)	0.027	0.019	0.023	0.043	0.043	0.059
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the heterogeneous intent-to-treat (ITT) effects of being quote-tweeted by established economists on Twitter on the number of job interviews received by candidates, comparing those from top 30 PhD institutions versus other institutions. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.38: Number of Flyouts (ITT) — Heterogenous Effects by Top 30 Institution

Dependent variable:	**Number of Flyouts**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	-0.207	0.240	0.100	-0.004	0.151	0.072
	(0.639)	(0.647)	(0.626)	(0.520)	(0.544)	(0.543)
Top 30 PhD institution	2.097***	1.805***	1.238**	1.943***	1.759***	1.481***
	(0.596)	(0.598)	(0.621)	(0.507)	(0.506)	(0.532)
Treatment group × Top 30 PhD institution	2.068**	2.026**	2.072**	1.320*	1.389*	1.333*
	(0.941)	(0.939)	(0.914)	(0.781)	(0.784)	(0.768)
URG	0.721	0.585	0.368	0.602	0.366	0.275
	(0.519)	(0.532)	(0.540)	(0.451)	(0.459)	(0.476)
Age		-0.238***	-0.119**		-0.148***	-0.091*
		(0.056)	(0.059)		(0.050)	(0.051)
Parental income class		0.545*	0.488		0.020	0.065
		(0.308)	(0.320)		(0.255)	(0.272)
US citizen		0.429	0.421		-0.972**	-1.056**
		(0.638)	(0.621)		(0.445)	(0.452)
Twitter account		0.886	0.674		0.682	0.588
		(0.539)	(0.538)		(0.424)	(0.428)
First-time JMC			1.840***			1.026**
			(0.499)			(0.453)
Predoc			0.535			0.001
			(0.612)			(0.485)
Postdoc			-1.011**			-0.326
			(0.481)			(0.438)
Publication or R&R (1+)			0.917*			1.062**
			(0.489)			(0.414)
# applications (51-100)			2.107***			1.537**
			(0.652)			(0.602)
# applications (101-150)			3.292***			2.374***
			(0.691)			(0.632)
# applications (151-200)			2.934***			1.868***
			(0.758)			(0.663)
# applications (200+)			2.861***			1.600***
			(0.667)			(0.551)
AEA signal sent: 2			0.448			0.424
			(0.507)			(0.458)
Constant	4.259***	9.785***	1.793	2.333***	6.682***	1.685
	(0.406)	(2.033)	(2.389)	(0.316)	(1.771)	(1.997)
Treatment × Top 30 + Treatment = 0 (p-values from *t*-tests)	0.014	0.003	0.004	0.049	0.020	0.034
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the heterogeneous intent-to-treat (ITT) effects of being quote-tweeted by established economists on Twitter on the number of flyouts received by candidates, comparing those from top 30 PhD institutions versus other institutions. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.39: Number of Offers (ITT) — Heterogenous Effects by Top 30 Institution

Dependent variable:	**Number of Offers**					
	All Jobs			Tenure-Track Jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	0.185	0.368	0.315	0.153	0.218	0.215
	(0.281)	(0.281)	(0.282)	(0.233)	(0.236)	(0.245)
Top 30 PhD institution	1.024***	0.965***	0.714**	0.914***	0.889***	0.841***
	(0.311)	(0.318)	(0.316)	(0.252)	(0.254)	(0.258)
Treatment group × Top 30 PhD institution	0.210	0.201	0.203	-0.009	0.034	-0.064
	(0.464)	(0.466)	(0.469)	(0.395)	(0.400)	(0.402)
URG	0.262	0.203	0.069	0.380*	0.286	0.244
	(0.233)	(0.238)	(0.236)	(0.198)	(0.201)	(0.201)
Age		-0.147***	-0.099***		-0.081***	-0.066***
		(0.025)	(0.028)		(0.021)	(0.022)
Parental income class		0.143	0.128		-0.127	-0.094
		(0.154)	(0.148)		(0.141)	(0.138)
US citizen		-0.367	-0.445*		-0.778***	-0.866***
		(0.259)	(0.257)		(0.187)	(0.194)
Twitter account		0.307	0.247		0.050	0.027
		(0.264)	(0.264)		(0.220)	(0.228)
First-time JMC			0.765***			0.259
			(0.275)			(0.248)
Predoc			0.249			-0.117
			(0.340)			(0.253)
Postdoc			-0.497*			-0.115
			(0.267)			(0.237)
Publication or R&R (1+)			0.598**			0.619***
			(0.246)			(0.214)
# applications (51-100)			1.155***			0.695**
			(0.316)			(0.292)
# applications (101-150)			1.239***			0.811***
			(0.340)			(0.308)
# applications (151-200)			1.179***			0.681*
			(0.396)			(0.355)
# applications (200+)			1.189***			0.630**
			(0.327)			(0.284)
AEA signal sent: 2			0.466*			0.356
			(0.255)			(0.226)
Constant	2.416***	6.571***	2.975**	1.012***	3.971***	2.094**
	(0.193)	(0.982)	(1.159)	(0.154)	(0.871)	(0.947)
Treatment × Top 30 + Treatment = 0 (p-values from *t*-tests)	0.285	0.136	0.175	0.648	0.438	0.645
Observations	417	403	394	417	403	394
Sample	Post-market	Post-market	Post-market	Post-market	Post-market	Post-market

Notes: This table presents the heterogeneous intent-to-treat (ITT) effects of being quote-tweeted by established economists on Twitter on the number of job offers received by candidates, comparing those from top 30 PhD institutions versus other institutions. For a description of the variables, see the table notes in Appendix Table A.10. OLS estimates with robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.40: Number of Tweets Posted by Job Market Candidates — before and after the Intervention Period

	All Tweets	**Econ-relevant Tweets**
Treatment group	2.405	1.3278
	(2.446)	(1.727)
Post-intervention period	-4.544***	-3.665***
	(0.864)	(0.727)
URG	2.423	0.914
	(2.245)	(1.602)
Treatment group × Post-intervention period	1.400	1.407
	(1.792)	(1.411)
Constant	11.551***	9.367***
	(1.434)	(1.133)
Observations	353	353

Notes: For job market candidates who reported their Twitter handles, this table presents the Difference-in-Differences (DiD) estimates of how being quote-tweeted by established economists affected job market candidates' own tweet volumes. The treatment group consists of candidates who were quote-tweeted by established economists, while the control group consists of those who were not. Pre-treatment tweet counts cover Sep 28, 2022 - Nov 27, 2022 (two months before the intervention), while Post-treatment tweet counts cover Nov 28, 2022 - Jan 28, 2023 (two months during and after the intervention). DiD estimates are presented with robust standard errors clustered by individual job market candidate in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Email Invitation, Consent Form, Pre-market Survey

This appendix includes (1) the email invitation template sent to the influencers; (2) the consent form sent to job market candidates; and (3) the questions and instructions for the pre-market survey. 849 JMCs completed the pre-market survey. Among them, 590 submitted a tweet of their JMP. Among those who submitted a tweet, 519 participants posted their JMP online prior to the intervention, and were included in the intervention.[38] *We therefore report the summary statistics of these 519 participants, as they were later randomized into the treatment and control conditions.*

(1) Email Invitation Template: *Below is the template for the email invitation to the influencers.*

Dear [FirstName],

Hope all is well. Al, Alain, Jingyi and I are working on a field experiment to evaluate the extent to which social media might be able to help job market candidates from under-represented groups (women, URM, LGBTQ+). We are going to recruit students on the econ job market this year, asking them to fill out a baseline survey and submit a summary of their job market paper in 280 characters. We will then tweet every submission from our Twitter account, Econ Job Market Helper.

Afterwards, we will randomize a subset of these JMPs to be retweeted by economist influencers in their field, such as yourself. Would you be willing to help us retweet (quote tweet) a number of these JMPs from your field? We will provide you with templates for the quote tweet. For example: "Retweeting a JMP from @econ_jmp to help publicize job market candidates in my field." The templates should make it clear that it is about exposure rather than endorsement. You can always edit the sentence if you like. Here is an example of a quote tweet.

We are not sure how many JMPs we will be sending your way at this point, but our best guess is somewhere between 10-20. We will get the list ready so that you just need to click on a link to quote tweet a JMP in your field. While we hope that you will retweet every JMP we send to you, you should feel free to choose which one(s) to retweet.

We are mindful that you are extremely busy, and would completely understand if you can't help out. Either way, please let me know. Thanks so much for considering our request!

Best,
Yan
On behalf of Alain Cohn, Jingyi Qiu and Al Roth

(2) Consent to Participate in Survey Research

Principal Investigators: Yan Chen (University of Michigan), Alain Cohn (University of Michigan), Jingyi Qiu (University of Michigan), Alvin Roth (Stanford University)

[38] We require JMPs be posted online for inclusion into our experiment so that influencers can read them before quote-tweeting.

Online Consent

Description This study is designed to understand social media exposure on job market outcomes. We therefore invite everyone who participates in the 2022-2023 economics job market to participate in our study. In this survey, you will be asked questions about your demographics, job market paper and the use of social media. Your responses will help us better understand the impact of social media on the job market outcomes.

Duration The survey should take 10-15 minutes. Your participation is voluntary, and you may exit the survey at any time.

What will happen if you take part in this study If you agree to participate, your responses might be linked to American Economic Association institutional records to draw information on job market outcomes. Once these data have been extracted, any information that can directly identify you will be removed from the data file and stored separately as part of the project.

What will be done with the information collected from the survey The data are being collected by the research team (Yan Chen, Alain Cohn, Jingyi Qiu and Alvin Roth). Your responses will be held confidential. This means that only the research team will be able to access any identifying information about respondents. Additionally, your data will be anonymized and results will only be analyzed and reported at the aggregate level. Data may be stored in a repository for future research and you may be asked to participate in future surveys.

Benefits and risks of participation By participating in this study, you will be invited to a virtual workshop on how to prepare for academic job interviews. We will also promote your job market paper on Twitter. Moreover, the results of this study has the potential to help future cohorts of job market candidates. This study involves no more than minimal risk. You may discontinue participation at any time during the research activity.

Contact information If you have questions about this study, you may contact Jingyi Qiu (jaqiu@umich.edu).

The University of Michigan Institutional Review Board Health Sciences and Behavioral Sciences has determined that this study is no more than minimal risk and exempt from on-going IRB oversight (IRB Study Number: HUM00221663).

Please indicate below that you are at least 18 years old, have read and understand this consent form, and you agree to participate in this research study.

- No
- Yes

(3) Pre-Job-Market Survey and Summary Response Statistics

B.1 Academic background

1. Are you on the 2022-2023 job market?
    - Yes (100%)
    - No (0%)

    →If "No" is selected, skip to the end of the survey
2. Is this the first time you are on the Economics Job Market?
    - Yes (86.3%)
    - No (13.7%)
3. If no: Which year did you go on the Economics Job Market the first time?
4. What is the name of the institution at which you (are expected to) finish your PhD?
5. Have you ever been a full-time research assistant (also known as "pre-doc") before entering your PhD program?
    - Yes (17.7%)
    - No (82.3%)
6. If yes: what is/are the name(s) of your pre-doc advisor(s)?
    - Advisor 1's name:
    - Advisor 2's name:
    - Advisor 3's name:
    - Advisor 4's name:
7. Have you done (are you doing) a postdoc?
    - Yes (14.8%)
    - No (85.2%)

B.2 Field of specialty

1. Please indicate your research fields (You can identify at most three research fields).
    - Behavioral economics (5.83%)
    - Development economics (7.41%)
    - Econometrics (4.16%)
    - Economic history (0.92%)
    - Economics of education (3.96%)
    - Environmental/Agricultural economics (4.66%)
    - Financial economics (5.00%)
    - Health economics (4.00%)
    - Industrial organization (5.41%)
    - Information economics (2.75%)
    - International economics (3.66%)
    - Labor economics (11.91%)
    - Law and economics (1.00%)
    - Macroeconomics (10.16%)
    - Microeconomics (8.66%)
    - Political economy (4.08%)
    - Public economics (7.08%)
    - Urban economics (3.91%)
    - Other, please specify (5.41%)
2. What are the names of your primary advisors?
    - Advisor 1's name:
    - Advisor 2's name:
    - Advisor 3's name:
    - Advisor 4's name:
    - Advisor 5's name:
3. Please upload the latest version of your CV:
4. Do you have a personal webpage?
    - Yes (99.2%)
    - No (0.8%)
5. If yes, what is the URL of your personal webpage?

B.3 Support from advisors

1. How satisfied are you with the support you received from your dissertation advisor(s) during your PhD? (1-7)
   Rating: Not at all satisfied (1) - Very satisfied (7)

   (Count 518, Mean 6.07, Std Dev 1.17, Median 6, Min 1, Max 7)

B.4 The types & locations of jobs you are looking for

1. Please describe what types of jobs you are interested in / applying to:
   Rating: Not at all interested (1) - Very interested (7)

   - Assistant professor (tenure-track) at a college or university
     (Mean 6.63, Std Dev 0.96, Median 7, Min 1, Max 7)
   - Lecturer (non-tenure track) at college or university
     (Mean 3.24, Std Dev 1.92, Median 3, Min 1, Max 7)
   - Postdoctoral fellowship at college or university
     (Mean 4.67, Std Dev 1.88, Median 5, Min 1, Max 7)
   - Government, including central banks
     (Mean 4.76, Std Dev 1.92, Median 5, Min 1, Max 7)
   - Non-profit or quasi-governmental organizations (IMF, World Bank)
     (Mean 4.93, Std Dev 1.90, Median 5, Min 1, Max 7)
   - Contract research organizations / think tanks (e.g., RAND, Mathematica, Research Triangle Institute)
     (Mean 4.58, Std Dev 1.72, Median 5, Min 1, Max 7)
   - Private sector (e.g., banking, finance, tech, consulting, or other business/ industry)
     (Mean 3.99, Std Dev 1.85, Median 4, Min 1, Max 7)

2. In which geographic regions are you applying for jobs? You can select multiple choices.

   - U.S. (29.87%)
   - Other North America (20.10%)
   - Africa (0.32%)
   - Asia (9.70%)
   - Oceania/Australia/New Zealand (11.55%)
   - South America (4.08%)
   - Europe (23.99%)
   - Other, please specify (0.38%)

B.5 Twitter account

1. Do you have a Twitter account?
    - Yes (69.7%)
    - No (30.3%)
2. If yes: What is your Twitter handle?
   Your Twitter handle (e.g., @abc):

B.6 Demographics

1. What is your gender?
    - Woman (29.67%)
    - Man (67.82%)
    - Non-Binary (0.39%)
    - Prefer not to say (2.12%)
2. Do you consider yourself to be transgender?
    - Yes, I am transgender (0.39%)
    - No, I am cisgender (72.64%)
    - I do not consider myself either transgender or cisgender (19.65%)
    - Don't know / Not sure (1.54%)
    - Prefer not to say (5.78%)
3. What is your sexual orientation?
    - Straight (84.59%)
    - Gay (2.50%)
    - Lesbian (0.39%)
    - Bisexual (1.35%)
    - Pansexual (0.19%)
    - Queer (0.58%)
    - Asexual (0.19%)
    - Prefer not to say (10.21%)
4. In what year were you born?
    - I was born in... YYYY (98.84%)

- Prefer not to say (1.16%)

5. What is your country of citizenship? (If you have dual citizenship then please indicate your primary citizenship.)
   - - Select Country - -

6. Are you of Hispanic, Latino, or Spanish origin?

   - Yes (13.10%)
   - No (84.01%)
   - Prefer not to say (2.89%)

7. What is the primary ethnicity or race you identify with?

   - White (49.71%)
   - Black or African American (2.31%)
   - American Indian or Alaska Native (0.38%)
   - Asian (36.42%)
   - Native Hawaiian or Other Pacific Islander (0%)
   - Other, please specify (5.20%)
   - Prefer not to say (5.97%)

8. What was the highest level of education achieved by your mother?

   - Less than high school (10.02%)
   - High school diploma or equivalent (17.73%)
   - Associate's degree (6.55%)
   - Bachelor's degree (28.71%)
   - Master's degree (20.42%)
   - Professional degree (e.g. MBA, J.D., M.D.) (5.01%)
   - Doctoral degree (e.g., Ph.D., Ed.D.) (9.25%)
   - Don't know (0.19%)
   - Prefer not to say (2.12%)

9. How would you describe the financial situation of your family when you grew up?

   - High income / wealthy (3.28%)
   - Upper middle class (30.25%)
   - Middle class (46.63%)
   - Low income (14.07%)
   - In poverty (2.70%)
   - Prefer not to say (3.08%)

B.7 Instructions for writing a job market paper tweet

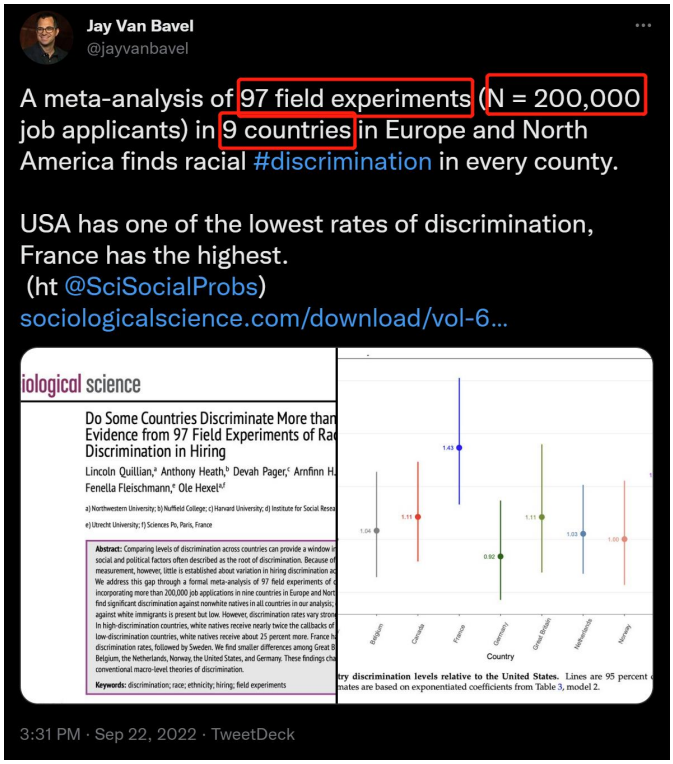
As a thank you for participation, we will post a tweet about your job market paper (JMP) on our Twitter account "Econ Job Market Helper" ($@econ_jmp$). This account is already followed by some influential economists.

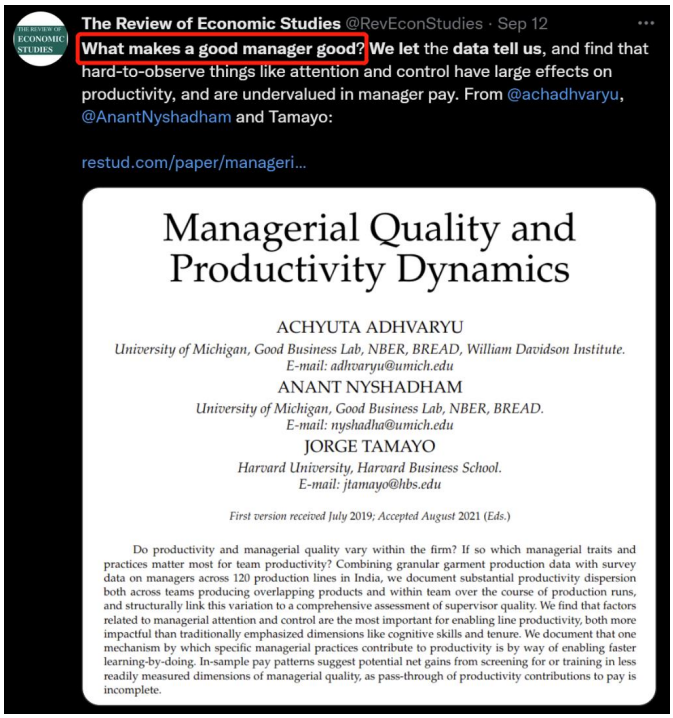
Because you know your JMP best, we are asking you to prepare the text that we will use verbatim for the tweet. It should describe the main idea and/or result of your job market paper. Note, the text limit is 280 characters. You can also use emojis (each emoji counts as two characters). Below are some guiding questions:

- What is the research question? Try to frame it in a broader context so that the tweet will create more interest.
- What data/method/modeling approach do you use and what is your main finding? Try to state your data/method/modeling approach and finding(s) in a precise way.
- Add a link to your personal website and, if you have a Twitter account, your Twitter handle (e.g., @abc).

Here are some additional tips to improve the quality of your tweet:
Do's:

1. Use numbers if applicable
2. Use open ended questions

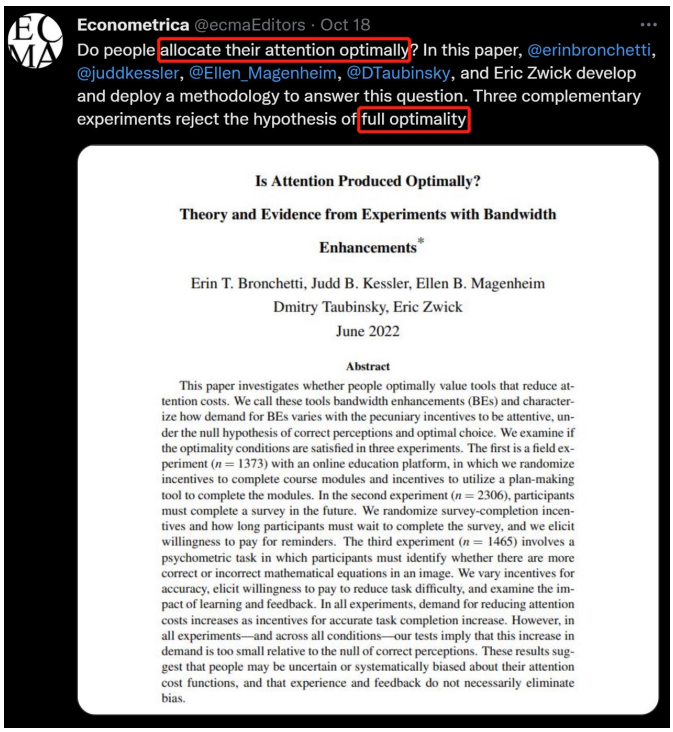

Jay Van Bavel
@jayvanbavel
A meta-analysis of 97 field experiments (N = 200,000 job applicants) in 9 countries in Europe and North America finds racial #discrimination in every county.
USA has one of the lowest rates of discrimination, France has the highest.
(ht @SciSocialProbs)
sociologicalscience.com/download/vol-6...
iological science
Do Some Countries Discriminate More than
Evidence from 97 Field Experiments of Ra
Discrimination in Hiring
Lincoln Quillian,[a] Anthony Heath,[b] Devah Pager,[c] Arnfinn H.
Fenella Fleischmann,[e] Ole Hexel[d,f]
Abstract: Comparing levels of discrimination across countries can provide a window i
social and political factors often described as the root of discrimination. Because of
measurement, however, little is established about variation in hiring discrimination ac
We address this gap through a formal meta-analysis of 97 field experiments of
incorporating more than 200,000 job applications in nine countries in Europe and Nort
find significant discrimination against nonwhite natives in all countries in our analysis;
against white immigrants is present but low. However, discrimination rates vary strong
In high-discrimination countries, white natives receive nearly twice the callbacks of
low-discrimination countries, white natives receive about 25 percent more. France h
discrimination rates, followed by Sweden. We find smaller differences among Great B
Belgium, the Netherlands, Norway, the United States, and Germany. These findings cha
conventional macro-level theories of discrimination.
Keywords: discrimination; race; ethnicity; hiring; field experiments
1.43
1.11
1.04
0.92
1.11
1.03
1.00
Belgium
Canada
France
Germany
Great Britain
Netherlands
Norway
Country
try discrimination levels relative to the United States. Lines are 95 percent
mates are based on exponentiated coefficients from Table 3, model 2.
3:31 PM · Sep 22, 2022 · TweetDeck


The Review of Economic Studies @RevEconStudies · Sep 12
What makes a good manager good? We let the data tell us, and find that hard-to-observe things like attention and control have large effects on productivity, and are undervalued in manager pay. From @achadhvaryu, @AnantNyshadham and Tamayo:
restud.com/paper/manageri...
Managerial Quality and Productivity Dynamics
ACHYUTA ADHVARYU
University of Michigan, Good Business Lab, NBER, BREAD, William Davidson Institute.
E-mail: adhvaryu@umich.edu
ANANT NYSHADHAM
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Do productivity and managerial quality vary within the firm? If so which managerial traits and practices matter most for team productivity? Combining granular garment production data with survey data on managers across 120 production lines in India, we document substantial productivity dispersion both across teams producing overlapping products and within team over the course of production runs, and structurally link this variation to a comprehensive assessment of supervisor quality. We find that factors related to managerial attention and control are the most important for enabling line productivity, both more impactful than traditionally emphasized dimensions like cognitive skills and tenure. We document that one mechanism by which specific managerial practices contribute to productivity is by way of enabling faster learning-by-doing. In-sample pay patterns suggest potential net gains from screening for or training in less readily measured dimensions of managerial quality, as pass-through of productivity contributions to pay is incomplete.

3. Use emojis



4. Focus on first and last words



5. Your tweet:

6. Please provide one keyword about your job market paper

7. Please upload a picture of the title page of your job market paper (this will be included in the tweet).

8. Please upload a picture of the main graph/table/theorem of your job market paper (this will be included in the tweet)

B.8 Participation in mentoring workshops & open-ended questions

1. What mentoring workshops, summer programs or job market panels have you attended?
    - AEA Summer and Scholarship Program (1.66%)
    - AEA Mentoring Program (CSMGEP) (1.11%)
    - Association for Mentoring & Inclusion in Economics (AMIE) Mentoring Program (2.59%)
    - CSQIEP LGBTQ+ Mentorship Program (1.29%)
    - $\#econ_prosem$ (3.33%)
    - Job Market Workshops by Economists for Ukraine (6.28%)
    - Panel on the Job Market by Committee on the Status of LGBTQ+ Individuals in the Economics Profession (CSQIEP) (0.55%)
    - Royal Economic Society (RES) Mentoring Programme (3.14%)
    - Russell Sage Foundation Summer Institutes (1.29%)
    - Southern Economic Association Mentoring Workshop (0.55%)
    - Other, please specify (16.82%)
    - I did not attend any workshops / summer program / job market panels (61.37%)
2. What questions do you want to ask the panelists regarding how to prepare for academic job interviews?
3. Do you have any comments or suggestions that you would like to share with the researchers who designed this survey? Is there anything you found unclear or confusing? Are there questions you wished we had asked? Please let us know what you think.

C Top 30 Institutions in and outside the US

Below is a summary of how we obtain the institution rankings:

1. Our list of top 30 institutions in the U.S. is obtained from the Top 30 Econ Schools from the U.S. News directly.

2. Our list of top 30 institutions outside the U.S. is obtained from Top 25% Economics Departments on RePEc (October 2022) after excluding all the U.S. institutions from this list.

3. Three institutions from our list of top 30 institutions in the U.S. are not in Tilburg's Top 100 list: California Institute of Technology, University of Rochester, and Washington University in St. Louis.

4. Six institutions from our list of top 30 institutions outside the U.S. are not in Tilburg's Top 100 list: University of Groningen, Sciences Po, Queen's University, University of Western Ontario, Aix-Marseille University, and CEMFI.

5. Five institutions from our list of top 30 institutions in the U.S. are not in the Top 100 Econ department on RePEc: California Institute of Technology, Carnegie Mellon University, Pennsylvania State University, University of Rochester, and University of North Carolina–Chapel Hill.

Table C.1: Top 30 Institutions in the U.S.

Institution	**Ranking**
Harvard University	top10
Massachusetts Institute of Technology	top10
Stanford University	top10
Princeton University	top10
University of California, Berkeley	top10
University of Chicago	top10
Yale University	top10
Northwestern University	top10
Columbia University	top10
University of Pennsylvania	top10
New York University	top11-20
University of California–Los Angeles	top11-20
University of Michigan	top11-20
California Institute of Technology	top11-20
Cornell University	top11-20
University of California, San Diego	top11-20
University of Wisconsin	top11-20
Duke University	top11-20
University of Minnesota	top11-20
Brown University	top11-20
Carnegie Mellon University	top21-30
Boston University	top21-30
Johns Hopkins University	top21-30
University of Maryland	top21-30
University of Texas–Austin	top21-30
University of California, Davis	top21-30
Boston College	top21-30
Pennsylvania State University–University Park	top21-30
University of Rochester	top21-30
University of North Carolina–Chapel Hill	top21-30
University of Virginia	top21-30
Vanderbilt University	top21-30
Washington University in St. Louis	top21-30

Table C.2: Top 30 Institutions outside the U.S.

Institution	**Ranking**
Paris School of Economics	1
Toulouse School of Economics (TSE)	2
Oxford University	3
Barcelona School of Economics (BSE)	4
University College London (UCL)	5
London School of Economics and Political Science	6
University of British Columbia	7
Universiteit van Tilburg	8
University of Warwick	9
University of Toronto	10
University of Zurich	11
Monash University	12
University of Nottingham	13
University of Cambridge	14
Rijksuniversiteit Groningen	15
Alma Mater Studiorum - Università di Bologna	16
Sciences Po	17
University of Queensland	18
Aarhus Universitet	19
Queen's University	20
Erasmus Universiteit Rotterdam	21
KU Leuven	22
Vrije Universiteit Amsterdam	23
University of York	24
Universiteit van Amsterdam	25
University of Western Ontario	26
Australian National University	27
Aix-Marseille University	28
CEMFI	29
Københavns Universitet	30

D Cosine Similarity

Cosine similarity is a widely used measure of semantic similarity between two documents in the area of information retrieval (Singhal et al., 2001). To compute the cosine similarity between two documents, a and b, we converted each document into a collection of words, cleaned them,[39] took their union, and generated two vectors, A and B. Each entry in a vector represents the frequency of a word's appearance in that document. We then calculated the cosine value of the angle, θ, between the two word vectors as follows:

$$\cos\theta = \frac{\mathbf{A}^T \cdot \mathbf{B}}{||\mathbf{A}||\,||\mathbf{B}||} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}. \tag{2}$$

Cosine similarity, $\cos\theta \in [0, 1]$, is therefore a linguistic distance metric. A one-unit increase in the cosine similarity measure corresponds to a transition from a match with no overlapping words ($\cos\theta = 0$) to a perfect match ($\cos\theta = 1$). See the Electronic Companion EC.6. of Chen et al. (2024) for examples of how to compute cosine similarity.

In our sample, the mean cosine similarity is 0.50 (stdev 0.079), indicating a good match.[40] It has been applied in economic research which involves natural language processing (Chen et al., 2024). The pseudo code is presented as an Algorithm on the next page.

[39] Cleaning involves dropping "stop" words that appear frequently across all documents , such as "and" and "the," as well as converting variants of the same word, such as "consider,' "considered," and "considering," into its root"consider."

[40] Note that because this algorithm limits the maximum number of matches for each influencer to five, there were 30 JMPs left unmatched. These unmatched JMPs were not considered when computing the cosine similarity. We then manually matched these 30 JMPs to influencers.

Algorithm 1 Match JMCs to Influencers Based on Cosine Similarity with Embeddings

Input:
    JMP abstracts
    Abstracts of influencers' top 20 most cited papers
    email_suffix_jmp - list of email suffixes corresponding to JMP authors' institutions
    email_suffix_influencer - list of email suffixes corresponding to influencers' institutions
Output:
    Influencer_Assignments - DataFrame with JMPs assigned to influencers
Initialize the SentenceTransformer model with "all-MiniLM-L6-v2"
Encode JMP abstracts and influencer abstracts to obtain embeddings_jmp and embeddings_influencer
Compute cosine_scores between embeddings_jmp and embeddings_influencer
Initialize Influencer_Assignments DataFrame with columns ['JMP', 'Influencer', 'Institution Match']
Initialize a list counter to keep track of how many JMPs are assigned to each influencer
for each Influencer in Influencer_data **do**
    Initialize a counter for JMP assignments to this Influencer
    for each JMP in JMP_data **do**
        if counter < 5 **then**
            Extract cosine similarity score for this JMP-Influencer pair from cosine_scores
            Identify if this JMP has the highest similarity score for this Influencer
            if JMP is the best match so far for this Influencer **then**
                Check if email suffix of JMP matches with email suffix of Influencer
                if email suffixes match **then**
                    Append to Influencer_Assignments with 'Institution Match' as True
                else
                    Append to Influencer_Assignments with 'Institution Match' as False
                end if
                Increment counter for this Influencer
            end if
        else
            Continue to the next Influencer
        end if
    end for
    Update counter with the final count for this Influencer
end for

E Post-market Survey

This appendix includes the questions and instructions for the post-market survey. Among the 519 participants randomized to treatment and control conditions, 417 reported their job market outcomes.[41] *Unless otherwise specified, the summary statistics presented in this Appendix are based on the 412 complete survey responses.*

Consent to Participate in Survey Research

Principal Investigators: Yan Chen (University of Michigan), Alain Cohn (University of Michigan), Jingyi Qiu (University of Michigan), Alvin Roth (Stanford University)

Online Consent

Description We are conducting a follow-up survey to gain insight into the impact of social media on job market outcomes in economics. In this survey, you will be asked questions about your job applications, job market outcomes, and the use of social media.

Duration The survey should take 5-10 minutes. Your participation is voluntary, and you may exit the survey at any time.

What will happen if you take part in this study If you agree to participate, your responses might be linked to American Economic Association institutional records to draw information on job market outcomes. Once these data have been extracted, any information that can directly identify you will be removed from the data file and stored separately as part of the project.

What will be done with the information collected from the survey The data are being collected by the research team (Yan Chen, Alain Cohn, Jingyi Qiu and Alvin Roth). Your responses will be held confidential. This means that only the research team will be able to access any identifying information about respondents. Additionally, your data will be anonymized and results will only be analyzed and reported at the aggregate level. Data may be stored in a repository for future research and you may be asked to participate in future surveys.

Benefits and risks of participation In appreciation of your consideration for participating in our survey, we are offering a $10 Amazon gift card to you regardless of your survey completion. Moreover, the

[41] We removed three participants from our analysis who had completed the pre-market survey twice using different email addresses and were assigned to both treatment and control conditions. Of the 417 participants, 412 completed the post-market survey, and five emailed us their job market outcomes, one of whom had partially completed the survey before the part E.3. This participant's response was included in the summary statistics.

results of this study has the potential to help future cohorts of job market candidates. This study involves no more than minimal risk. You may discontinue participation at any time during the research activity.

Contact information If you have questions about this study, you may contact Jingyi Qiu (jiaqiu@umich.edu).

The University of Michigan Institutional Review Board Health Sciences and Behavioral Sciences has determined that this study is no more than minimal risk and exempt from on-going IRB oversight (IRB Study Number: HUM00221663).

Study Consent:

- No, I do not wish to participate in the survey. Please exit this survey now.
- Yes, I agree to participate in the survey. Please proceed to the survey.

E.1 Personal background

1. What was your title or position in December 2022?
   (a) Ph.D. Student / Ph.D. Candidate (79.90%)
   (b) Postdoc (12.59%)
   (c) Lecturer (1.21%)
   (d) Assistant Professor (2.91%)
   (e) Other, please specify (3.39%)

   (Count 413)

E.2 Number of jobs JMC applied for

1. How many jobs did you apply for?
   (a) 1-50 jobs (12.35%)
   (b) 51-100 jobs (17.19%)
   (c) 101-150 jobs (26.88%)
   (d) 151-200 jobs (19.61%)
   (e) 201+ jobs (23.97%)

   (Count 413)

2. Did you apply primarily for academic or non-academic jobs? [1 = primarily academic, 5 = primarily non-academic]

   (a) 1

   (b) 2

   (c) 3

   (d) 4

   (e) 5

   (Count 413, Mean 1.60, Std Dev 0.88, Median 1, Min 1, Max 5)

3. Did you send AEA job market signals?

   (a) Yes, I sent one signal (3.87%)

   (b) Yes, I sent two signals (76.27%)

   (c) No (19.85%)

   (Count 413)

4. If yes: How many interviews or fly-outs or job offers did you receive from the institutions/employers to which you send signals?

   (a) Interviews: 0/1/2
   (Count 331, Mean 0.57, Std Dev 0.69, Median 0, Min 0, Max 2)

   (b) Fly-outs: 0/1/2 (Count 331, Mean 0.24, Std Dev 0.49, Median 0, Min 0, Max 2)

   (c) Job offers: 0/1/2 (Count 331, Mean 0.14, Std Dev 0.38, Median 0, Min 0, Max 2)

E.3 Interviews/fly-outs/offers received by types

1. How many interviews did you receive for the following types of jobs?

   (a) Tenure-track positions (or equivalent) at a college or university
   (Count 417, Mean 11.74, Std Dev 10.38, Median 9, Min 0, Max 60)

   (b) Non-tenure track positions at college or university, such as postdoc positions
   (Count 412, Mean 2.40, Std Dev 3.06, Median 2, Min 0, Max 22)

   (c) Public-sector: Government, non-profit and quasi-governmental organizations, such as central banks, IMF, World Bank
   (Count 412, Mean 1.77, Std Dev 2.98, Median 1, Min 0, Max 16)

   (d) Contract research organizations / think tanks, such as RAND, Mathematica, Research Triangle Institute)
   (Count 412, Mean 0.42, Std Dev 1.51, Median 0, Min 0, Max 25)

(e) Private-sector: banking, finance, business, industry, consulting
(Count 412, Mean 1.21, Std Dev 2.14, Median 0, Min 0, Max 12)

2. How many fly-outs (on-site visits) did you receive for the following types of jobs?

   (a) Tenure-track positions (or equivalent) at a college or university
   (Count 412, Mean 3.80, Std Dev 4.12, Median 2, Min 0, Max 24)

   (b) Non-tenure track positions at college or university, such as postdoc positions
   (Count 412, Mean 0.77, Std Dev 1.35, Median 0, Min 0, Max 12)

   (c) Public-sector: Government, non-profit and quasi-governmental organizations, such as central banks, IMF, World Bank
   (Count 412, Mean 0.82, Std Dev 1.64, Median 0, Min 0, Max 12)

   (d) Contract research organizations / think tanks, such as RAND, Mathematica, Research Triangle Institute)
   (Count 412, Mean 0.13, Std Dev 0.42, Median 0, Min 0, Max 3)

   (e) Private-sector: banking, finance, business, industry, consulting
   (Count 412, Mean 0.41, Std Dev 1.01, Median 0, Min 0, Max 6)

3. How many job offers did you receive for the following types of jobs?

   (a) Tenure-track positions (or equivalent) at a college or university
   (Count 417, Mean 1.68, Std Dev 2.02, Median 1, Min 0, Max 14)

   (b) Non-tenure track positions at college or university, such as postdoc positions
   (Count 412, Mean 0.74, Std Dev 1.04, Median 0, Min 0, Max 5)

   (c) Public-sector: Government, non-profit and quasi-governmental organizations, such as central banks, IMF, World Bank
   (Count 412, Mean 0.42, Std Dev 0.91, Median 0, Min 0, Max 7)

   (d) Contract research organizations / think tanks, such as RAND, Mathematica, Research Triangle Institute)
   (Count 412, Mean 0.09, Std Dev 0.36, Median 0, Min 0, Max 4)

   (e) Private-sector: banking, finance, business, industry, consulting
   (Count 412, Mean 0.22, Std Dev 0.58, Median 0, Min 0, Max 4)

4. (Optional) If you kept a record of your job applications, including the interview invitations, fly-out invitations, and job offers you received, and you are willing to share with us, could you upload your record here? We will never share the file outside of the research team.

5. Did you receive any very early or short-duration offers that made it hard to wait for other interviews/fly-outs/offers?

   (a) Yes (47.8%)

   (b) No (52.2%)

6. Did you register for and participate in the AEA scramble?

   (a) Yes (16.0%)

   (b) No (84.0%)

E.4 Job offer acceptance

1. Did you accept a job offer?

   (a) Yes (91.7%)

   (b) No (8.3%)

2. What type of job offer did you accept?

   (a) Academia (college, university) (76.98%)

   (b) Government, including central banks (9.26%)

   (c) Non-profit or quasi-governmental organizations (e.g., IMF, World Bank) (3.97%)

   (d) Contract research organizations / think tanks (e.g., RAND, Mathematica, Research Triangle Institute) (3.70%)

   (e) Private-sector: tech, banking, finance, business, industry, consulting (5.56%)

   (f) Other, please specify___ (0.53%)

   (Count 378)

3. What is the name of the institution or organization at which you will be working?

4. Which of the following best describes your position?

   (a) Tenure Track Assistant Professor (50.40%)

   (b) Lecturer (4.00%)

   (c) Adjunct (0%)

   (d) Visiting Professor (2.67%)

   (e) Postdoctoral Fellow (18.13%)

   (f) Research Scientist (12.80%)

   (g) Other, please specify___ (12.00%)

   (Count 375)

5. In what country is your new job?

   (a) –Select Country–

6. How satisfied are you with your job placement?
   Rating: Not at all satisfied (1) - Very satisfied (7)

   7: (35.20%), 6: (31.20%), 5: (18.93%), 4: (6.40%), 3: (3.47%), 2: (3.20%), 1: (1.60%)

7. (Optional) At your new job, what will be your annual pre-tax salary for the coming year? If your base salary is not in USD, please report the approximate value in USD. (Count 281, Mean 107,969.42, Std Dev 62,582.35, Median 90,000, Min 140,000, Max 600,000)

E.5 Twitter

1. Did you promote your JMP on Twitter? (check all that apply)

   (a) Yes, I wrote a separate tweet about my JMP BEFORE the Econ Job Market Helper tweeted my JMP (19.00%)

   (b) Yes, I wrote a separate tweet about my JMP AFTER the Econ Job Market Helper tweeted my JMP (10.18%)

   (c) Yes, I retweeted/quote-tweeted my JMP tweet posted by the Econ Job Market Helper (26.47%)

   (d) No, I did not promote my JMP on Twitter (exclusive choice) (44.34%)

   (Count 408)

2. Did anyone else besides Econ Job Market Helper tweet about your JMP? (for example, your department placement officer, your advisor)

   (a) Yes, my placement officer (11.21%)

   (b) Yes, my advisor(s) (12.84%)

   (c) Yes, my co-author(s) (7.05%)

   (d) Yes, one or more renowned researcher (20.80%)

   (e) Yes, one or more researchers that I do not know (17.54%)

   (f) No, I am not on Twitter / I am not sure (30.56%)

   (Count 408)

E.6 Academic background

1. As of November 2022, what was your research record?

   (a) Number of working papers: _____ (Count 408, Mean 3.04, Std Dev 1.60, Median 3, Min 0, Max 20)

(b) Number of articles published or forthcoming in peer-reviewed journals or proceedings: _____ (Count 408, Mean 1.21, Std Dev 2.52, Median 0, Min 0, Max 20)

(c) Number of R&R (Revised and Resubmitted, or under revision for resubmission) articles in peer-reviewed journals or proceedings: _____ (Count 408, Mean 0.368, Std Dev 0.66, Median 0, Min 0, Max 4)

2. Please upload the latest version of your CV as .pdf:

3. Please upload the latest version of your job market paper as .pdf:

4. What is the URL of your personal webpage?

   - My personal webpage URL is _____
   - I don't have a personal webpage.

F Pre-analysis Plan

In our original pre-registration plan (Chen et al., 2022) (registered on November 4, 2022), we specified that we would recruit 400 participants each for the treatment and control groups. However, despite our best efforts to recruit as many participants as possible, we did not meet these target numbers.

F.1 Introduction

We conduct a field experiment to investigate the effects of social media exposure on job market outcomes. Although our sample includes any kinds of job market candidates, our focus is on individuals from under-represented groups (i.e., women, URM and LGBTQ+, denoted as "URG"). More specifically, we examine whether having economist influencers "quote tweet" (i.e., retweet with a comment) the job market papers on Twitter may help job market candidates achieve better success on the economics job market, including increasing exposure for job market papers (e.g., more impressions, retweets, URL clicks, detail expands, engagements, likes, replies on Twitter) and getting better job market outcomes (e.g., more job interviews, flyouts, job offers etc.). We also examine whether there are heterogeneous treatment effects for under-represented groups.

For our study, we recruit job market candidates who register on either the AEA's job openings for economists (JOE) or the European Job Market for Economists (EJME), or who are listed as job market candidates on their department websites on the 2022-2023 Econ Job Market [42]. We first send out a pre-market survey to collect candidates' demographics, job market paper summary, and the use of Twitter. Then we tweet the job market papers of all survey respondents on our Twitter account "Econ Job Market Helper" ($@econ_jmp$).

Given the relatively small sample size[43], we use a matched-pair design to lower the mean-squared error and the standard error (Bai, 2022). We first split job market candidates into the URG group and the non-URG group based on their demographic information collected from our pre-market survey. Among the URG group (N=231) and the non-URG group (N=294), respectively, we order units (i.e., job market candidates) according to the number of their primary advisor's Google Scholar citations, and then pair the adjacent three units as triplets.

After stratified random assignment, we match job market candidates in the treatment group with academic economists with 4,500 or more Twitter followers ("influencers") by fields. Influencers are asked to quote tweet job market papers from the treatment group using templates provided by us and then we measure whether the quote tweets improve the visibility of job market papers of treated participants

[42] We refer to the economics or relevant departments according from two sources: PhD Candidates in Economics listed on NBER (https://www.nber.org/career-resources/phd-candidates-economics); and EconJobMarket (https://econjobmarket.org/placementOfficers).

[43] Our sample size limitations come from two sources: 1) Only a subset of job market candidates who completed our pre-market survey submitted a complete tweet about their job market paper; 2) Only a subset of job market candidates' job market papers are available to be downloaded on their personal websites during the time when we collected our pre-market survey.

on Twitter (i.e., more impressions, retweets, URL clicks, detail expands, engagements, likes, replies etc.), and job market outcomes of treated participants (i.e., more job interviews, flyouts, job offers etc.).

We are focusing on job market candidates from under-represented groups because they typically do not have access to the same high-quality mentoring resources and professional networks as other candidates (Lundberg and Stearns, 2019; Bayer, Hoover and Washington, 2020). Amplifying the visibility of URG job market candidates may provide a low-cost alternative to help young economists, especially those from underrepresented groups succeed in the job market. More generally, our study will shed light on the causal effect of promoting research on social media on academic success.

In addition, we want to learn about the extent to which economist influencers can accurately predict the impact of our social media intervention. After we send out our post-market survey and finish the data collection and analysis, we will conduct a prediction study with the economist influencers who agreed to help with our field experiment earlier. We will ask how the treatment affects the number of job interviews/fly-outs/job offers. We will ask this question separately for URG and non-URG job applicants.

F.2 Research Strategy

Our experiment consists of three stages: (i) a pre-market survey, (ii) an intervention period, and (iii) a post-market survey.

Pre-market survey (late October to mid November, 2022): We compile a list of job market candidates who register on either the AEA's job openings for economists (JOE) or the European Job Market for Economists (EJME), or who are listed as job market candidates on their department websites on the 2022-2023 Econ Job Market. Then, we invite them to participate in the pre-market survey. The survey asks job market candidates questions about demographics, job market paper, and use of Twitter. We also ask participants to summarize their job market paper as a tweet.

Intervention period (mid November to early December, 2022): We use our Twitter account "Econ Job Market Helper" ($@econ_jmp$) to post the job market paper tweets of all job market candidates who fill out the pre-market survey. After stratifying by URG/non-URG and ordering job market candidates according to the number of primary advisor's Google Scholar citations, we use the matched-pair design as described in the introduction section to randomly assign participants to the treatment or control group. Since we want more URG job market candidates to receive treatment for ethical reasons, URG job market candidates will have a higher probability (2/3) of being assigned to the treatment group compared to non-URG job market candidates, who have a 1/3 probability of being assigned to the treatment group. Those assigned to the treatment group will be matched with an influencer in their respective field. The influencers are then asked to quote tweet the original tweet according to a predefined time schedule. The texts in the quote tweets are randomly drawn from a list of templates. For example: "Retweeting a JMP from $@econ_jmp$ to help publicize job market candidates in my field." Influencers can edit the sentence if they want to.

Post-market survey (April-June, 2023): The survey will collect data on each candidate's number

of job applications and job market outcomes, such as the number of interviews, fly-outs and offers received from different types of jobs (e.g., tenure-track positions, non-tenure track positions, public-sector, contract research organizations, and private-sector etc.), as well as and additional compensation/perks.

Twitter data: In addition, after the intervention period we also collect intermediate outcomes generated by the job market paper tweets via Twitter API and Twitter Analytics, including the number of URL clicks of candidates' personal websites, the number of replies, likes, retweets, impressions, engagements, detail expands, etc.

F.3 Outcomes

- **Primary outcome measures**
  - Number of job interviews / fly-outs / job offers received for different types of jobs
- **Intermediate outcome variables**
  - Twitter influence index (impressions, retweets, URL clicks, detail expands, engagements, likes, replies etc.)
- **Secondary outcome variables**
  - Satisfaction with job placement
- **Additional descriptive variables**
  - Asian (including Asian American and Asian)
  - Gender
- **Long-term outcomes** (not included in this paper)
  - Number of citations of the job market paper within 2 years of the experiment
  - Number of co-authors within 2 years of the experiment
  - Publications (how many, journal ranks) within 2 years of the experiment
- **Key control variables**
  - Number of primary advisor's citations
  - Rookie (i.e., job market candidates who go on the Econ Job Market for the first time)
  - Did (doing) postdoc (or not)
  - Top 30 U.S. institutions (or not)
  - Top 30 institutions outside the U.S. (or not)
  - Research subfields

- Sent job market signals (0, 1, 2)
- Participation in job market scramble (or not)
- Number of publications, R&R, working papers
- Number of jobs applied for multiple choice: 1-50 jobs, 51-100 jobs, 101-150 jobs, 151-200 jobs, 200+ jobs Types of jobs applied for 1 = primarily academic, 5 = primarily non-academic
- Interest in different types of jobs likert scale rating 1-7: lecturer, postdoc, government, NGO, thinktank, industry
- Interest in jobs in different locations binary: U.S., Other North America, Africa, Europe, Asia, Oceania/Australia/New Zealand, South America

- **Prediction Study**

  We will conduct a prediction study with influencers, where we ask them to guess how many more or less job interviews, fly-outs and job offers the job market candidates in the treatment group on average received relative to the control group.

  Focusing only on the candidates from underrepresented groups (i.e., women, underrepresented minorities, LGBTQ+), we will also ask influencers to guess how many more or less job interviews, fly-outs and job offers the job market candidates in the treatment group on average received relative to their counterparts in the control group.

F.4 Empirical Strategy

Anticipating one-sided non-compliance (on the side of influencers), we will estimate intent-to-treat (ITT) effects. We will estimate regression models of the following form using OLS:

$$lm(DV\ treat + URG + X) \tag{3}$$

$$lm(DV\ treat + URG + treat : URG + X) \tag{4}$$

Where "treat" is 1 if assigned to the treatment and zero otherwise, X is a matrix of pre-treatment covariates, and URG is a dummy variable for JMC from under-represented groups. Standard errors are at the individual level.

Depending on the distribution of the outcome variables, we might perform robustness checks (e.g., negative binomial models for count data, log transformation for long-tail distributions etc.).

We will also use our randomization as an instrument to estimate local average treatment effects (LATE):

$$ivreg(DV\ d + URG + X | treat + URG + X) \tag{5}$$

$$ivreg(DV\ d + URG + d : URG + X | treat + URG + treat : URG + X) \tag{6}$$

Where d represents the actual received treatment and "treat" refers to assigned treatment. Standard errors are clustered at the individual level.

We might also explore t-tests and randomization tests based on Bai, Romano and Shaikh (2022) and Bai (2022). None of these tests need pair dummies or clustering, but they both need adjustment terms (which are in the form of "pairs of pairs") in the standard errors in order for rejection probability for large n to be 5%. Alternatively, we might also do covariate adjustment based on Bai et al. (2023).

G Prediction Study

This appendix includes the questions for the prediction study survey.[44] *Among 81 economist influencers who received our prediction study survey, 31 influencers made predictions. On the Social Science Prediction Platform, 75 SSPP experts completed the prediction survey, of which 73 made predictions. Two SSPP experts reported that they had seen the results of this study at a conference and were therefore excluded from making forecasts. We therefore report the summary statistics of these influencers and SSPP experts respectively.*

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Consent Form

Task and duration We will ask you to make predictions about the effects of social media promotion on job market outcomes. It should take you 5 minutes or less to complete the survey.

Compensation The three most accurate colleagues will each receive a $100 Amazon gift card.

What will be done with the information collected from the survey Your responses will be held confidential. Your data will be anonymized and results will only be analyzed and reported at the aggregate level.

Contact information If you have questions about this study, you may contact Jingyi Qiu (jaqiu@umich.edu).

The University of Michigan Institutional Review Board Health Sciences and Behavioral Sciences has determined that this study is no more than minimal risk and exempt from on-going IRB oversight (IRB Study Number: HUM00221663).

Please indicate, in the box below, that you have read and understood this consent form, and that you agree to participate in this study.

- Yes, I agree to participate in the survey. Please proceed to the survey.
- No, I do not wish to participate in the survey. Please exit this survey now.

[44] The sample size provided to influencers and SSPP experts in the prediction study was 420, as we were unaware at that point that some participants had completed the pre-market survey twice using different email addresses and were assigned to both treatment and control conditions, potentially reporting job market outcomes twice. The actual sample size used in the analysis is 417, after removing the duplicate participants.

G.1 Experimental Design

In November and December 2022, we conducted a Twitter experiment with econ job market candidates, which aims to assess the impact of social media promotion on job market outcomes.

Study details We invited students who were on the economics job market to fill out a survey about their academic background and social media use. At the end of the survey, we asked them to summarize their job market papers (JMPs) so that we can tweet about it on our Twitter account, Econ Job Market Helper.

Treatment We asked influential economists to "quote tweet" a random subset of the JMPs from candidates in their field on Twitter. We provided templates for the quote tweets (e.g., Retweeting a JMP from $@econ_jmp$ to help publicize job market candidates in my field).

Now, we want to invite you to predict the results of this study.

The three most accurate colleagues will each receive a $100 Amazon gift card.

Questions

1. Have you seen the results of this study at a conference?

   (a) Yes, I have seen the results of this study at a conference (Influencers: 0%, SSPP: 2.67%)

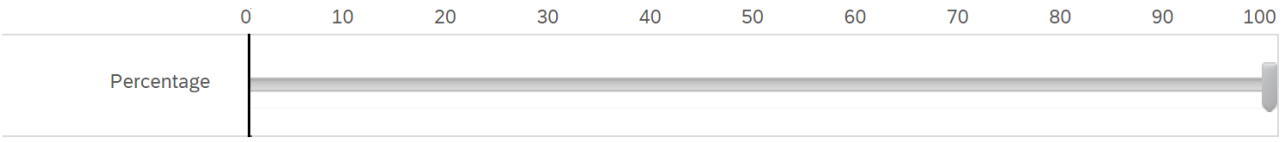
   (b) No, I haven't seen the results of this study (Influencers: 100%, SSPP: 97.33%)

2. Total number of job market candidates in our sample: 420

   Candidates in the control group on average received: 16.8 job interviews (standard deviation: 10.83)

   By what percentage did treated job market candidates receive more job interviews on average?

   If you predict there are no treatment effects on interviews, please move the slider to 0.



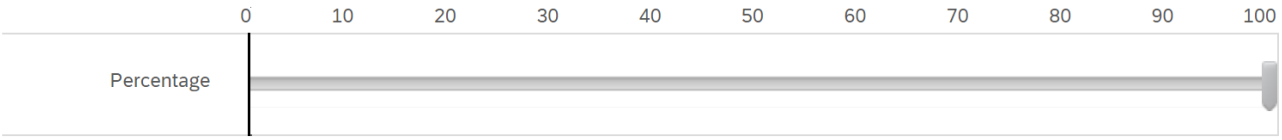
   (Influnecers: Mean 11.71, Std Dev 9.22, Median 9, Min 0, Max 34)
   (SSPP: Mean 17.59, Std Dev 18.73, Median 11, Min 0, Max 83)

3. Total number of job market candidates in our sample: 420

   Candidates in the control group on average received: 5.5 flyouts (standard deviation: 4.44)

By what percentage did treated job market candidates receive more flyouts on average?

If you predict there are no treatment effects on flyouts, please move the slider to 0.



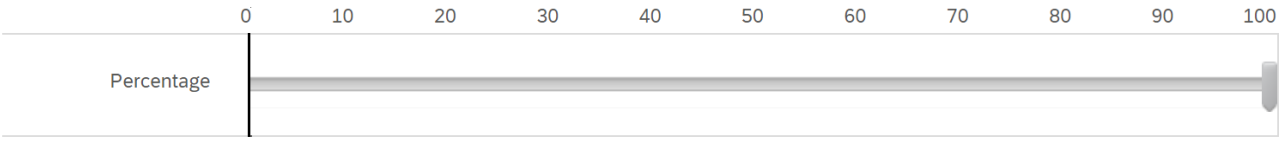
(Influnecers: Mean 7.55, Std Dev 9.04, Median 4, Min 0, Max 35)
(SSPP: Mean 12.63, Std Dev 19.74, Median 6, Min 0, Max 100)

4. Total number of job market candidates in our sample: 420

   Candidates in the control group on average received: 3.0 job offers (standard deviation: 2.28)

   By what percentage did treated job market candidates receive more job offers on average?

   If you predict there are no treatment effects on job offers, please move the slider to 0.



   (Influnecers: Mean 4.16, Std Dev 5.94, Median 2, Min 0, Max 21)
   (SSPP: Mean 10.71, Std Dev 18.26, Median 4, Min 0, Max 100)

5. How confident are you with your predictions?

   (a) Not confident at all (Influencers: 35.48%, SSPP: 12.33%)
   (b) Slightly confident (Influencers: 38.71%, SSPP: 39.73%)
   (c) Moderately confident (Influencers: 25.81%, SSPP: 31.51%)
   (d) Confident (Influencers: 0%, SSPP: 12.33%)
   (e) Very confident (Influencers: 0%, SSPP: 4.11%)

6. (For economist influencers only) Are you still active on Twitter?

   (a) Yes, I am active on Twitter (Influencers: 83.87%)
   (b) No, I was active on Twitter but not anymore (Influencers: 16.13%)

7. (For SSPP experts only) Are you still active on Twitter?

   (a) Yes, I am active on Twitter (SSPP: 53.42%)
   (b) Yes, I was active on Twitter but not anymore (SSPP: 21.92%)
   (c) No, I am not on Twitter (SSPP: 24.66%)

8. (For economist influencers only) Would you like to be acknowledged in this study?

   (a) Yes, I would like to be acknowledged in this study (Influencers: 54.84%)

   (b) No, I do not want to be acknowledged in this study (Influencers: 45.16%)

9. (For economist influencers only) If you would like to be acknowledged in this study, what is the name you want us to display?

H Instructions for Rating Quote-tweets

The instruction given to the human and GenAI raters used quote-tweets from our influencers as examples. To preserve the anonymity of our influencers and participants, we replace those examples with our made-up example in Appendix Figure A.2. The raters received the same instructions.

Endorsement: From 1 (no endorsement) up to 5 (very strong endorsement)

1 - No endorsement: The quote tweet does not contain any words or phrases indicating support, appreciation, or recommendation of the job market candidate or their job market paper (JMP).

Example: To promote young scholars in my field, I am retweeting a JMP on curiosity-driven news consumption.

5 - Very strong endorsement: The quote tweet contains strong expressions of endorsement such as "the best" or "transformative" JMP.

Example: A very cool job market study of over 100,000 WeChat news articles reveals how curiosity drives news consumption. Their findings show that people are more likely to read articles when the headline sparks a salient question, the content seems more important, and the topics are more surprising.

Specificity: From 1 (not specific at all) up to 5 (very specific)

1 - Not Specific At All: The tweet provides no additional information about the job market paper's approach, findings, or the unique aspects of their research. It is generic and does not offer any details beyond possibly mentioning the candidate's name or field.

Example: Take a look at this young scholar in my field. Here is their JMP on curiosity-driven news consumption.

5 - Very specific: The tweet is very detailed, providing in-depth information about the job market paper's research approach, detailed findings, and the unique aspects of their JMP. It might include specific results, the significance of the research, and how it contributes to the field.

Example: A very cool job market study illustrates how curiosity drives news consumption. Their findings show people are more likely to read articles when the headline sparks a salient question, the content seems more important, and the topics are more surprising.

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