Star Secrets? Gender differences in the impact of superstar coauthorship in economics*

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Abstract

The field of economics grapples with a persistent gender gap, with the underrepresentation of women worsening at higher academic ranks (CSWEP, 2020). This study investigates how gender shapes the benefits of collaboration with highly successful economists, or "superstars." Specifically, I examine whether early coauthorship with a female superstar has a differential impact on the publication success of junior researchers compared to coauthorship with a male superstar. Using a difference-in-differences design with a matched sample, I find that junior women who coauthor with female superstars experience significantly better publication outcomes compared to those who coauthor with male superstars. In contrast, junior men appear to perform similarly regardless of the gender of their superstar coauthor. These findings suggest that female superstars may offer unique benefits to junior women that encourage publication success. They highlight the importance of gender-specific factors in shaping success in economics and suggest that ongoing efforts for supporting women in economics should consider gender-specific approaches.

Keywords: Gender, Women in Economics, Research Superstars, Collaboration

*Work in progress. DO NOT CIRCULATE.

1 Introduction

The field of economics grapples with a persistent gender gap, with women underrepresented at all levels of the academic profession. Despite substantial efforts to address this issue, the proportion of female economics PhDs remains stagnant, hovering at around 30% since the early 2000s (Avilova and Goldin, 2018; Bayer and Rouse, 2016; Lundberg and Stearns, 2019; CSWEP, 2020). Women in economics face systemic barriers, including fewer publications, limited networking opportunities, reduced credit for coauthored work, and obstacles to tenure (CSWEP, 2018; Ginther and Kahn, 2009, 2014; McDowell et al., 2001). These challenges contribute to the ongoing discussion surrounding the gender gap in academia, the causes of which remain a subject of ongoing research and debate (Cheryan et al., 2017; Cole and Zuckerman, 1984, 1987; Xie and Shauman, 1998).

For a discipline dedicated to solving real-world inefficiencies and inequities, the persistent gender gap is concerning. First, it poses an equity and fairness issue. Research attributes the gender gap to systemic barriers that discourage women from pursuing careers in economics, limiting their overall influence and representation in the field. Second, it can limit the diversity of perspectives and hinder the field's ability to address complex real-world issues. A lack of gender diversity can lead to "echo chambers," stifling innovation and compromising the quality of research (Bayer and Rouse, 2016; Belot et al., 2023; Koffi, 2021; Liu et al., 2020; Maddi and Gingras, 2021; May et al., 2014).

The underrepresentation of women in economics, particularly at higher ranks, raises questions about the distribution of talent within the field. This raises the questions: Does the scarcity of highly successful ("superstar") women have broader impacts on junior women? Could these superstar women possess unique knowledge and skills that contribute to their success and that they may pass on to junior women? To address this, this paper explores the potential benefits that superstar economists offer to their junior collaborators, and whether these benefits differ by gender.

In this paper I investigate how gender differences in superstar coauthorship impact the publication outcomes of junior economists. Specifically, I compare the impact of early coauthorship with a female superstar on publication outcomes of junior men and women, relative to coauthorship with a male superstar. By focusing on coauthorship as a channel for knowledge and skill transfer, this study aims to uncover whether coauthoring with a male or female superstar offers different benefits for early-career economists.

Prior literature demonstrates that research superstars can positively influence the research productivity of their peers by possessing expert knowledge and offering valuable "helpfulness" throughout the research process (Azoulay et al., 2010; Agrawal et al., 2017; Khanna, 2021; Oettl, 2012). However, few studies have explored whether these "star spillovers" may differ by gender. Given the documented gender-based barriers in economics, it's possible that the skills and knowledge possessed by stars for navigating a successful career might differ for men and women.

A major challenge in studying coauthorship, however, stems from the non-random selection of collaborators. Researchers choose partners based on factors that also influence publication success, potentially leading to biased estimates. To address this, I employ a matching technique called coarsened exact matching (CEM). CEM essentially finds a control group for researchers who collaborate with superstars by identifying comparable researchers across observable characteristics related to coauthorship decisions, such as past coauthorship experience, proximity to superstars, and publication trends before coauthoring with a superstar. By establishing balanced comparisons across these relevant factors, CEM helps isolate the causal effect of superstar coauthorship on publication outcomes.

I use publication data of US economists to investigate the influence of coauthorship with research superstars on the publication outcomes of early-career junior economists. Following Li et al. (2019), research superstars are defined as those attaining the top 5th percentile in cumulative citations in a given year. Using a difference-in-differences framework with a matched-sample design, I compare the changes in publication outcomes of junior economists before and after coauthoring with a superstar to that of matched controls. To examine potential gender-specific effects, I include an interaction term for superstar gender in my analyses, and conduct separate analyses for female and male junior economists.

My findings support Li et al. (2019) and Yadav et al. (2023) by demonstrating that early coauthorship with superstars improves publication outcomes for both female and male junior economists. However, a more nuanced picture emerges when considering the gender of the superstar. Junior women who coauthor with a female superstar publish more frequently and into higher-impact factor journals, compared to those who coauthor with a male superstar. In contrast, junior men's publication outcomes appear largely unaffected by the gender of their superstar collaborator.

These results suggest that female superstars may possess unique knowledge or skills that they transfer to junior women. This knowledge seems to equip junior women to address the specific challenges they face, leading to greater publication success. In contrast, junior men do not appear to benefit as much from gender-specific insights. This gendered effect is particularly pronounced among high-ability junior women, as measured by their pretreatment publication impact factor, compared to matched controls. This suggests that the combination of strong prior ability and female superstar mentorship is particularly effective in boosting publication success.

This research contributes to several areas of literature. First, it adds to the literature exploring the link between collaboration and research production (Jones, 2009; Lee and Bozeman, 2005; Li et al., 2013). Within this literature, it contributes to a growing subset specifically interested in research superstars and their influence on peers (Abramo et al., 2009; Aguinis et al., 2018; Azoulay et al., 2010; Ductor, 2015; Hussey et al., 2022; Jadidi et al., 2018; Khanna, 2021; Li et al., 2019; Oettl, 2012; Wuchty et al., 2007; Yadav et al., 2023). This paper extends this literature by focusing on the context of economics, where there is a persistent gender gap, and investigating potential gender differences in superstar effects.

Second, this work contributes to the literature exploring the determinants of success in economics research (Bryan, 2019; Hamermesh, 2013; Heckman and Moktan, 2020). This work demonstrates that coauthorship with superstars can improve publication outcomes for junior economists, and that these benefits differ by gender.

Third, this paper contributes to the research exploring gender dynamics in the workplace, particularly the growing research on "women helping women" in professional settings (De Paola and Scoppa, 2015; Bagues and Esteve-Volart, 2010; Bagues et al., 2017; Bertrand et al., 2019; De Paola and Scoppa, 2015; Kurtulus and Tomaskovic-Devey, 2012; Maida and Weber, 2022; Matsa and Miller, 2011). This work contributes to this discussion by highlighting the gender dynamics inherent in coauthorship and demonstrating the differential impact that female superstars have on their female coauthors in economics.

Finally, this study contributes to the ongoing discussion surrounding gender equity in economics. Despite growing efforts to support women in the field, the gender gap persists (Buckles, 2019). This study adds to the literature by 1) highlighting a channel for the self-reinforcement of the gender gap, 2) demonstrating benefits of female superstar coauthorship on women's publication outcomes, and 3) identifying potential gender differences in the factors contributing to research productivity .

The contents of the paper is organized as follows. Section 2 provides background on the gender gap in economics and presents a framework that motivates the research question. Section 3 describes the data used in analyses, and Section 4 details the empirical strategy, including the difference-in-differences design and matching methodology. Section 5 presents the results and their interpretations. Finally, Section 6 concludes by discussing the implications of the findings for future research.

2 A Framework for Understanding the Gendered Superstar Effect

Could coauthorship with female superstars lead to different publication outcomes for junior women compared to coauthorship with male superstars? To explore this question, I present a framework that discusses four key areas: 1) the role of research collaboration and knowledge exchange in research productivity, 2) the potential for coauthorship with superstars to facilitate knowledge spillovers, 3) the gender-based barriers that women face in economics, and 4) the potential for gender differences in the knowledge and skills offered by male and female superstars.

The Role of Collaboration in Knowledge Production

Collaboration is a fundamental element of knowledge production, fostering innovation and research excellence. Prior research establishes a direct link between collaboration and researcher productivity, with publications and citations increasing as collaboration intensifies (Abramo et al., 2017).

This positive effect can be attributed to several factors. Collaboration fosters an exchanging of ideas by bringing together individuals with diverse perspectives and expertise (Beaver and Rosen, 1979; Beaver, 2001; Waldinger, 2010, 2016). This diversity can fuel innovation and enable teams to tackle complex challenges more effectively (Beaver, 2001; Ellison, 2002; Katz and Martin, 1997). Moreover, collaboration can improve research efficiency through effective task division and allocation, leveraging individual strengths and optimizing time management (Beaver, 2001; Barnett et al., 1988).

Beyond technical benefits, collaboration can boost motivation through shared enthusiasm and social interaction (Beaver and Rosen, 1979; Medoff, 2003). Teaming up with prominent researchers can enhance visibility and reputation (Katz and Martin, 1997; Schmoch and Schubert, 2008; Goldfinch et al., 2003).

While collaboration can manifest in various forms, this paper specifically focuses on coauthorship as a central mode of collaboration to study its effects on researcher productivity (Abramo et al., 2017; Bidault and Hildebrand, 2014; Ductor, 2015; Hamermesh, 2013; Laband and Tollison, 2000; Lee and Bozeman, 2005; Li et al., 2013).

Coauthorship and the Influence of Superstars

Coauthorship serves as an ideal conduit for potential knowledge spillovers. It offers a sustained environment for tacit knowledge transfer and skill sharing beyond the impact of shorter-term interventions. It provides an opportunity for collaborators to gain valuable insights throughout an entire research process, observing each other's work styles, navigating publication complexities together, and sharing personal perspectives.

Within the literature exploring knowledge spillovers, there is growing attention on "superstar" academics—those renowned for their exceptional productivity and expertise. Studies by Azoulay et al. (2010) and Khanna (2021) demonstrate a decline in research output for colleagues following the death of a superstar coauthor, highlighting their role as valuable sources of knowledge. Similarly, Mas and Moretti (2009) find evidence of a "productivity spillover" when a highly productive researcher joins a team, but with the benefit limited to those with frequent interactions with the "star." Studies looking specifically at the effects of coauthoring with a superstar demonstrate that stars significantly improve the publication outcomes of their coauthors, potentially accelerating their career advancement and contributing to higher-quality research (Li et al., 2019; Yadav et al., 2023).

However, the "superstar effect" isn't without potential drawbacks for junior coauthors. Shared work with superstars may lead to unbalanced credit allocation, where the superstar's reputation can overshadow the contributions of less established researchers (Merton, 1968). This phenomenon, known as the "Matthew Effect", can skew credit allocation, favoring prominent names over lesser-known contributors. Additionally, gender dynamics might further complicate credit distribution within coauthorship teams. The "Matilda Effect" describes the tendency to attribute women's achievements to their male colleagues (Rossiter, 1993), potentially impacting credit allocation in teams with varying gender compositions. While it's possible that these biases can disproportionately impact female researchers and hinder their career advancement, further research is needed to fully understand the extent of these effects and their implications for gender equity in academia.

Female Barriers in Economics

Economics struggles with a persistent gender gap, with women underrepresented at all levels of the academic profession. A rich literature points to a myriad of challenges that contribute to these disparities. Understanding these gender-based barriers can highlight how female superstars, in navigating a successful career, may possess unique knowledge and skills that can benefit junior women.

Studies suggest that women face implicit gender biases in disseminating research, including higher standards for publication (Card et al., 2020; Hengel, 2022) and fewer opportunities to present their work (Doleac et al., 2021). Combined with a male-dominated environment and a tendency for men to prefer male collaborators (Abraham, 2020; Ductor et al., 2018; McDowell et al., 2006), these biases can limit women's collaboration opportunities and visibility, hindering their professional advancement in the field (Van den Brink and Benschop, 2014). Even when women do collaborate, they often receive less credit for coauthored work, especially when their coauthors are men (Sarsons, 2017).

Women often face societal norms and gender stereotypes that exacerbate these challenges. They are more likely to prioritize family commitments over career advancement (Goldin, 2014), and marriage and children disproportionately affect the tenure prospects of female economists (Ginther and Kahn, 2004). Even gender-neutral tenure clock stopping policies may inadvertently disadvantage women, as they may be more likely to focus on childcare while men may leverage the time extension for research (Antecol et al., 2018).

Additionally, female academics often shoulder unequal workloads. They spend more time on teaching and service (Harter et al., 2011; Manchester and Barbezat, 2013; Taylor et al., 2006), and other "low-promotable" tasks that are considered undesirable yet necessary for the department (Babcock et al., 2017). These contributions are often overlooked in tenure and promotion evaluations, ultimately hindering women's career progression.

The niche culture of academic economics can present unique challenges for women. Traditional economic concepts and assumptions, often rooted in notions of rationality and individualism, may inadvertently favor male-stereotypical traits (May, 2022; Stephens and Levine, 2011; Uhlmann and Cohen, 2007). Economics teaching materials can perpetuate gender biases (Hahn and Blankenship, 1983; Walstad, 1992), and even formal economics education has been linked to increased sexism among its male students (Paredes et al., 2020).

The field's unique norms and practices, such as the style of academic discussions, presentations, and hiring practices, can create a hostile environment that disproportionally affects women (Wu, 2018; Dupas et al., 2021). A 2019 AEA survey reveals that only 25% of female economists feel valued in the field (Allgood et al., 2019), suggesting a problem unique to the field that discourages women from pursuing careers in economics.

These barriers are interconnected and manifest across various professional contexts. This overlap can make it difficult to identify targeted interventions that effectively address the systemic challenges faced by women. The complex nature of the problem may also by why well-intentioned approaches like implementing gender-neutral policies can be ineffective—or even counterproductive—in bridging the gender gap (Antecol et al., 2018).

Star Secrets? Potential Advantages of Female Star Coauthorship

If the goal is to better understand how to support women in economics, studying the effects of coauthorship with female superstars can provide valuable insights. Female superstars, having navigated the challenges faced by women in economics, may possess unique knowledge and skills that can benefit junior women.

But what skills might distinguish a superstar woman from a superstar man? Though the exact mechanisms are out of the scope of this paper, I discuss prior literature that supports the plausibility for gender differences in superstar effects.

It's clear that a difference in cognitive intelligence likely isn't the sole determining factor in male and female success. While intellectual sophistication is important in academia, a woman's technical skills in economics don't automatically address the systemic and social barriers that women face.

Instead, the emerging literature surrounding non cognitive skills lends more credibility to that female superstars likely leverage a range of non-cognitive skills that help them overcome challenges related to being seen, heard, and understood in the workplace.

There's been growing recognition of the importance of non-cognitive skills in shaping career and life outcomes (Chetty et al., 2011; Heckman and Kautz, 2012). Perhaps the most startling evidence is given by Chetty et al. (2011), which examine the long-term impacts of a Tennessee experiment where students and teachers were randomly assigned to classrooms from kindergarten to third grade. The authors find that students who were placed with more experienced kindergarten teachers earned significantly more money by age 25 than their peers. Further analysis reveals subsequent teachers consistently rated these students higher in their capacities to be proactive, prosocial, disciplined, and determined, and that these qualities were retained longer over time. Notably, these non-cognitive skills proved more powerful than early math and reading skills in predicting adult income. This challenges the notion that excellence is determined by natural talent. Instead, it suggests that success begins with nurturing a set of practical skills.

The seminal work of (Chetty et al., 2011) has spurred an emerging literature looking at the influence non-cognitive skills, also referred to as practical knowledge, social skills, and character strengths and how to nurture them (Gutman and Schoon, 2013; Heckman and Kautz, 2012). As the economist James Heckman concludes in a review of the literature, character skills "predict and produce success in life."

While studies have explored non-cognitive skills, fewer have delved into how these skills differ based on gender. Particularly, there's a gap in the research exploring whether men and women leverage different skills in navigating paths to success in economics.

Here are four areas where non-cognitive skills can hold advantage for women:

1. *Effective Communication*. Research by Hengel (2022); Card et al. (2020), and Koffi (2021) suggests women in top economics journals excel at communication, producing clearer and more accessible writing, and receiving more citations. Female superstars may excel at conveying complex ideas strategically and confidently, potentially due to honed communication skills developed in a challenging environment.
2. *Relationship Building*. Despite facing challenges in building networks (Jadidi et al., 2018;

McDowell et al., 2006), successful women may possess skills like emotional intelligence and cultural awareness that allow them to bridge this gap and build strong professional relationships that elevate their careers. (Ginther and Na, 2021) demonstrates that women who participated in a mentoring workshop expanded their networks beyond the workshop group. This highlights the transferable nature of relationship-building skills and the potential for women to develop them.

3. *Work Habits and Character*. Professional success often requires a set of attributes such as adaptability, initiative, time management, attention to detail, and perseverance. Studies looking at high-performing workers in various professions show evidence of women exhibiting qualities like conscientiousness, tenacity, and diligence, which are associated with both high-quality work in their respective fields and traits often attributed to femininity (Roter and Hall, 2004; Jenkins, 2008; Fang et al., 2013; Hatamyar and Simmons, 2003). This suggests that female star economists may develop their own work habits and character skills uniquely suited for the economics profession, differing from those of male economists.
4. *Strategic Savvy*. The world of economics publishing can be intimidating, especially for those unfamiliar with it or face greater scrutiny. Strategic acumen, including the ability to navigate social politics, make calculated decisions, and manage time effectively, is crucial for success. Superstars are often sources of this strategic savvy. Research by Oettl (2012) identifies "helpfulness" as a key mechanism for how superstars influence peers, suggesting that tailored guidance is important in producing research. Additionally, Blau et al. (2010) highlights how female mentors can provide guidance that enhances mentees' publication and tenure success in economics. Coutts et al. (2023) finds that men are more likely to withhold constructive criticism from female advisees, potentially hindering their growth. Early-career women may benefit from the insights and strategies of female superstars who have navigated similar experiences.

Non-cognitive skills, such as effective communication, relationship-building, work habits, and strategic career management, are crucial for professional success. Yet, these skills are often overlooked in academia, which tends to prioritize achievement tests and metrics. Studies indicate a mismatch between the "hard" technical skills prioritized by the education sector and the mounting demand for "soft" social skills by the industry (Börner et al., 2018). This might reflect a topic being overlooked by academic researchers, particularly in circles that extoll empirical evidence, which can favor the study of more tangible and readily measurable factors.

These skills can be particularly effective in overcoming gender barriers. Because non-cognitive skills involve understanding the cultural landscape, reading social contexts, and knowing how to employ them to fit one's agency, female superstars, who have successfully navigated these challenges, are likely the best group of people to possess the most valuable and relevant non-cognitive skills for junior women. Importantly, these skills are acquired through learning and nurture rather than nature. This is particularly comforting given the findings of Hale and Regev (2014); Patnaik et al. (2023); Porter and Serra (2020) that highlight the influence of female role models in inspiring and encouraging women to pursue careers in economics.

This paper explores the potential for such effects by focusing on coauthorships as a channel for skills transfer and female superstars as sources of knowledge. By investigating gender effects of superstar coauthorship on juniors' publication outcomes, this study aims to uncover whether there are "star secrets" that contribute to female success in economics. If so, it can illuminate a missing piece of the gender parity puzzle in economics.

3 Data

To evaluate the impact of superstar coauthorship on the publication outcomes of junior economists, I construct a comprehensive dataset of scholarly publications.

The source of my publication data is OpenAlex, a freely accessible online bibliographic catalog of scientific papers, authors, and institutions. To compile my dataset of publications, I identify economists[1] affiliated with US institutions who actively published between 2000 and 2021.[2] This timeframe ensures inclusion of junior researchers starting their publication careers during this period and their potential superstar coauthors. I collect full publication histories of these researchers, providing a complete record of US economists who were publishing into the 2000s. Researchers who ceased publication prior to 2000 are excluded in their entirety.

Each publication record includes details such as publication date, journal, ordered authors,

[1] The OpenAlex platform uses concept tags to categorize research. Each work is assigned multiple concepts based on its title, abstract, and journal title. These concepts are then aggregated to the author level. In this study, "economists" are defined as researchers whose top three assigned concepts include "economics." Detailed information on OpenAlex concepts and their generation process can be found at: https://docs.openalex.org/api-entities/concepts.

[2] Data collection was done in May, 2022.

their affiliated institutions, and total citations (at year of collection). To ensure data integrity, only published, peer-reviewed articles in journals indexed by Elsevier's Scopus Database are considered.

The publication data is supplemented with journal metrics from Elsevier's Scopus Database, using the source normalized impact factor (SNIP) as a proxy for journal quality. To identify the gender of authors, I use the Namsor software, which assigns predicted gender scores to full names. I link researcher affiliations to global rankings and institutional characteristics using data from IDEAS/RePEC and IPEDS, respectively.

Definition of Sample and Treatment

The data collection yields a comprehensive dataset of full publication histories for 60,054 US economists who were actively publishing between 2000 and 2021. Of these researchers, I'm interested in two specific groups: 1) early-career junior economists, who form the basis of my study, and 2) superstar economists, whose coauthorship defines my treatment variable.

Junior economists are defined as those initiating their publishing careers between 2000 and 2010 (11 cohorts). Since tenure is a key career milestone where women are particularly vulnerable, my study focuses on the pre-tenure years, which are assumed to be the first 5 years of a researcher's publishing career (considered the "treatment period").

Superstar economists are defined as those ranking within the top 95th percentile of cumulative citations of articles published over the past 10 years,[3] following the example of Li et al. (2019). Superstar status is determined year-by-year starting from 1980 and once achieved, it is retained.

Unmatched Sample of Junior Economists

Of the 60,054 actively publishing economists, 22,046 are junior economists, and 5,073[4] are identified as superstar economists. Among the 22,046 junior economists, I restrict the sample to those with at least a 5-year publishing career (17,703), measured from their first publication to their most recent publication. This ensures that all juniors in my analysis have persisted through an "early career"

[3]Cumulative citations for an individual in year y is the sum of their total citations from publications released in years k, where $y - k \leq 10$. For example, an author's cumulative citations in 2000 would encompass all citations from publications dated between 1990 and 2000.

[4]Note that although superstars are defined as the top 5% of cumulative citations, the annual determination of superstar status starting from 1980 leads to an accumulation of superstars over time in the sample. This is because once an economist achieves superstar status in a given year, they remain a superstar in subsequent years, even if their citation count falls below the top 5% in those later years.

period in which they have an opportunity to coauthor with a superstar within the treatment period. From this pool, I identify junior economists who collaborated with a superstar within their first 5 years of publication (4,547) as the treated group, while those who did not are the control group (13,156). To isolate the effects of superstar gender, I exclude junior economists who coauthored with both a female and male superstar in the same treatment year (196 out of 4,547). This yields 4,351 treated junior economists[5] and 13,156 controls.

For each junior, I collect the first 12 years of publications. This decision is primarily driven by data availability, as the last cohort begins their publication careers in 2010 and the latest publication data is from 2021, limiting the analysis to a 12-year window. Each junior's publication history is aggregated to the year level, creating a panel covering the publication histories of 17,507 juniors across 12 years, resulting in 210,084 author-year observations. I refer to this dataset as the unmatched sample.

While the control group (junior researchers without superstar coauthorship) provides a baseline for counterfactual outcomes, a simple comparison between treatment and control may not be sufficient due to potential selection bias. In the next section, I detail my identification strategy to address these concerns, including a matched-sample design that aims to identify comparable controls.

4 Identification Strategy

This study uses a difference-in-differences and a matching design to examine gender differences in the impact of superstar coauthorship on publication outcomes of junior economists. In this section, I discuss the primary sources of selection bias that threaten identification, how matching aims to address these sources, and the estimating equations used to estimate the effects of superstar coauthorship.

[5]This group of 4,351 treated juniors comprises those who coauthored with a superstar within the first 5 years into their career ($1 \leq t \leq 5$). When executing coarsened exact matching, however, only those with a previous publication history (t-1) are able to be matched, resulting in the exclusion of 2,272/4,351 juniors whose first star coauthorship occurred in year t=1. These juniors are excluded from the matched sample.

Sources of Selection Bias

There are three primary sources of selection bias in the context of my study: 1) the junior's willingness and opportunity to coauthor, 2) the junior's willingness and opportunity to coauthor or be asked to coauthor with a superstar, and 3) gender preferences in superstar coauthorship. The key underlying concern is whether any of these coauthorship choices are related to juniors' publication outcomes through potential omitted variables.

The first primary concern is that juniors who successfully coauthor may differ from those who don't. To address the first concern, I ensure that all matched controls have coauthored (with a non-superstar) in the same treatment year. This helps mitigate the potential bias from unobserved factors related to the decision to coauthor, such as resourcefulness or gregariousness. Since both treated and matched controls will have demonstrated coauthorship concurrently, they are also likely to be similar in unobserved factors related to the decision to coauthor.

The second source of bias arises from the possibility that juniors who coauthor with superstars may differ systematically from those who coauthor with non-superstars. More ambitious or productive juniors might be more likely to seek out superstar collaborators, or superstars may selectively choose to collaborate with high-potential junior researchers. To address this, I ensure that treated and control groups are balanced across observable characteristics related to pre-treatment ability and proximity to stars, such as past publication activity, network size, propensity to coauthor, institutional rank, and the presence of other superstars. Most notably, I match researchers based on the total stock and change of number of publications and publication quality up to the year of treatment. This helps ensure that treated and control researchers are publishing at comparable levels and rates up to the time of treatment, making it more likely that they would have continued to trend similarly absent of treatment.

The third potential source of selection bias is gendered preferences in collaborations between junior and superstar economists that are related to juniors' publication outcomes. The plausibility of this scenario affects how the results should be interpreted: whether the observed effects are due to a causal effect of superstar coauthorship or due to a selection effect.

It should be noted that for this third source of selection to be a concern, there must be unobservable covariates that are gender-specific, correlated with the junior's decision to coauthor with a superstar of a particular gender, and correlated with the juniors' publication outcomes. Nevertheless, even if this source of selection bias is present, the findings would still be interesting and warrant further investigation. Therefore I will discuss the potential plausibility of this third source of selection bias and their respective interpretations in more detail in Section 5 after presenting the results.

Essentially, in order for a matching method to address selection bias, it relies on the assumption that after matching treated and control units on observable characteristics, any difference in outcomes reflects the causal effect of treatment, and not the influence of some unobserved variable (i.e. selection is based only on observables).

Staggered Treatment Effects

Another potential concern is the "differential timing" of treatment, where there's staggered assignment of treatments across units over time (**?**). In these cases, the adoption of some treatment will tend to be differentially timed across units, leading to potential time-varying treatment effects that can bias estimates.

To mitigate this concern, I focus on early-career superstar coauthorship, limiting the treatment window to the first five years of a junior economist's career. This reduces the likelihood of significant treatment effect heterogeneity. Additionally, I match to ensure that control researchers never collaborate with a superstar during the analysis period (years 1-12)[6]. This approach avoids the potential for negative weights on the average treatment effect (ATE), which can occur when controls become treated over time (De Chaisemartin and d'Haultfoeuille, 2020).

Coarsened Exact Matching

To address potential sources of selection discussed above, I construct a matched sample using coarsened exact matching (CEM). This method involves selecting a set of covariates carefully governed by the criteria discussed above. Next, a large number of strata are created to cover the entire support of the joint distribution of the selected covariates. Finally, each observation is allocated to a unique strata, and for each observation in the treated group, a control observation is selected from within the same strata. This matching process aims to achieve balance between treated and matched controls across selected covariates, which can be checked.

[6] The decision to restrict the analysis to 12 years is primarily driven by data availability. Given that the last cohort begins their publication careers in 2010 and the latest publication data is from 2021, a 12-year window represents the maximum balanced panel I can construct.

A key advantage of CEM is the ability to guarantee the degree of covariate balance by determining the cutoff points of the strata. However, this decision comes at a cost: imposing narrower divisions of the support for the joint distribution (i.e., the higher the number of strata) risks a larger number of unmatched treated observations. Therefore, matching involves a trade-off between balance and sample size (full support).

A major concern is that treated and control juniors may differ in terms of unobserved ability. While matching methods aim to control for observable characteristics, ability can be difficult to capture directly. To mitigate this concern, I tighten the matching criteria by requiring all treated and potential matched controls to have a pretreatment period. This allows for more accurate matching, as I can observe juniors' pre-existing ability based on their publication history. This approach aims to capture unobserved ability, to the extent that it is reflected in publication outcomes, more effectively.

Construction of Matched Sample

Figure 1a provides a visual illustration of the pool of treated and control juniors to be matched. Of the treated and control juniors in the unmatched sample, a select subset are candidates for matching. The treated candidates consist of junior economists who collaborated with a superstar in years 2 - 5 of their career (2,079), which introduces a pretreatment period to tighten the match. The control candidates consist of juniors who did not coauthor with a superstar within the balanced panel period of 12 years (10,465), which mitigates potential treatment effects in this group.

The following covariates are used for matching (measured at the year prior to the first superstar collaboration, t-1): the cumulative stock of publications in year t-1, the flow of publications into year t-1, the cumulative stock of SNIP-weighted publications in year t-1, the flow of SNIP-weighted publications into year t-1, the number of previous co-authorships at t-1, the average team size per publication at t-1, the share of coauthored publications at t-1, the rank of affiliated institution in t-1, and the presence of superstars within affiliated institution in t-1. Strata are also defined to guarantee exact match in gender and to guarantee that both treated and controls have a coauthored publication in year t.

The CEM procedure is applied yearly (by career age), and it involves one-to-one matching without replacement. This ensures that a superstar collaborator (treated) is matched with a non-star collaborator (control) of the same career age and gender, with similar publication history, institutional affiliation, and coauthoring behavior. A detailed explanation of the matching procedure can be found in the Appendix.

Of the 2,079 treated juniors who exhibited prior publication history, 1,687 (81.5%) were successfully matched with 1,687 controls, resulting in a total of 3,374 juniors. Ensuring equal post-treatment observation periods for this group of juniors, this yields a panel of 36,106 author-year observations. I refer to this dataset as the matched sample.

There are three key features of my matched sample:

1. *Pre-publication history*: Treated and control researchers must have published prior to collaborating with a superstar (or non-superstar). This means that the matched sample will exclude treated juniors who initiate their publication career with a superstar collaboration (i.e., in year 1). While this reduces the sample size and imposes a stricter restriction than that of previous matching studies (Li et al., 2019), it ensures that I can observe and thereby control for a junior's preexisting publication ability.
2. *Non-treated controls*: Control researchers are identified from the pool of those who do not collaborate with a superstar during the analysis period (years 1-12). This helps mitigate concerns related to staggered treatment effects.
3. *Equal follow-up periods*: The matched sample is restricted to a panel covering the subsequent 7 years after treatment (star collaboration) for all matched researchers, ensuring equal post-treatment observation periods. Because the latest cohort is 2010, with 2021 as the last year of the panel, 12 years is greatest lower bound of observed years, and the treatment period is the first 5 years into a junior's career, this leaves 7 years following treatment as the. Ensuring equal post-treatment observation periods helps minimize selection bias that may arise from differences in the length of time researchers are followed while enforcing this cutoff point ensures that treatment effects do not emerge in controls (who are treated after 12 years into their career).

The matched sample is not perfectly representative of junior economists. The publication histories collected consist of peer-reviewed publications in Scopus-indexed journals, potentially limiting the representativeness of the sample. Additionally, the matched sample includes only individuals with at least a pretreatment period, meaning they must have at least two separate years of Scopus journal publications, and a publication career spanning at least 5 years (time from first to most recent publication). This may exclude some junior economists who did not publish in Scopus indexed journals or who had shorter publication careers. Because matched units in each treatment group will not resemble the overall sample, estimates represent an average treatment effect for the matched sample (ATM). While the matched sample may not be perfectly representative of the population, it provides a more robust approach to studying the question of gender differences in superstar coauthorship effects.

Covariate Balance & Sample Size

After obtaining the matched pairs, I confirm that the CEM process successfully balances pre-treatment outcomes and key covariates across treated and control groups. The results in Table 1 indicate that the matched sample is comparable in terms of publication productivity, history of coauthorship, and institutional affiliations.

However, achieving tighter comparisons can come at the cost of reduced sample size. Of the pool of 2,079 treated candidates to be matched, 1,687 (81.14%) were successfully matched to a control, leaving 392 treated juniors unable to be matched. The exclusion of these high-impact cases could lead to biased estimates of the overall impact of superstar coauthorship.

Table 2 displays a means comparison of covariates for treated juniors unable to be matched and those successfully matched. We can see that the 392 unmatched treated juniors are significantly different from the matched juniors, primarily in terms of pre-existing publication ability. Unmatched juniors are more prolific, more likely to coauthor, and more likely to be affiliated with top institutions. While these unmatched juniors may experience even larger benefits from superstar collaboration, their exclusion from the analysis may lead to a conservative estimate of the treatment effect.

Table 4 illustrates this point by splitting the matched sample into higher and lower quality publishing groups (based on SNIP-weighted publications prior to treatment). It demonstrates that the impact of superstar coauthorship is stronger for both men and women in the higher-publishing group, suggesting that the excluded high-performing researchers are likely to experience even larger positive effects, and therefore positive estimates may be interpreted as the lower bound.

Empirical Specification

Using the matched sample, I examine the effect of early superstar coauthorship on juniors' publication outcomes in a difference-in-differences. I conduct this analysis separately for a sample of junior female economists and a sample of junior male economists.

The following equation compares the changes in publication outcomes of junior researchers who collaborate with a (any gender) superstar economist to those who collaborate with a non-superstar, before and after collaboration occurs:

$$Y_{it} = \alpha_1 PostTreat_{it} + \beta(PostTreat_{it} \times Superstar_i) + f(age)_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

where Y_{it} represents the annual number of publication outcomes by junior author i in year t. The main independent variable, $(PostTreat_{it} \times Superstar_i)$, is an indicator that captures the years following superstar collaboration, multiplied by an indicator for whether the junior researcher is treated (i.e., collaborates with a superstar within the first 5 years of their career). I include a full set of career age fixed effects, denoted as $f(age_{it})$, which is defined as the number of years passed since an author's first publication. The terms $\gamma_i and \delta_t$represent author and year fixed effects, respectively. To address potential correlations and unobserved differences among researchers, standard errors are clustered at the author level.

My primary analyses are interested in differential effects by superstar gender. This involves a triple-differences approach to compare publication changes pre and post-collaboration across three groups: 1) junior researchers who coauthor with a female superstar, 2) junior researchers who coauthor with any gender superstar, and 3) matched junior researchers who coauthor with a non-superstar. To do this, I run the following equation separately for female junior researchers and for male junior researchers:

$$\begin{aligned} Y_{it} = \ & \alpha_1 PostTreat_{it} + \alpha_2(PostTreat_{it} \times Superstar_i) \\ & + \beta(PostTreat_{it} \times FemaleSuperstar_i) \\ & + f(age)_{it} + \gamma_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where the variable of interest, $(PostTreat \times FemaleSuperstar)$, is an interaction term capturing the differential effect of collaborating with a female superstar compared to a male superstar.

Estimates are reported using ordinary least squares models where outcome variables are transformed using the inverse hyperbolic sine. Given that my outcome variable pertains to an author's annual publication counts, which is countable and a relatively long publication cycle, this is a popular approach for count data that is censored at zero and often highly skewed toward zero.

Estimates are robust to using a maximum-likelihood Poisson regression, which is also specifically suited for count data (see Appendix).

5 Results

Before delving into regression analysis, I examine trends emerging in the raw data of the matched sample. Figure 2 illustrates average annual publication counts for junior economists, categorized by gender of the junior. The x-axis represents years from first superstar coauthorship (time of treatment) for matched treated and controls, where 0 indicates the year of treatment, -4 to -1 are years pre-treatment, and years 1 to 7 are post-treatment. Each data point represents annual publication counts for a given year, averaged across junior women (red) and junior men (blue) who coauthor with a superstar (solid lines) and their respective controls (dotted lines).

First, it's important to note from these figures that, in the years leading up to the year of treatment, treated and control groups for both men and women trend quite similarly in annual publication rates. Additionally, in the year of treatment, treated and control groups publish at a similar level of publication counts. This suggests that, absent treatment, these groups would likely continue to trend similarly (parallel trends).

Figure 2a, presents trends in annual publication rates leading up to and following star coauthorship, when superstar gender isn't considered. We see that in years leading up to treatment, treated and control researchers are trending similarly in publication counts. However, immediately after treatment, a stark difference emerges. Junior men who coauthor with a superstar (solid blue line) appear to produce a higher rate of annual publications compared to junior women who coauthor with a superstar (solid red line), although both female and male juniors who coauthor with a superstar publish at higher rates following treatment than matched controls (dotted lines). This may lead one to believe that, if superstar gender isn't considered, junior men seemingly benefit more from superstar coauthorship than junior women.

A more interesting pattern emerges, however, when the superstar effect is disaggregated by superstar gender. Figure 2b presents publication trends when considering only star coauthorship with a male superstar. It shows a fairly consistent narrative, with junior men outperforming women after male superstar collaboration. This is somewhat to be expected given the greater prevalence of male superstars in the field that contribute to the aggregate superstar effect. But, if we look at publication trends following coauthorship with a female superstar, the gap between junior male and female publication rates significantly narrows after star coauthorship (Figure 2c). This suggests that the gender of the superstar plays a pivotal role in how star coauthorship affects junior collaborators, particularly when the superstar and junior partnerships are between women. We see that, when the superstar is a woman, junior women coauthor with a star seem to be able to close the productivity gap and produce publications at a comparable rate to that of junior men who coauthor with a star. This indicates that there's a potentially gender-specific knowledge being transferred that leads to a publication boost for women.

Figure 2d and Figure 2e present the data from another perspective, depicting the trends disaggregated by superstar gender but comparing the trends within a sample of female juniors and a sample of male juniors. This allows us to more easily see how junior males or females are affected by the gender of their star coauthor. Here, the gender effect among female juniors is more evident: junior women seem to be significantly more affected by the superstar's gender, showing a marked improvement in publication rate after coauthorship with a female star (Figure 2d). In contrast, junior men seem less affected by their superstar coauthor's gender, with those who coauthor with a female star and those who coauthor with a male star trending more similarly following treatment (Figure 2e).

Turning to regression analyses, I compare the change in publication outcomes of juniors who coauthor with superstars with that of matched controls. Table 3 presents regression results using an OLS regression with inverse-hyperbolic sine-transformed outcomes of annual publication counts (top panel) and SNIP-weighted publications (bottom panel). The estimated coefficients can be interpreted as elasticities and represent the average treatment effect in the matched sample. Columns 1 - 6 report regression results for the matched sample of female juniors, and Columns 7 - 12 for male juniors.

Table 3, Columns 1 and 7 report the average change in annual publication outcomes following collaboration with a superstar (of any gender), compared to matched controls (Equation 1). Consistent with the trends shown in Figure 2a, regression results find that, following superstar collaboration of any gender, both junior men and women experience an average boost in annual publication rate and publication quality compared to matched controls. Specifically, coefficients indicate that, on average, junior women produce 18% more publications per year and a 25% increase in annual SNIP-weighted publications after coauthoring with a superstar (Columns 1), while junior men produce 20% more publications per year on average and a 28% increase in annual SNIP-weighted publications (Columns 7). This supports previous findings of Li et al. (2019) and Yadav et al. (2023) who find evidence of positive impact of superstar coauthorship on publication outcomes of researchers outside of economics.

However, I am particularly interested in disaggregating the superstar effect by superstar gender. Table 3, Columns 2 - 6 and 9 - 12 report estimates when I interact superstar treatment with a female dummy of the star's gender (Equation 2). The coefficient of interest here is ($PostTreat \times FemaleSuperstar$) which captures the differential change in outcomes of collaborating with a female superstar, holding the general superstar effect constant. Confirming the narrative depicted in Fig:trends-female-junior, the positive and significant coefficient for ($PostTreat \times FemaleSuperstar$) in the female junior sample indicates that junior women improve in publication outcomes after coauthoring with any gender superstar, but they publish even more frequently and in higher impact journals when their superstar coauthor is a woman (Columns 2 - 6). Junior men, on the other hand, seem to be potentially hindered if their star collaborator is a woman, as indicated by a negative coefficient (Columns 8 - 12), although these estimates are not statistically significant. This reinforces the finding that junior women are significantly impacted by the superstar's gender, benefiting particularly when their coauthor is female, while junior men benefit from coauthoring with any gender superstars, but without a significant difference based on star gender. These findings are robust when using a Poisson maximum-likelihood regression.

Thus far, the evidence suggests that female junior economists benefit more from coauthoring with female superstars, while no such gender effect is apparent for junior men. Now, I ask: which type of junior women may benefit most from female superstar coauthorship?

It might be the case that junior women who struggle most in the field have the most to gain from learning from seasoned women, as they might face more salient obstacles in publishing that star knowledge can help mitigate. Alternatively, more capable junior women might be better equipped to apply practical knowledge gained from female superstars to increase their research productivity. It's possible that the specific knowledge imparted by star women alone is not enough to help junior women overcome challenges, but rather requires a combination of prior publication ability to effectively apply the knowledge.

To delve deeper into these hypotheses, I explore potential heterogeneous effects. Specifically, I examine whether the publication boost from collaborating with a female superstar varies based on a junior's pre-existing publication ability. To do this, junior women and men are subsetted into quantile groups based on their cumulative level of SNIP-weighted publications taken at the year prior to treatment. I focus on SNIP-weighted publications as opposed to publication counts because SNIP-weighted publications provide a more continuous measurement that serves as a proxy for publication quality. Using the middle quantile cutoff, I run separate regression analyses on superstar coauthorship effects of juniors for the upper and lower median of cumulative SNIP-weighted publications.

Table 4 presents results from subsetting junior women and men into two groups: those with below-median and above-median cumulative SNIP-weighted publications before collaboration (at t-1).

When we focus on the group of junior women (Columns 1-4), the positive and significant coefficient for $(PostTreat \times AnyGenderSuperstar)$ in both below and above median cumulative SNIP-weighted publications junior women indicates that junior women across the board see an improvement in publication outcomes following superstar coauthorship compared to matched controls. A comparison of the $(PostTreat \times FemaleSuperstar)$ coefficients for the sample of junior women below median SNIP (Columns 2) to the sample of junior women above median SNIP (Columns 4) reveals that the positive differential effect of coauthoring with a female superstar compared to a male superstar is larger for junior women of higher observed publication ability. This suggests that junior women with higher pre-existing publication ability are better equipped to leverage the potential benefits of female superstar coauthorship, which contributes to their larger improvements in publication quantity and quality.

When focusing on the group of junior men (Columns 5 - 8), the table shows little evidence of differential effects of the superstar coauthor's gender, as expected from the main analysis. It shows that coefficients for $(PostTreat \times AnyGenderSuperstar)$ remain positive and significant when including the interaction $(PostTreat \times FemaleSuperstar)$ in the estimating equation. This indicates that junior men who coauthor with any gender superstar experience an increase in the quantity and quality of publications in following years. Rather interestingly, the table reports a positive coefficient for $(PostTreat \times FemaleSuperstar)$ for junior men below the median SNIP (Columns 6) and a negative coefficient for junior men above the median SNIP (Columns 8), suggesting that having a female superstar coauthor may be less beneficial only for higher ability men. However, these estimates are quite noisy, with the coefficient for outcomes of annual publication counts being only significant only at the $\alpha < 0.1$ level, and coefficient for outcomes of annual SNIP-weighted publications being statistically insignificant.

Overall, Table 4 suggests that junior women with higher pre-existing publication ability may be better able to leverage the potential benefits of female superstar coauthorship compared to matched controls. The same seems to apply to high ability men who benefit more from male superstars, although the gender effect is less pronounced for that group as a whole. This implies that both men and women may be receiving valuable gender-specific knowledge from superstars, but this knowledge is more effective or applicable when combined with prior ability.

Potential Selection Effect

In order to imply causality for the results above, the assumption must hold that any difference in outcomes between the treated and control groups reflects the causal effect of treatment, and not the influence of unobserved variables that were not controlled for in the matching process. While the matching process strives to balance treated and control groups on observable characteristics, the possibility of unobserved gender-specific factors influencing coauthorship decisions remains.

Given that the results indicate a positive gender effect of female superstars on female juniors, I focus on considering whether highly productive junior women may be more likely to select into coauthorship with female superstars. For this source of selection to be a concern, there must be unobservable factors that are specific to female juniors, correlated with their decision to coauthor with a female superstar over a male superstar, and correlated with the juniors' publication outcomes. While there is limited research directly addressing this issue, we can draw on existing literature on gender dynamics in academia to consider the plausibility of such selection.

There are two primary channels for this to happen. In one channel, the selection may be influenced by the juniors' choices regarding which gender of superstar to coauthor with. If highly driven and productive junior women systematically choose to coauthor with female superstars, then the positive effects of female superstar coauthorship may be upwardly biased. While possible, there is evidence to suggest variation in gender preferences. In general, there's no clear consensus in the literature on whether male or female star coauthorship would be generally more advantageous for a junior woman. Moreover, although individuals may have strong preferences in the gender of their coauthors, these decisions are often personally motivated, and intentions can vary widely. For example, an ambitious junior woman might choose to coauthor with a male star to benefit from their reputation, while another might prefer a female star to avoid potential gender biases in credit allocation. These varying motivations make it less likely that a systematic selection effect is driving the results.

There are two primary channels for this to happen. In one channel, the selection may be influenced by the juniors' choices regarding which gender of superstar to coauthor with. If highly driven and productive junior women systematically choose to coauthor with a female superstar of a particular gender, then the positive effects of female superstar coauthorship may be upwardly biased.

While it is possible that productive junior women may have a preference for female superstar coauthors, there is limited evidence to support this claim. For an ambitious junior woman, it is unclear whether coauthoring with a female superstar is more advantageous than a male superstar. While individual preferences may influence these decisions, the personal motivations behind coauthorship choices are complex and can vary widely. For example, a junior woman might choose to coauthor with a male star to benefit from their reputation (Sekara et al., 2018), while another might prefer a female star to avoid potential gender biases in credit allocation (Sarsons, 2017). These varying motivations make it less likely that a systematic selection effect is driving the results.

In another channel, selection bias could arise if superstar women systematically select high-performing women. Since the matching process aims to control for observable characteristics, this potential selection effect implies that superstar women must be able to recognize and selected based on unobserved talent in junior women that male superstars may overlook.

Although there is limited literature exploring the potential for women to recognize unobserved female talent, the literature on gender biases offers a complex picture. While both men and women may exhibit biases, there is also evidence of variation in individual behavior. For instance, research has identified the "queen bee phenomenon," where women in leadership positions, particularly in male-dominated organizations, may distance themselves from other women and perpetuate gender inequality (Derks et al., 2016; Kanter, 1977; Staines et al., 1974). Given this complexity, it makes it less likely that superstar women are systematically selecting junior women based on their unobserved productivity.

Due to the lack of prior research specifically on this topic, it is difficult to definitively state whether female superstars are more likely to recognize and select productive junior women. Further research is needed to explore this possibility and accurately determine the direction and magnitude of any such effect.

Alternative Explanations of the Gender Differences in the Superstar Effect

Even if productive junior women systematically pursue superstar coauthorships with women or that superstar women are better able to recognize the most promising junior females based on unobservable characteristics and systematically choose to coauthor with them, these findings are still valuable. Although this would violate a causal interpretation of the superstar coauthorship effect, it alludes to other mechanisms at play.

One potential alternative explanation is that, rather than coauthorship with female superstars having a causal effect on women's publication outcomes, talented junior women may simply choose to work with female stars. This would suggest that junior women who tend to persist and succeed in publishing in economics have a preference to work with female stars over male stars. If the goal is to understand how to recruit and support women in economics, this could imply that the field's lack of female superstars (15%) may be contributing to its difficulty in attracting and retaining talented women.

Another alternative explanation is that female superstars may be more effective at identifying and selecting talented junior women for coauthorship. This could suggest that female superstars possess a unique ability to recognize potential in junior women, or may be more willing to collaborate with them. If the goal is to understand the factors contributing to female success in economics, this can highlight potential female-specific characteristics of success that may go unnoticed by male-dominated networks.

However, there is limited evidence that these alternative mechanisms are at play. Instead, the more robust literature on non-cognitive skills and their effect on professional outcomes provides a more plausible explanation.

Nevertheless, even if superstar women are better able to recognize the most promising junior females based on unobservable characteristics, examining gender effects in this scenario could still be valuable. This could reveal unobserved determinants of female success in the field that go unnoticed by the male majority. This would support the mechanism of female superstar "secret" of understanding the most promising skillsets for junior females to succeed in the field. However, because there is limited evidence that this mechanism, the ability of female superstars to recognize unobserved female talent, is likely to be systematically driving the observed gender effects. Instead, the more robust literature on non-cognitive skills and their effect on professional outcomes provides a more plausible explanation.

While both men and women have been documented to exhibit gender bias, there is also evidence of variation in individual behavior. It is unclear whether female superstars would systematically select female junior researchers based on gender, or if other factors, such as research interests and potential for collaboration, would be more influential.

Therefore, while the possibility of selection bias cannot be entirely ruled out, it is important to consider the complexity of human behavior and the various factors that influence coauthorship decisions In another channel, selection may originate from the superstar's perspective. If superstar women systematically select high-performing women, this could lead to a biased estimation of the treatment effect. Because I strive to match juniors based on observable measures related to pre-existing publication ability and I match them exactly on gender, this helps to ensure that treated and control men and women are similar in terms of observed ability. Therefore, superstar women must be able to recognize unobserved talent in junior women that male superstars cannot. To assess the plausability of this, it might be worth noting that research on gender bias and stereotypes presents a complex picture. Assuming that one's internal biases influence their perception of others or how they interact with them, the literature offers little consensus on how star women or star men would engage with juniors. Although the literature provides strong evidence that both men and women are prone to female discrimination in academia (Bagues et al., 2017; Bohren et al., 2019; Bornmann et al., 2007; De Paola and Scoppa, 2015; Hospido and Sanz, 2021), it also offers heterogeneity in how individuals behave under their biases. For instance, a body of research has identified the "queen bee phenomenon" in specific scenarios, whereby aspiring women leaders assimilate into male-dominated organizations by dissociating themselves from junior women and legitimizing gender inequality in their organization (Derks et al., 2016; Kanter, 1977; Staines et al., 1974). While underlying gender biases can certainly be systematic, there seems to be contextual and behavioral variation (Arvate et al., 2018; Derks et al., 2011; Kremer et al., 2019), and it's not clear how female or male superstars would make individual selections for coauthorship.

Although there's literature to suggest that gender preferences are likely to be varied as opposed to driving a selection effect, this does not necessarily mean that they do not exist.

Nevertheless, even if superstar women are better able to recognize the most promising junior females based on unobservable characteristics, examining gender effects in this scenario could still be valuable. This could reveal unobserved determinants of female success in the field that go unnoticed by the male majority. This would support the mechanism of female superstar "secret" of understanding the most promising skillsets for junior females to succeed in the field. However, because there is limited evidence that this mechanism, the ability of female superstars to recognize unobserved female talent, is likely to be systematically driving the observed gender effects. Instead, the more robust literature on non-cognitive skills and their effect on professional outcomes provides a more plausible explanation.

6 Conclusion

This study investigates the impact of coauthorship with "superstar" economists on the publication outcomes of junior economists, with a particular focus on potential gender differences. Analyzing a dataset of U.S. economists, I find that early coauthorship with a superstar, regardless of gender, benefits both junior men and women. However, the study reveals a more nuanced picture when examining gender effects.

For junior women, coauthorship with a female superstar leads to a greater increase in publication frequency and impact compared to coauthorship with a male superstar. This suggests that female superstars may be transferring knowledge or skills that are particularly valuable for junior women in navigating the economics profession. Conversely, junior men's publication outcomes did not differ significantly based on the superstar's gender. This implies that female star knowledge spillovers may not be as crucial for male success.

Further analysis reveals that for junior women, the benefits of female superstar coauthorship are amplified for those with higher pre-existing publication ability. This suggests that a combination of prior ability and the knowledge gained from female superstars is most effective for driving publication success.

While the specific mechanisms remain to be explored, existing literature highlights the importance of non-cognitive skills in career outcomes. These skills, such as communication, relationship building, and work habits, can be crucial for navigating professional obstacles, particularly for women facing gender-based barriers. Female superstars, having successfully navigated such challenges, may be uniquely positioned to transfer these skills to junior women.

This work contributes to the understanding of superstar effects, gender dynamics in academia, and how to promote gender equity in economics. First, it expands our knowledge of how superstar coauthorship affects peers by considering gender. Second, it highlights superstar economists as potential sources of knowledge transfer, particularly for junior women. Third, it contributes to research on "women helping women" in academia by demonstrating coauthorship as a channel for skill transfer. Finally, this study emphasizes the influence of gender-specific skills and knowledge in supporting women in economics.

This study has limitations. One limitation is the reliance on publication outcomes as the sole measure of success. This can perpetuate existing biases in how academics are valued. Future research should also consider other forms of research contributions. Additionally, the exact nature of the knowledge transfer from female superstars remains unclear. Future work should delve deeper into the specific skills and contexts that influence successful knowledge transfer across genders.

Moreover, although these findings support the potential of gender-based approaches for supporting women in economics, the ultimate goal should be to create a truly equitable research environment. While female superstar knowledge may help women compensate for current inequalities, the larger aim should be to address the underlying barriers that hinder women in the first place.

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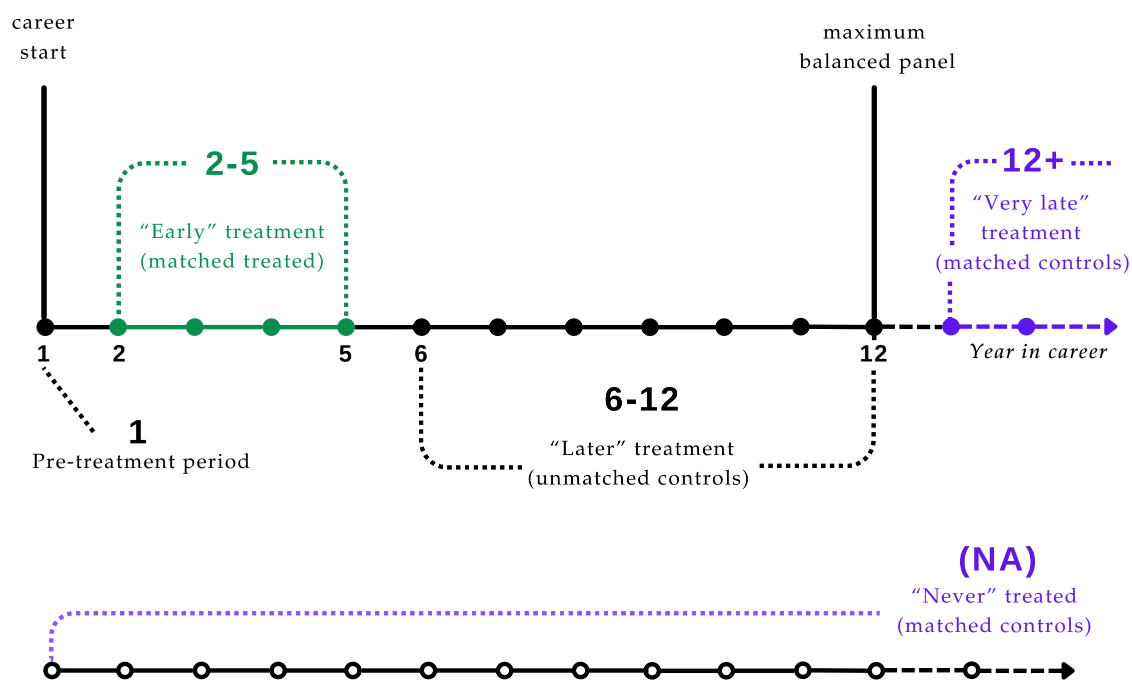
Tables and Figures

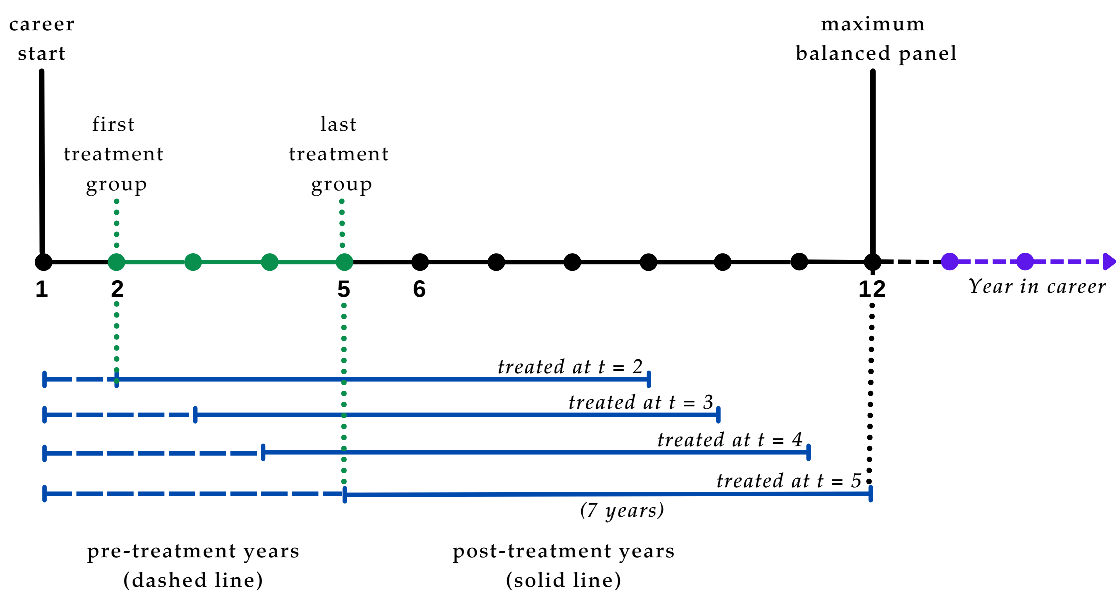
Figure 1: Visualizing the Matched Sample Construction

(a) Definition of Treated and Control Groups



Notes: This figure demonstrates how treatment groups are defined, the treatment group for which controls are matched, and the pool of potential controls for matching.
[a] The timeline represents the years of a junior economist's publication career, and each solid dot indicates the year in which a junior first collaborates with a superstar. Given that the last cohort begins their publication careers in 2010 and the latest publication data is from 2021, a 12-year window represents the maximum balanced panel I can construct. [b] Pre-treatment period: Years before the first superstar collaboration (year 1). [c] Treated group: Juniors who collaborate with a superstar in years 2-5. [d] "Later" treated group: Juniors who collaborate with a superstar in years 6-12 (excluded from the matched sample due to staggered treatment concerns). [e] Clean controls: Juniors who never collaborate with a superstar or collaborate after year 12. [f] Matching criteria: Only juniors who have published prior to collaborating with a superstar (or non-superstar) are eligible for matching to ensure pre-treatment comparability.

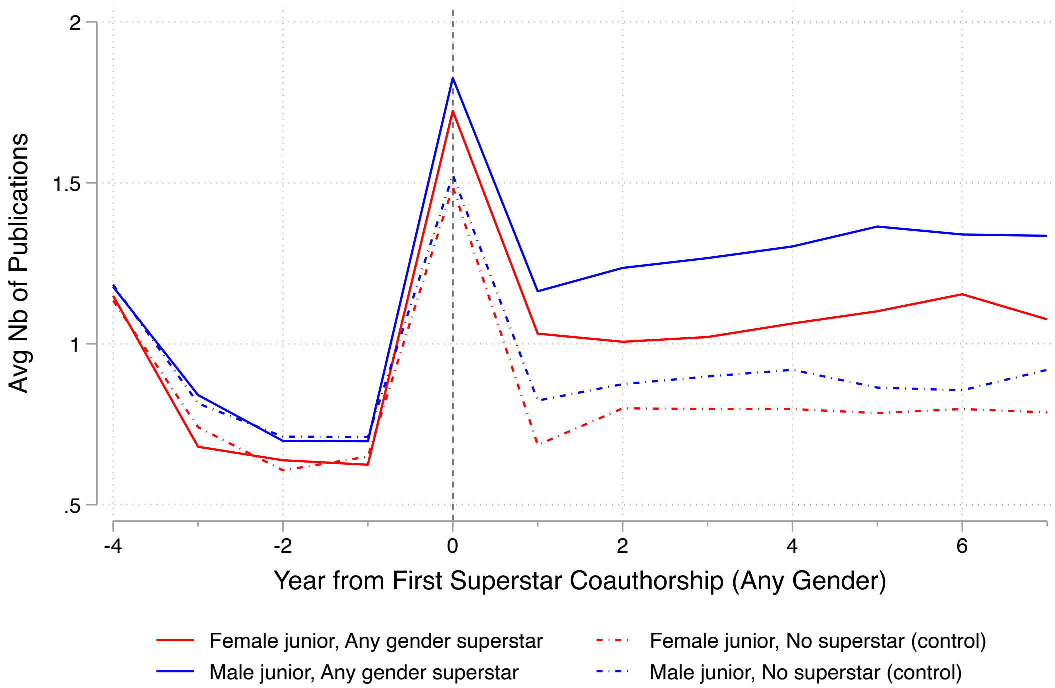
(b) Graphical Representation of Matched Sample Panel Data



Notes: After matching is executed, this figure illustrates the years included in the panel data of the matched treatment and controls (represented by blue segments).
[a] The timeline represents the years of a junior economist's publication career, and the 12 year panel used for matching. [b] Blue segments indicate the years included in the matched sample panel data for each researcher, of which the dashed portion represents the pre-treatment years, and the solid portion represents the post-treatment years. [c] To ensure a balanced comparison, the panel is restricted to 7 years post-treatment for all matched researchers. [d] The lengths of the blue segments vary based on the career age at which the researcher first collaborates with a superstar. For example: A researcher who coauthors with a superstar in their second year will have 1 pre-treatment year and 7 post-treatment years, for a total of 8 observed periods in the panel.

Figure 2: Trends in Annual Publication Counts

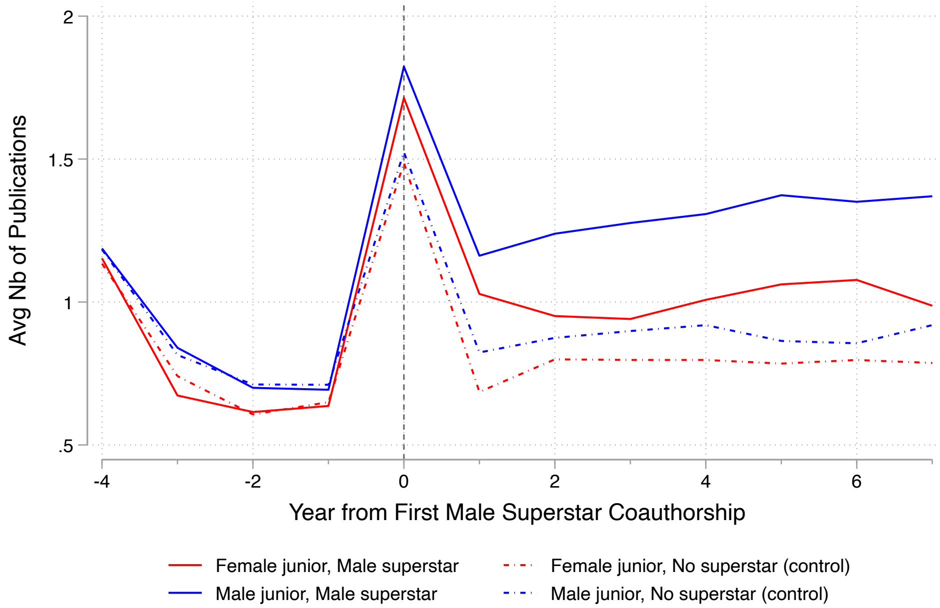
(a) Following coauthorship with any gender superstar



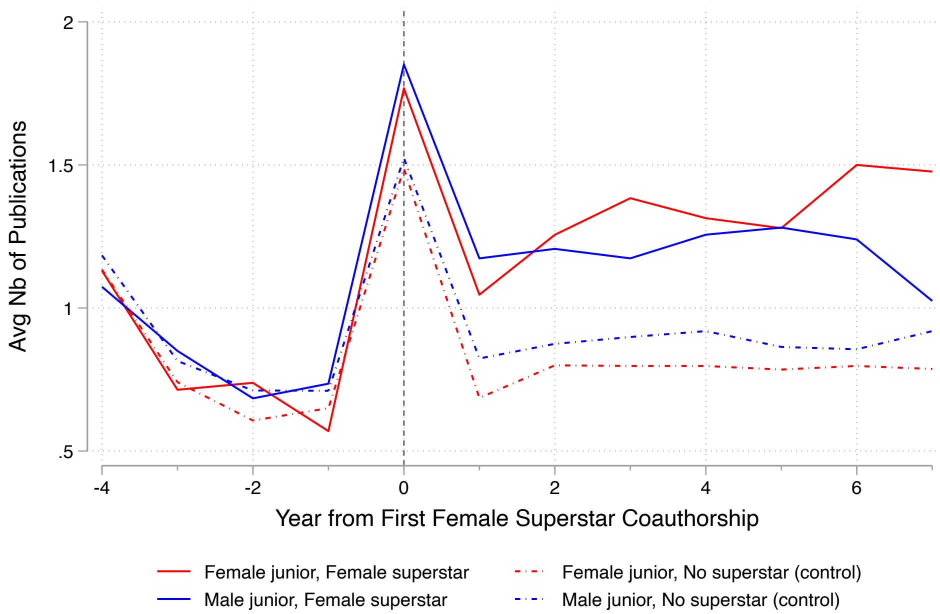
Source: Open Alex database.

Notes: [a] The sample consists of junior economists matched on CEM criteria, who initiated their publication careers between 2000 and 2010. [b] The treated group includes junior economists who coauthored with a superstar within 2-5 years of their career start. The control group includes junior economists who did not coauthor with a superstar during the analysis period (years 1-12). [c] The matched sample is restricted to a panel covering the subsequent 7 years after treatment for all matched researchers, ensuring a balanced comparison. [d] Each data point represents the average number of publications per year for junior women (red) and junior men (blue) who collaborate with a superstar (solid line) and their respective controls (dotted line). [e] The x-axis represents years relative to the year of treatment (star collaboration). Negative values indicate pre-treatment years, while positive values represent post-treatment years.

(b) Following coauthorship with male superstar



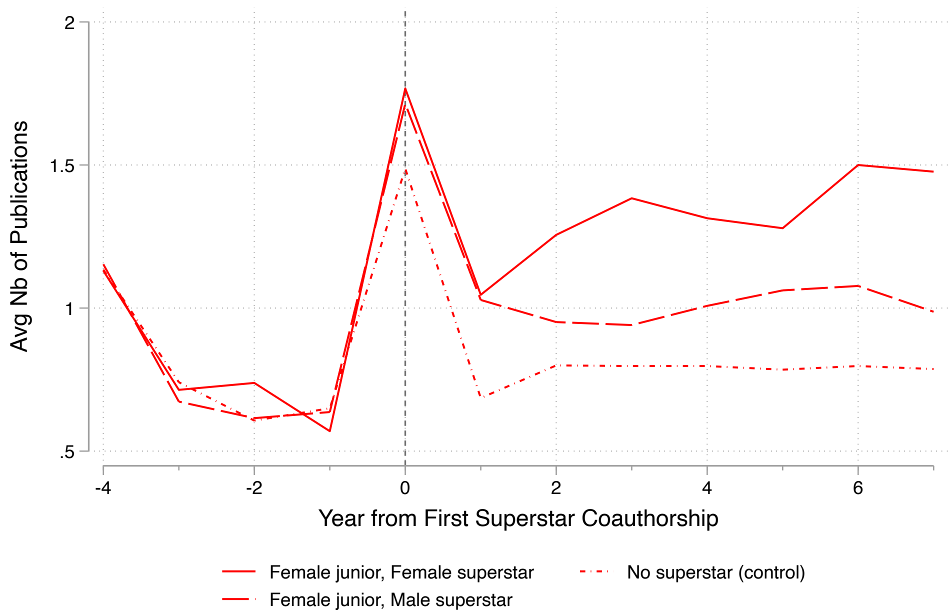
(c) Following coauthorship with female superstar



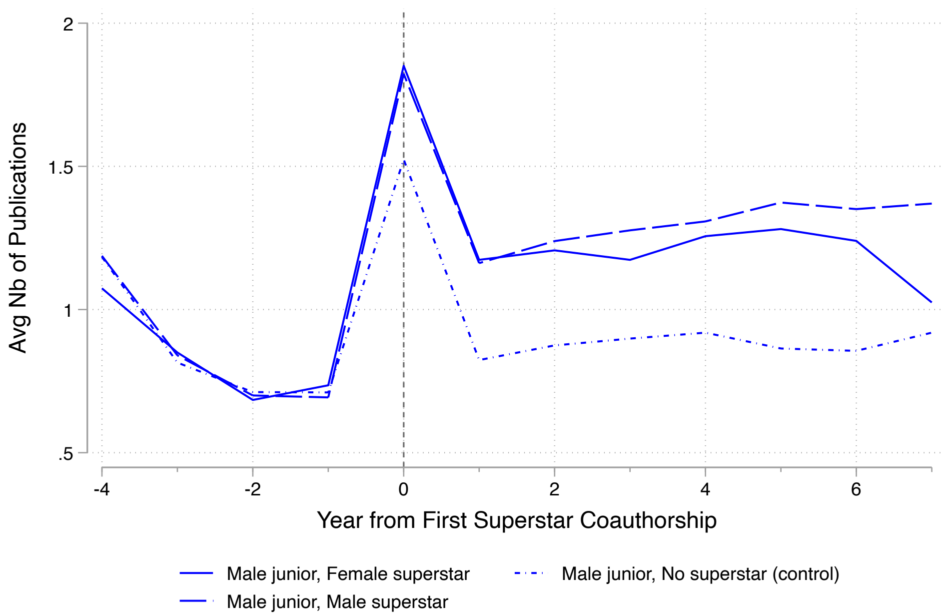
Source: Open Alex database.

Notes: [a] The sample consists of junior economists matched on CEM criteria, who initiated their publication careers between 2000 and 2010. [b] The treated group includes junior economists who coauthored with a superstar within 2-5 years of their career start. The control group includes junior economists who did not coauthor with a superstar during the analysis period (years 1-12). [c] The matched sample is restricted to a panel covering the subsequent 7 years after treatment for all matched researchers, ensuring a balanced comparison. [d] Each data point represents the average number of publications per year for junior women (red) and junior men (blue) who collaborate with a superstar (solid line) and their respective controls (dotted line). [e] The x-axis represents years relative to the year of treatment (star collaboration). Negative values indicate pre-treatment years, while positive values represent post-treatment years.

(d) Sample of female junior economists



(e) Sample of male junior economists



Source: Open Alex.

Notes: [a] The sample consists of junior economists with at least 5 years of publishing career, matched on CEM criteria, who initiated their publication careers between 2000 and 2010. [b] The treated group includes junior economists who coauthored with a superstar within 2-5 years of their career start. The control group includes junior economists who did not coauthor with a superstar during the analysis period (years 1-12). [c] The matched sample is restricted to a panel covering the subsequent 7 years after treatment for all matched researchers, ensuring a balanced comparison. [d] Each data point represents the average number of publications per year for junior women (red) and junior men (blue) who collaborate with a superstar (solid line) and their respective controls (dotted line). [e] The x-axis represents years relative to the year of treatment (star collaboration). Negative values indicate pre-treatment years, while positive values represent post-treatment years.

Table 1: Comparing Treatment and Control Researchers, Prior to Collaboration
(Matched Sample of Junior Economists)

	(1)	(2)	(3)	(4)
	Full Sample	Matched Controls	Matched Treated	Difference
	mean/sd	mean/sd	mean/sd	diff/se
Female (exact match)	0.28	0.28	0.28	0.00
	(0.45)	(0.45)	(0.45)	(0.02)
Coauthored a publication in year t (exact match)	1.00	1.00	1.00	0.00
	(0.04)	(0.04)	(0.04)	(0.00)
Career age in t-1 (exact match)	2.50	2.50	2.50	0.00
	(1.13)	(1.13)	(1.13)	(0.04)
Average year of first publication	2005.42	2005.30	2005.54	-0.24**
	(3.11)	(3.12)	(3.10)	(0.11)
Nb. publications in t-1	1.89	1.90	1.88	0.02
	(1.26)	(1.26)	(1.26)	(0.04)
Change in pub rate from t-2 to t-1	0.18	0.19	0.17	0.02
	(1.05)	(1.05)	(1.06)	(0.04)
Nb. solo-authored pubs in t-1	0.51	0.51	0.50	0.01
	(0.79)	(0.81)	(0.78)	(0.03)
Nb. coauthored pubs in t-1	1.38	1.39	1.38	0.01
	(1.16)	(1.14)	(1.17)	(0.04)
Cumulative nb. coauthorships in t-1	1.34	1.37	1.32	0.05
	(1.23)	(1.27)	(1.19)	(0.04)
Cumulative SNIP weighted pubs in t-1	1.03	1.02	1.04	-0.02
	(1.16)	(1.14)	(1.18)	(0.04)
Cumulative H-index in t-1	1.75	1.73	1.78	-0.05
	(1.14)	(1.13)	(1.16)	(0.04)
Affiliated in top 30 US econ dept in t-1 (exact match)	0.25	0.25	0.25	0.00
	(0.43)	(0.43)	(0.43)	(0.01)
In institution with SS in t-1 (exact match)	0.72	0.72	0.72	0.00
	(0.45)	(0.45)	(0.45)	(0.02)
N	3,374	1,687	1,687	3,374

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] The sample consists of junior economists with at least 5 years of publishing career, matched on CEM criteria, who initiated their publication careers between 2000 and 2010. All statistics are based on the year prior to first superstar coauthorship (t-1). [b] The treated group includes junior economists who coauthored with a superstar within 2-5 years of their career start. The control group includes junior economists who did not coauthor with a superstar during the analysis period (years 1-12). [c] The table reports the means and standard deviations of pre-treatment levels of select covariates, calculated individually and then averaged across the full sample, treated group, and control group. Column 4 presents the difference in means between matched controls and matched treated, along with the standard error of a t-test for this difference. [d] The cumulative H-index at t-1 is calculated using the stock number of publications at t-1 and how often they are cited (based on total citations at 2021, the year of collection). Because of the lack of panel data on citation counts, this value may not be fully reflective of the true H-index at t-1.

Table 2: Comparing Matched and Unmatched Treated Researchers, Prior to Collaboration
(Sample of Treated (Early Star Coauthorship) Junior Economists)

	(1) Full Sample mean/sd	(2) Unmatched Researchers mean/sd	(3) Matched Researchers mean/sd	(4) Difference diff/se
Female	0.29	0.31	0.28	0.03
	(0.45)	(0.46)	(0.45)	(0.03)
Career age at first superstar collab	3.52	3.59	3.50	0.09
	(1.11)	(1.01)	(1.13)	(0.06)
Collab w/ female star in t	0.12	0.12	0.12	-0.01
	(0.33)	(0.32)	(0.33)	(0.02)
Collab w/ male star in t	0.88	0.88	0.88	0.01
	(0.33)	(0.32)	(0.33)	(0.02)
Becomes superstar during career	0.17	0.29	0.14	0.16***
	(0.37)	(0.46)	(0.34)	(0.02)
Career age at first superstar status	7.22	6.81	7.42	-0.61**
	(2.59)	(2.41)	(2.66)	(0.29)
Nb. publications in t-1	2.42	4.72	1.88	2.84***
	(2.07)	(3.05)	(1.26)	(0.10)
Nb. solo-authored pubs in t-1	0.63	1.16	0.50	0.66***
	(0.98)	(1.46)	(0.78)	(0.05)
Nb. coauthored pubs in t-1	1.79	3.56	1.38	2.18***
	(1.86)	(2.95)	(1.17)	(0.09)
Avg nb of coauthors per pub in t-1	1.43	1.92	1.32	0.59***
	(1.59)	(2.66)	(1.19)	(0.09)
Cumulative SNIP weighted pubs in t-1	3.64	7.02	2.86	4.16***
	(3.16)	(4.57)	(2.05)	(0.15)
Cumulative H-index in t-1	2.22	4.12	1.78	2.35***
	(1.78)	(2.55)	(1.16)	(0.09)
Affilated in top 30 US econ dept in t-1	0.27	0.36	0.25	0.11***
	(0.45)	(0.48)	(0.43)	(0.02)
Initiate career in top 5%ile grad program	0.61	0.63	0.60	0.03
	(0.49)	(0.48)	(0.49)	(0.03)
Affiliated in institution with star in t-1	0.73	0.77	0.72	0.05*
	(0.44)	(0.42)	(0.45)	(0.02)
N	2,079	392	1,687	2,079

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] The sample consists of treated junior US economists who initiated their publication careers between 2000 and 2010, have at least 5 years of publishing experience, and coauthored with a superstar within 2-5 years of their career start. [b] The table reports the means and standard deviations of pre-treatment levels of select covariates, calculated individually and then averaged across the full sample, unmatched treated group, and CEM matched treated group. Column 4 presents the difference in means between unmatched and matched treated, along with the standard error of a t-test for this difference. [c] The cumulative H-index at t-1 is calculated using the stock number of publications at t-1 and how often they are cited (based on total citations at 2021, the year of collection). Because of the lack of panel data on citation counts, this value may not be fully reflective of the true H-index at t-1.

Table 3: Impact of Superstar Collaboration on Early-Career Junior Scholars
(Matched Sample of Junior Economists)

Dep Var: **Nb of Publications**

	Sample of Female Junior Scholars						Sample of Male Junior Scholars					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
POST TREAT × ANY GENDER SS	0.1832***	0.1484***	0.1596***	0.1560***	0.1593***	0.1579***	0.2004***	0.2072***	0.2047***	0.1990***	0.2051***	0.2057***
	(0.030)	(0.031)	(0.032)	(0.032)	(0.031)	(0.031)	(0.019)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
POST TREAT × FEMALE SS		0.1252**	0.1392**	0.1449**	0.1411**	0.1403**		-0.0382	-0.0502	-0.0435	-0.0533	-0.0525
		(0.060)	(0.064)	(0.064)	(0.062)	(0.062)		(0.049)	(0.050)	(0.052)	(0.050)	(0.050)
Observations	9996	9996	9996	9996	9996	9996	25442	25442	25442	25442	25442	25442
Mean of Dep. Variable	0.9340	0.9340	0.9340	0.9340	0.9340	0.9340	1.0668	1.0668	1.0668	1.0668	1.0668	1.0668
Author FE	X		X	X	X	X	X		X	X	X	X
Year FE	X			X		X	X			X		X
Career Age FE	X				X	X	X				X	X

Dep Var: **SNIP Weighted Pubs**

	Sample of Female Junior Scholars						Sample of Male Junior Scholars					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
POST TREAT × ANY GENDER SS	0.2574***	0.2139***	0.2297***	0.2249***	0.2292***	0.2274***	0.2887***	0.3005***	0.2947***	0.2872***	0.2951***	0.2956***
	(0.037)	(0.039)	(0.040)	(0.041)	(0.039)	(0.039)	(0.024)	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)
POST TREAT × FEMALE SS		0.1555**	0.1641**	0.1726**	0.1664**	0.1664**		-0.0477	-0.0663	-0.0577	-0.0700	-0.0690
		(0.073)	(0.077)	(0.077)	(0.077)	(0.077)		(0.063)	(0.065)	(0.067)	(0.065)	(0.065)
Observations	9996	9996	9996	9996	9996	9996	25442	25442	25442	25442	25442	25442
Mean of Dep. Variable	1.3739	1.3739	1.3739	1.3739	1.3739	1.3739	1.5907	1.5907	1.5907	1.5907	1.5907	1.5907
Author FE	X		X	X	X	X	X		X	X	X	X
Year FE	X			X		X	X			X		X
Career Age FE	X				X	X	X				X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] The sample consists of junior economists with at least 5 years of publishing career, matched on CEM criteria, who initiated their publication careers between 2000 and 2010. Columns 1-6 present results for female-named junior economists, while Columns 7-12 present results for male-named junior economists. [b] Estimates stem from OLS regressions with IHS-transformed publication outcomes. Coefficients represent elasticities. The top panel presents results using publication counts per researcher per year, while the bottom panel uses publication counts per researcher per year weighted by the journals' source-normalized impact factor. [c] (Post Treat x Any Gender SS) interacts between the post-treatment period and superstar coauthorship. It equals 1 for juniors who coauthor with a star after first star coauthorship and 0 otherwise. (Post Treat x Female SS) interacts superstar treatment with a female dummy of the star's gender. It captures the differential change in outcomes of collaborating with a female superstar, holding the general superstar effect constant. [d] Heteroskedastic robust standard errors, clustered by individual, are given in parentheses.

Table 4: Impact of Superstar Collaboration on Early-Career Junior Scholars
(Split by Quantile Groups of Cumulative SNIP Publications at t-1)

Dep Var: **Nb of Publications**

	Female Sample				Male Sample			
	Below Median		Above Median		Below Median		Above Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST TREAT × ANY GENDER SS	0.189***	0.177***	0.222***	0.186***	0.195***	0.192***	0.219***	0.230***
	(0.041)	(0.044)	(0.040)	(0.040)	(0.027)	(0.027)	(0.027)	(0.028)
POST TREAT × FEMALE SS		0.066		0.208**		0.031		-0.101*
		(0.076)		(0.094)		(0.081)		(0.058)
Observations	5258	5258	4738	4738	11780	11780	13662	13662
Mean of Dep. Var	0.8650	0.8650	1.0106	1.0106	0.9163	0.9163	1.1966	1.1966
Author FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Career Age FE	X	X	X	X	X	X	X	X

Dep Var: **SNIP Weighted Pubs**

	Female Sample				Male Sample			
	Below Median		Above Median		Below Median		Above Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST TREAT × ANY GENDER SS	0.272***	0.254***	0.305***	0.264***	0.301***	0.299***	0.304***	0.316***
	(0.050)	(0.055)	(0.049)	(0.050)	(0.033)	(0.034)	(0.033)	(0.034)
POST TREAT × FEMALE SS		0.096		0.232**		0.022		-0.119
		(0.088)		(0.117)		(0.098)		(0.076)
Observations	5258	5258	4738	4738	11780	11780	13662	13662
Mean of Dep. Var	1.2253	1.2253	1.5387	1.5387	1.3097	1.3097	1.8330	1.8330
Author FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Career Age FE	X	X	X	X	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] The sample consists of junior economists with at least 5 years of publishing career, matched on CEM criteria, who initiated their publication careers between 2000 and 2010. Columns 1-4 present results for female-named junior economists, while Columns 5-8 present results for male-named junior economists. These groups are further divided into those with below-median (Columns 1-2 and 5-6) and above-median (Columns 3-4 and 7-8) cumulative SNIP-weighted publications before collaboration (at t-1). [b] Estimates stem from OLS regressions with IHS-transformed publication outcomes. Coefficients represent elasticities. The top panel presents results using publication counts per researcher per year, while the bottom panel uses publication counts per researcher per year weighted by the journals' source-normalized impact factor. [c] (Post Treat x Any Gender SS) interacts between the post-treatment period and superstar coauthorship. It equals 1 for juniors who coauthor with a star after first star coauthorship and 0 otherwise. (Post Treat x Female SS) interacts superstar treatment with a female dummy of the star's gender. It captures the differential change in outcomes of collaborating with a female superstar, holding the general superstar effect constant. [d] Heteroskedastic robust standard errors, clustered by individual, are given in parentheses.

Table 4: Impact of Superstar Collaboration on Early-Career Junior Scholars
(Split by Quantile Groups of Cumulative SNIP Publications at t-1)

Dep Var: **Nb of Publications**

	Female Sample				Male Sample			
	Below Median		Above Median		Below Median		Above Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST TREAT × ANY GENDER SS	0.124***	0.114**	0.095**	0.059	0.140***	0.136***	0.181***	0.190***
	(0.042)	(0.044)	(0.041)	(0.041)	(0.026)	(0.027)	(0.027)	(0.028)
POST TREAT × FEMALE SS		0.050		0.214**		0.047		-0.085
		(0.074)		(0.096)		(0.074)		(0.058)
Observations	5095	5095	5155	5155	12327	12327	13853	13853
Mean of Dep. Var	0.8999	0.8999	1.0729	1.0729	0.9269	0.9269	1.2640	1.2640
Author FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Career Age FE	X	X	X	X	X	X	X	X

Dep Var: **SNIP Weighted Pubs**

	Female Sample				Male Sample			
	Below Median		Above Median		Below Median		Above Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST TREAT × ANY GENDER SS	0.193***	0.183***	0.162***	0.126**	0.235***	0.230***	0.258***	0.270***
	(0.051)	(0.056)	(0.050)	(0.051)	(0.032)	(0.033)	(0.033)	(0.034)
POST TREAT × FEMALE SS		0.053		0.220*		0.045		-0.113
		(0.087)		(0.120)		(0.090)		(0.075)
Observations	5095	5095	5155	5155	12327	12327	13853	13853
Mean of Dep. Var	1.2851	1.2851	1.5905	1.5905	1.3321	1.3321	1.9111	1.9111
Author FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Career Age FE	X	X	X	X	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] The sample consists of junior economists with at least 5 years of publishing career, matched on CEM criteria, who initiated their publication careers between 2000 and 2010. Columns 1-4 present results for female-named junior economists, while Columns 5-8 present results for male-named junior economists. These groups are further divided into those with below-median (Columns 1-2 and 5-6) and above-median (Columns 3-4 and 7-8) cumulative SNIP-weighted publications before collaboration (at t-1). [b] Estimates stem from OLS regressions with IHS-transformed publication outcomes. Coefficients represent elasticities. The top panel presents results using publication counts per researcher per year, while the bottom panel uses publication counts per researcher per year weighted by the journals' source-normalized impact factor. [c] (Post Treat x Any Gender SS) interacts between the post-treatment period and superstar coauthorship. It equals 1 for juniors who coauthor with a star after first star coauthorship and 0 otherwise. (Post Treat x Female SS) interacts superstar treatment with a female dummy of the star's gender. It captures the differential change in outcomes of collaborating with a female superstar, holding the general superstar effect constant. [d] Heteroskedastic robust standard errors, clustered by individual, are given in parentheses.