Discussion Paper Series

IZA DP No. 18868

August 2026

Expanding Opportunities: New Facts about the Placement of PhD Economists

Markus Eberhardt
University of Nottingham
and CEPR

Giovanni Facchini
University of Nottingham,
CEPR, IZA@LISER and CESifo

Valeria Rueda
University of Nottingham
and CEPR

IZA@LISER NETWORK
ISSN: 2365-9793

IZA DP No. 18868 August 2026

Expanding Opportunities: New Facts about the Placement of PhD Economists*

Abstract

Is the top of the economics profession becoming more insular? We study the placement of top PhD graduates over the past quarter-century matching them to their advisors. Three trends point towards greater openness: graduates increasingly place outside academia, outside the US, and into a tech sector recruiting broadly across gender, ethnicity, and program prestige. The disaggregated picture is less reassuring: the Emerging South is largely sidelined in the global job market, East Asians face persistent gaps in top academic placement, and elite advisors continue to confer substantial advantages within academia. Tech placement, meanwhile, is dominated by a single employer.

JEL classification

J16, A11, D9

Keywords

gender, ethnicity, diversity, economics, job market

Corresponding author

Giovanni Facchini
Giovanni.Facchini@nottingham.ac.uk

* We thank Andrés Martignano and Kieran Stockley for outstanding research assistance. The usual disclaimers apply.

1 Introduction

Recent research has documented that in most disciplines, award-winning scholars work in an expanding number of universities and research centres, while in economics, they are increasingly concentrated in fewer institutions and trained in a narrow set of elite PhD programs (Freeman et al., 2024). In an article in the *The Atlantic*, David Deming suggests that these findings illustrate the influence of institutional prestige in the evaluation of research and cautioned that “the marketplace of ideas in economics is becoming less efficient and fair” and that the profession “has become insular and status–obsessed”. While the literature has focused on the distribution of established academics, less is known about elite early-career researchers. If the allocation of talent is increasingly driven by prestige, the concern is that the profession is isolating into an exclusive circuit of institutions, both housing leading academics and channelling their graduates into one another’s ranks.

In this paper, we investigate the placement outcomes of PhD graduates from top U.S. economics programs, from the late 1990s until the 2020s. We uncover three broad trends pointing towards increasing diversity in the professional horizons of recent PhD cohorts. First, the share of graduates taking jobs in universities and research institutions has decreased — a pattern also documented in Foster et al. (2023) for an earlier period. Second, placements in academia have become more geographically dispersed, with a growing share of graduates taking jobs *outside* the United States. Third, placement in the private sector has grown, especially in tech.

These trends point to a broad increase in geographical and sectoral diversity of placements. Analysing the individual characteristics of candidates in each sector and the jobs they take reveals a more nuanced picture. First, large swathes of the Emerging South, such as India and some African countries, remain on the sidelines of the global job market, despite sustained economic growth during the sample period. Second, when considering determinants of academic placement, women appear as likely as men to obtain academic positions; however, a less optimistic picture emerges for ethnic minorities. In particular, candidates of East Asian descent — who represent approximately 28% of graduates — are significantly less likely to obtain top academic positions, even in recent years. We also observe that academic placement in top institutions is significantly and consistently more likely for candidates advised by ‘elite’ academics (e.g. Nobel Prize winners or editors of top-5 journals). Third, the tech sector — which has seen the most significant expansion in placements — has absorbed a very broad pool of graduates. It equally attracts male and female candidates, from diverse ethnic backgrounds, all programs, and advised by all types of scholars, including the most respected ones. However, the set of employers in tech is starkly dominated by a single player: Amazon.

Our findings offer a qualified reassessment of Deming’s insularity hypothesis. The aggregate trends point toward *decreasing* insularity: recent cohorts of elite PhD graduates are more likely to leave academia, more likely to take jobs outside the United States, and increasingly to be absorbed by a tech sector that draws broadly across gender, ethnicity, and program prestige. In this sense, the ‘exclusive circuit’ is not fully closed and might even be opening up. Yet, the disaggregated picture is less reassuring. East Asian candidates face a substantial and persistent penalty in access to top academic positions. And within academia, elite advisor networks continue to confer advantages, reinforcing stratification at the top of the profession. The marketplace of ideas may be widening at the edges; at its center, prestige and networks continue to shape careers.

Related Literature Our paper relates to the body of work analyzing the career outcomes of PhD graduates in Economics. This literature has predominantly focused on the quality of academic placement (Krueger and Wu, 2000; Athey et al., 2007; Fortin et al., 2021; Rose and Shekhar, 2023) and salaries (Siegfried and Stock, 1999, 2004; McFall et al., 2015) for selected cross-sections of graduates. Related papers have also looked at the long-term evolution of academic careers (Smeets et al., 2006; Conley and Qnder, 2014). Some of this work explores diversity, primarily related to gender (e.g. Siegfried and Stock, 2004; Hilmer and Hilmer, 2007; Fortin et al., 2021), but also regarding socioeconomic background (Stansbury and Schultz, 2023; Stansbury and Rodriguez, Forthcoming).

We contribute to this literature by considering granular information on all placements, allowing us to identify emerging trends in the increasingly important international market and the private sector. Related to our work, Foster et al. (2023) study the employment and earning dynamics of graduates from US economics PhD programs who stayed in the country. Our analysis adds to this research by considering placements outside the US, and expanding the time horizon, which enables us to uncover the globalization of academic placement and the increased prominence of tech recruitment in more recently.

2 Data

Candidates We focus on 33 institutions ranked in the top 30 US PhD programs in economics by *US News* in 2022. Since this ranking is based on reputation, it is quite stable over time.[1] For each institution, we manually collect information on the candidates entering the job market over the period 1998-2022, including their gender and their placement, whether in academia or elsewhere, both in the U.S. and abroad. The starting point is the list of job market candidates posted by each institution on its website. We trace these records using the *Wayback Machine* on the *Internet Archive*. To ensure that we have as complete a list of graduating candidates as possible, we cross-reference the information gathered from institutional websites with the *Annual List of Doctoral Dissertations in Economics* published by the *Journal of Economic Literature (JEL)*. Using the list of job market candidates as a starting point, rather than the JEL list provides a better estimate of the timing of job market entry. Placement information and candidate characteristics are taken from the *Internet Archive* of the Economic Departments' placement websites and supplemented with internet searches using personal websites and LinkedIn, among others. As a result, out of a total of 11,625 individuals entering the job market between 1998-2022, we have a detailed record of first placement for 11,042 individuals (or 95% of the total). For comparison, the Survey of Earned Doctorates (SED) records 13,041 students from the same institutions during the same time period. The difference is due to the fact that SED records candidates from all Economics-related PhDs, including programs such as Agricultural

[1]For example, 82% of the institutions in the top 30 in 2022 have been ranked in this group in every ranking between 1998/99 and 2021/22. The corresponding figure is 90% for institutions ranked in the top 10.

Economics or Environmental Economics. An advantage of our data is that our placement records are granular (exact employer name, in academia and beyond), global (we can track placements outside the US), and we can match them to advisors' characteristics. These features are not typically available in survey-based placement data. We clean the information on placement to obtain a harmonized list of employer names. Moreover, for academic placement, we geocode the institution and match it to its RePEc ranking.

Regarding candidate demographic characteristics, we manually record gender using names, images, pronouns, among other information. We use a LLM (Gemini) to determine their ethnic origins from their full names (first and surname) and categorise them into eight groups: White/Caucasian, East Asian, Hispanic or Latino, Middle Eastern, South Asian, South East Asian, Black or African, and unknown. The attribution was then manually cross-validated by the authors with an average accuracy rate exceeding 92%.[2]

Advisors Dissertation advisors are known to play a central role in PhD placement, both through mentoring and through the networks they provide access to (see e.g. Hilmer and Hilmer, 2007; Angrist and Diederichs, 2024). A key feature of our data collection strategy is that it allows us to systematically link each candidate to their advisor team. In doing so, we expand on the data collected by Angrist and Diederichs (2024), which focuses on eight top PhD programs.[3]

The institutional placement webpages typically report the advisor team of each candidate. When this information is not available, we obtain it from PhD dissertations, in particular the acknowledgements sections or institutional cover sheets naming the advisor team, which are available on ProQuest or analogous institutional repositories. We clean and harmonise the advisor name and manually collect their more recent CVs from publicly available sources. From these, we compile information related to their academic career, such as the PhD year, PhD institution, full career history, academic rank, and editorial positions, and manually determine their gender. We have information for a total of 3,850 advisors.[4]

Summary Statistics The summary statistics of our data are presented in Appendix Table C.2. Panel A shows that overall, the share of women graduating from top programs has remained stable at roughly 28%, in line with the 'stalled progress' of female representation in the profession highlighted by Lundberg and Stearns (2019). Candidates come from diverse ethnicities, with roughly 44% of white background, 28% East or South East Asian, and 13% Hispanics among others. Black candidates remain substantially underrepresented (1%). Two in five candidates come from top-10 programs. The most notable change in recent years has been the increase in East and South East Asians and the corresponding decline in whites.

Panel C shows the characteristics of the advising committees. The share of committees in which

[2]For more information on the harmonization and ethnic attribution processes, see Appendix A.1 and A.2

[3]These programs are, in alphabetical order, Berkeley, Chicago, Harvard, MIT, Northwestern, Princeton, Stanford, and Yale.

[4]This information is missing for a few advisors, in particular those who passed or retired early in our sample period.

all advisors are men has declined from 65% to 58%. We proxy for outstanding quality and networks of advisors by creating binary variables indicating the presence of Nobel Prize Laureates and Top-5 editors, respectively, as well as flagging committees in which all members graduated from top-10 PhD programs. In the full sample, 11% of candidates were advised by a past or future Nobel Prize winner, 11% by a Top-5 editor at the time of the job market (10% in the past), and 30% had a an advising team exclusively composed of alumni from Top-10 PhD programs.

3 Academic Placement

Placement in academia has seen a significant decline in recent years. Figure 1 shows that overall academic placement followed an inverted U-shape over the sample period, peaking in 2009 at around 67%. Since then, the share has decreased significantly, dropping to 52% in 2021 (all figures are 3-year moving averages). With the exception of the period 2007-2012, the patterns are very similar for male and female candidates.[5] This broad decline confirms trends documented for all PhD programs up to the mid-2010s by Foster et al. (2023).

Comparing placement by the rank of the PhD-granting institution reveals starker differences. First, academic placement is substantially higher for graduates from top-10 institutions, with an advantage in placement ranging between 3 and 15 percentage points. Second, while top-10 graduate placement in academia was still increasing until 2018, it had instead started declining since the early 2010s for those from institutions ranked 11-30. As a result of these dynamics, the average academic placement from top-10 (11-30) is around 58% (48%) in the most recent periods.

The academic job market is globalizing, with China becoming an important player. Figure 2 illustrates the geographic patterns of academic placement, distinguishing four broad regions: North America, Europe, East Asia, and Rest of the World. Placement in North American institutions has decreased substantially from around 75% in the early 2000s to around 50% most recently.[6] Accompanying this decline, placement in European institutions rose (particularly in the mid-2010s), as did placement in East Asia.

Panels (b) and (c) indicate that the drop in US placement is more pronounced among graduates from institutions ranked 11-30, where North American placement is rapidly approaching just 40%. Interestingly, depending on institutional ranking, the overall decline translates into different regional dynamics. While graduates from top-10 PhD programs experience a larger increase in European placements compared to East Asia (panel (b)), the reverse occurs for those from institutions ranked 11-30 (panel (c)). The growth in academic placement in East Asian institutions for PhD programs outside the top-10 is particularly pronounced: it reaches 30% in 2021.

A more detailed description of geographical patterns is presented in Appendix Figures B.1. Within Europe, Great Britain remains the dominant player throughout the period (recruiting 4.4% of can-

[5] These years coincide with the expansion of PhD graduates in institutions ranked 11 to 30 in the mid-2000s.
[6] Patterns are broadly similar for men and women (results available on request).

didates, around 50% more than France, Germany, and Italy combined). Spain used to be the second most common European destination, but it lost ground after the Global Financial Crisis and has not recovered since (Figure B.1a). The rise in East Asian placements is in part due to a substantial pull from Chinese institutions (Figure B.1b). Despite increased geographic diversification, large swathes of the Emerging South, such as India and parts of Africa, remain on the sidelines of the economics job market, even though these areas experienced sustained economic growth over the past two decades. For instance, while Latin American institutions hired 164 candidates, India only recruited 34, and the whole of Africa 7.

4 Jobs Outside Academia: The Emergence of the Tech Sector

The tech sector has become a major employment destination for Economics PhDs. On average, 42% of graduates in our sample find jobs outside academia, and this share has increased over time (see Figure 1). Yet, existing research largely misses the evolution of this important employment option for Economics PhD graduates, with the exception of Foster et al. (2023). To analyze the evolution of non-academic placement, we distinguish four broad categories: public sector, consulting, finance and industry, and the tech sector (Figure 3) — see appendix section A.1 for details on the classification. While the public sector is still the most important destination outside academia, its overall share has declined from a peak of approximately 25% in the early 2000s, to less than 20% most recently. The relevance of consulting fluctuates over time, but starts and ends at around 10%, and a similar pattern is also detectable in the case of finance — albeit at a lower share of around 6-7%. The most striking pattern emerging from the data is the rapid rise in the role of the tech sector as an employer of PhD economists — this was still only 1.3% in 2010, but starting from 2015 grew rapidly, reaching 12% by the end of our sample.

Placement in the tech sector is highly concentrated in a single firm: Amazon. For a more granular view of the institutions that recruit PhD economists outside of academia, we clean and harmonize the placement information and plot the distribution in the word clouds in Figure 4 (see Appendix A.1 on the data harmonization). The red markers in the word clouds present the total placement share of each company within that broad sector on the y—axis, which is proportional to the size of the label. Companies are randomly placed across the x—axis for visibility. In this way, the word clouds are comparable across panels. We note that finance is very competitive, with many equally sized recruiters. There is more concentration in the public sector and in consulting. The IMF, the World Bank, and the Fed each capture a significant share of the public sector market. Similarly, Bates White, Charles River Associates, and particularly Analysis Group and Cornerstone dominate placement in consultancies. These levels of concentration are dwarfed by those in the tech sector, where a single company – Amazon – accounts for over 42% of all PhD placements.

5 Drivers of Diversity in and out of Academia

We now turn to investigate **the drivers** of placement in different sectors. Recent literature in economics has devoted significant attention to the impact of gender (Eberhardt et al., 2023; Baltrunaite et al., 2025), ethnic (Hirtle and Kovner, 2024) and social (Stansbury and Schultz, 2023) diversity on the career prospects of PhD candidates. This research has exclusively focused on placement into academia, with the exception of Foster et al. (2023) who analyze earnings patterns of Economics PhDs who graduated from US institutions and remained in the country.

Given recent evidence on the impact of advisor **attributes** on the future research potential of PhD candidates, accounting for the characteristics of the advisory team is crucial for understanding the career prospects of recent graduates (Angrist and Diederichs, 2024). More broadly, professional networks play a central role in shaping academic careers (Colussi, 2018; Carrell et al., 2024).

Methodology We estimate a candidate level multinomial logit (MNL) model of placement sector on candidate and advisor team characteristics. Our dependent variable is categorical and captures six distinct outcomes: academic placement in the top-50, dto. outside the top 50; non-academic placement in a public institution, consulting, finance & industry or tech. MNL is particularly suited to our application, as we wish to compare multiple placement outcomes without imposing any ranking. We are then able to gauge the marginal effect of a particular characteristic (e.g. female candidate) on the probability of placement in a specific sector relative to the comparison group (e.g. male candidate). We estimate the placement MNL model including candidate and advisor (team) attributes as well as a set of additional controls. We discuss these variables in turn in the following.

First, we measure the impact of gender, ethnicity, and prestige of the PhD institution on placement outcomes. To do so, we study indicators for female, ethnic background (Black, East- and South-East Asian, Hispanic & Latino, Middle Eastern, South Asian, White), and whether the candidates are from a top-10 PhD programme.[7]

Second, some advisors may be more likely to secure prestigious academic placements for their students. In particular, this could be due to assortative matching — the best candidates pairing with the most well-known researchers — or the idiosyncratic networks of these academics. Moreover, identifying advisors' role in *non-academic* placement can potentially provide information with respect to the attractiveness of these sectors, as well as to the quality of candidates who end up there. We assess the impact of advisor team quality using the academic CV data we manually collected.

Reflecting outstanding academic achievements, we flag the presence of a Nobel Prize laureate on the advisor team (11% of the candidates). Next, top-5 economics journals exert a "powerful influence" on the Economics profession (Heckman and Moktan, 2020, 419). Editors at these journals are typically among the most accomplished academics, and may also have large networks enhancing the placement prospects of their students. We devise indicators for advisor teams with at least one

[7]The process of attributing gender and ethnic background to each candidate (as well as gender for advisors) is described the Data section and in Appendix section A.2.

top-5 editor, prior to and at the time of the candidate's job market, respectively.[8] Given evidence on the influence of academics with PhDs from top-ranked institutions on the profession, we also consider the role of advisors' academic history (Wapman et al. 2022, Freeman et al. 2024). In particular, we include an indicator variable flagging teams where all advisors graduated from top-10 PhD programmes. Finally, to capture more directly how well connected an advisor is to other economists, we use RePEc's measure of author closeness to the network, which evaluates the average shortest co-authorship distance between an author and every other researcher registered on RePEc. High-ranking authors can reach most of the network in fewer steps, indicating that they are closer to the core of the discipline.[9] We flag teams that have at least one member within the top-250 scorers in our sample (32% of the candidates have such committees).

It is possible that other attributes of candidates or advisors also influence placement outcomes. For instance, female and male candidates may systematically differ in the types of advisor networks they build. In addition, candidates from under-represented groups may feel less comfortable reaching out to academics in their departments (Boustan and Langan, 2019) and this could affect their career prospects. To account for this, we control for the number of advisors in the team. In addition, we control for all-male advisor teams. Candidates with different attributes may also sort into different fields, which could correlate with placement outcomes (Fortin et al., 2021). To account for this possibility, we control for candidate JEL field, which we extract from the *Annual List of Doctoral Dissertations in Economics.* Advisor team seniority will likely also impact candidates' career prospects. For example, contacts in the networks of more senior economists are more likely to be in positions of power within recruitment committees. We control for this possibility by including the advisor team average years since PhD and for the academic seniority of the team members.

Finally, all specifications include cohort fixed effects to absorb common shocks affecting PhD candidates entering the job market in a given year. To address institutional sorting — for example, the possibility that minority candidates are disproportionately concentrated in certain programs — we include fixed effects for PhD program tier (rank 1–10, 11–20, and 21–30). These enable comparisons within programs selecting candidates who are likely more similar in their academic profiles.[10]

Standard errors are clustered at the candidate PhD institution level. The full sample of 10,942 candidates covers the graduating cohorts between 1998 and 2021,[11] whereas our analysis for the most recent years (2012–2021) is based on data for 4,892 candidates.

Results Our findings are presented in Figure 5 as well as in Appendix Tables D.1 and D.2. We report marginal effects from two regressions, one for the entire sample period (column (A) in Figure 5), and one focusing on the recent years, 2012-2021 (column (B)). For ease of interpretation, the

[8] The top-5 journals are the *American Economic Review*, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies.*

[9] For more information on the rankings, see RePEc.

[10] Since the specification already accounts for cohort and research field fixed effects, using program-tier fixed effects ensures sufficient variation to estimate our relationship.

[11] We note again that we use the date for the *start* of the annual job market, hence candidates of the 2021 cohort formally completed their studies by the summer of 2022.

coefficients and confidence bands are transparent if they do not meet the 5% significance level. The six markers in each row report the marginal effects of the candidate or advisor team characteristic — relative to the comparison group — on the probability of placement in each of the sectors (academia, public sector, etc.).

We begin by discussing candidate characteristics (top panel). The figure shows that gender does not have a large effect on placement. Compared to men (the reference group), differences only emerge in Consulting (more women) and in the more recent sample in Finance & Industry (fewer women), but these are comparatively small, confirming the aggregate patterns documented in Figure 3.

Substantial gaps emerge instead along ethnic characteristics, most markedly for East Asian candidates. Compared to whites, a particularly salient difference emerges for academic placement, with East Asians being the least likely to be recruited by top-50 institutions (−8.45 p.p.) and the most likely to end up in lower-ranked ones (+7.85 p.p.). These gaps have become *larger* in the recent period, see Panel (B). The academic placement gaps for South Asians and Hispanics are comparatively smaller. Hispanics are the only ethnic group to exhibit a strong propensity to find public sector jobs (+5 to +5.70 p.p.). Symmetrically, Middle Easterners are the least likely to find employment in that sector, both in the entire sample (−5.24 p.p.) and in the recent period (−5.82 p.p.).

A striking feature that emerges from the analysis is that tech is the only placement destination which is *entirely unaffected* by any candidate characteristics. Effects are always insignificant and close to zero. This is particularly stark when compared with top academic placement among candidates from ethnic minorities, where significant gaps instead occur. These patterns stand in contrast with prior evidence of under-representation of women in tech more broadly (see e.g. Ashcraft et al. 2016).

Turning to advisor characteristics, candidates with all-male advisory teams are consistently less likely to place in academia outside the top 50, in consulting, or in tech. In recent years, they also have become more likely to place at top academic institutions. Rather than diminishing in relevance, an all-male advisory team has become a stronger predictor of top academic placement.

Focusing on the prestige attributes of the advisor team for academic placement, candidates with Nobel Prize winners in their committees are significantly more likely to secure a job in top-ranked academic institutions, both in the full sample and in the more recent period (+3.8 p.p.). This result is consistent with both assortative matching between advisors and candidates and the role of networks. Analysing indicators for top-5 editors in the team (past or at the time of the candidate's job market), effects are positive and statistically significant (ranging between +2.1 and +2.9 p.p.). Finally, capturing the role of networks, the effect of having all committee members alumni of top-10 institutions is positive and significant for top academic placement (+2.2 p.p.), and *negative* for less prestigious ones in the full sample (−3.7 p.p.). The former results remains unchanged in the recent sample. Similarly, having a committee with more better connected advisors in terms of co-authorships is also positively associated with top placement in academia and negatively with lower ranked placements (2.16 p.p and -3.65 p.p. respectively). Interestingly, these candidates are also more likely to place in public institutions. Since these variable are included alongside the Nobel and Top-5 editor indicators

— which should proxy for outstanding quality — our results indicate that broad academic networks are likely to play an important role in our estimates. Taken together, the results point to advisor teams as a meaningful determinant of top academic placement, operating through both quality and network reach.

Regarding non-academic placement, the quality and networks of advisor teams has no significant effect on public sector placement, and if anything some negative effects on consulting and finance and industry. This is consistent with the common view that these placements are perceived as less prestigious by PhD candidates. A striking exception is tech, which is the only non-academic sector for which these variables have any *positive* impact. In particular, students advised by Nobel Prize winners are significantly more likely to place in this sector (+1.3 p.p.), with especially strong effects in the recent period (+4.2 p.p.), which corresponds to the time when the sector took off. Taken together, these patterns suggest that tech has emerged as a well-regarded placement option for high-quality PhD candidates in Economics, attracting students from the same high-status advisors that also shape elite academic placement.

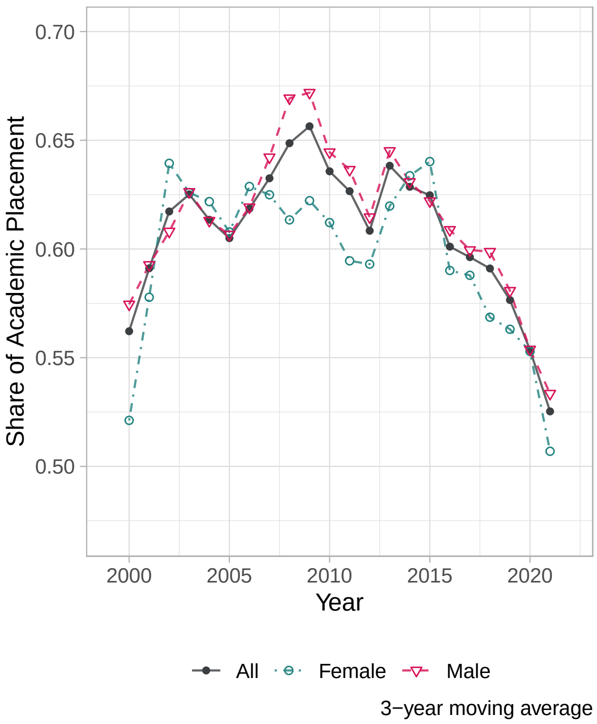
6 Concluding Remarks

This paper investigates the professional outcomes of PhD graduates from the top US economics programs over a quarter-century. Our findings offer a qualified reassessment of the insularity hypothesis: in aggregate, the profession's early-career pipeline is becoming more open — geographically, sectorally, and in its gender and ethnic composition. The tech sector has emerged as the profession's most open destination, recruiting graduates equally across gender, ethnicity, and program prestige — including those from the very top programs. Yet, the disaggregated picture is less reassuring. East Asian candidates face a persistent penalty in access to top academic positions that has not narrowed in recent years, and elite advisor networks continue to confer meaningful advantages at the apex of the profession. The marketplace of ideas may be widening at its edges; but prestige and networks continue to shape careers.

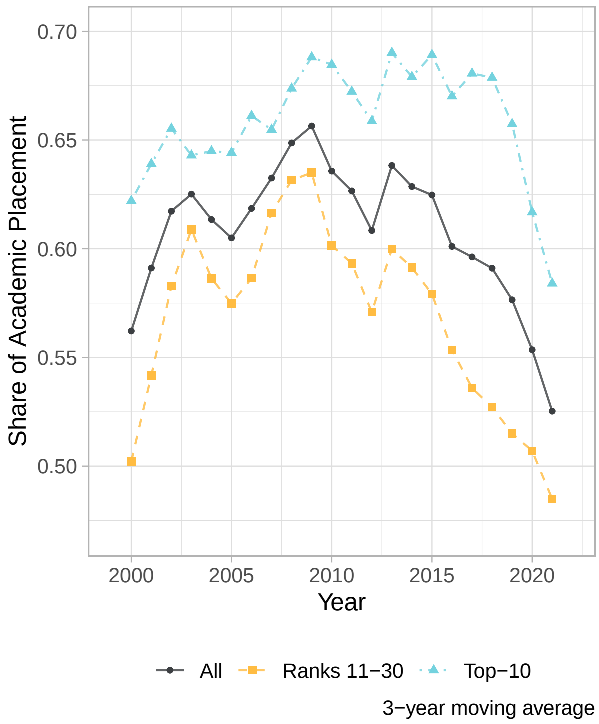
Several of the trends we document may already face headwinds. Tech sector recruitment expanded rapidly but future trends are far from certain: a single firm, Amazon, accounted for over 42% of placements in that sector, and the post-2022 retrenchment in tech hiring may have eroded some of this demand. The rise of AI introduces further uncertainty, expanding the skill set of economics graduates while potentially also redirecting recruitment toward engineering talent or undergraduate economists rather than those with PhDs. On the academic side, fiscal pressures on European universities and demographic change in East Asia could slow the globalisation of academic placement. In addition, contracting public funding for policy research and development assistance may dampen demand in the public sector.

Our analysis is limited to top US programs. A natural extension would apply the same framework to leading European and Chinese institutions, which would both broaden the picture and allow for direct comparisons across academic systems that are increasingly competing for the same talent.

Figure 1: Evolution of Academic Placement



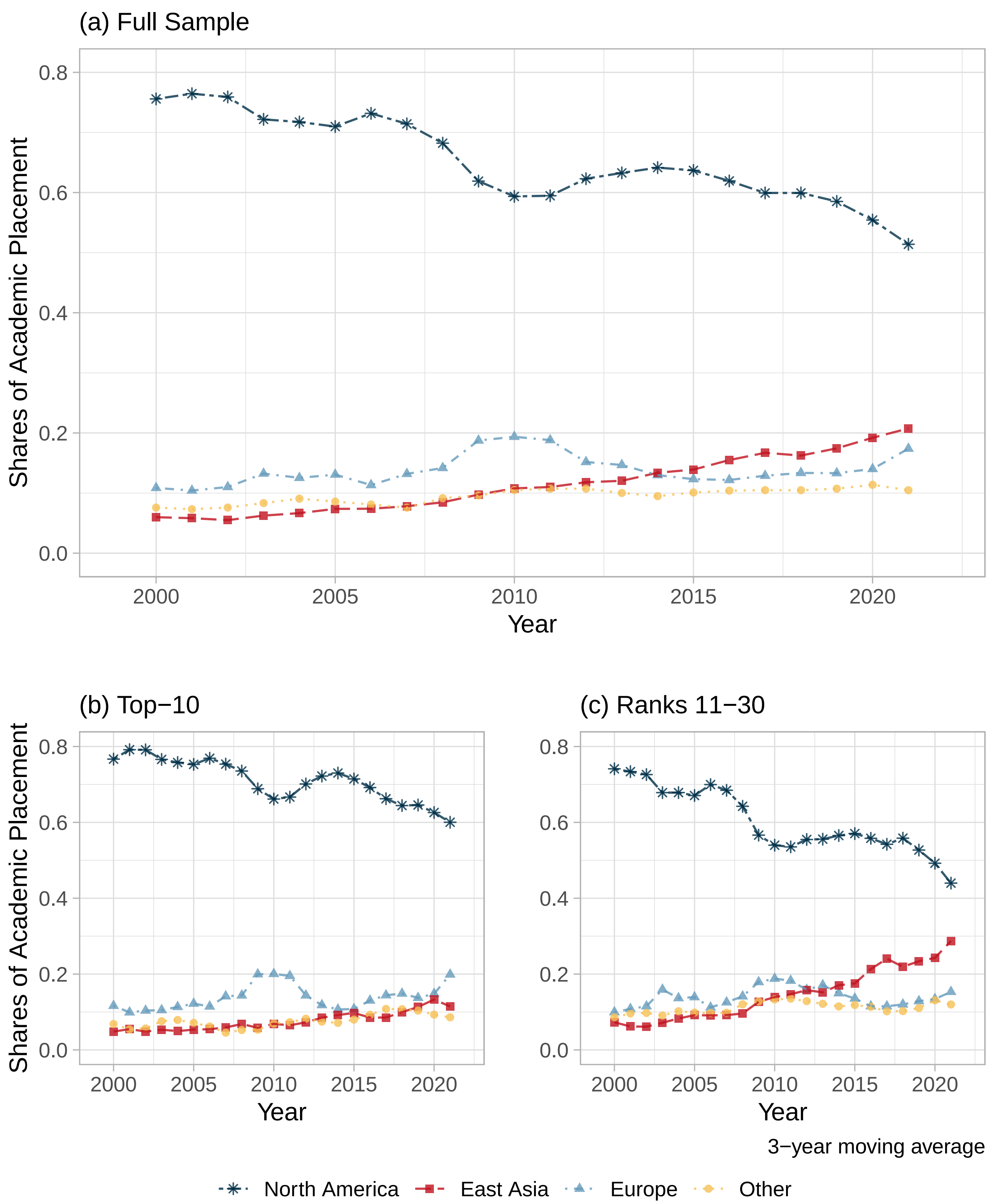
(a) By Gender



(b) By Rank of PhD Institution

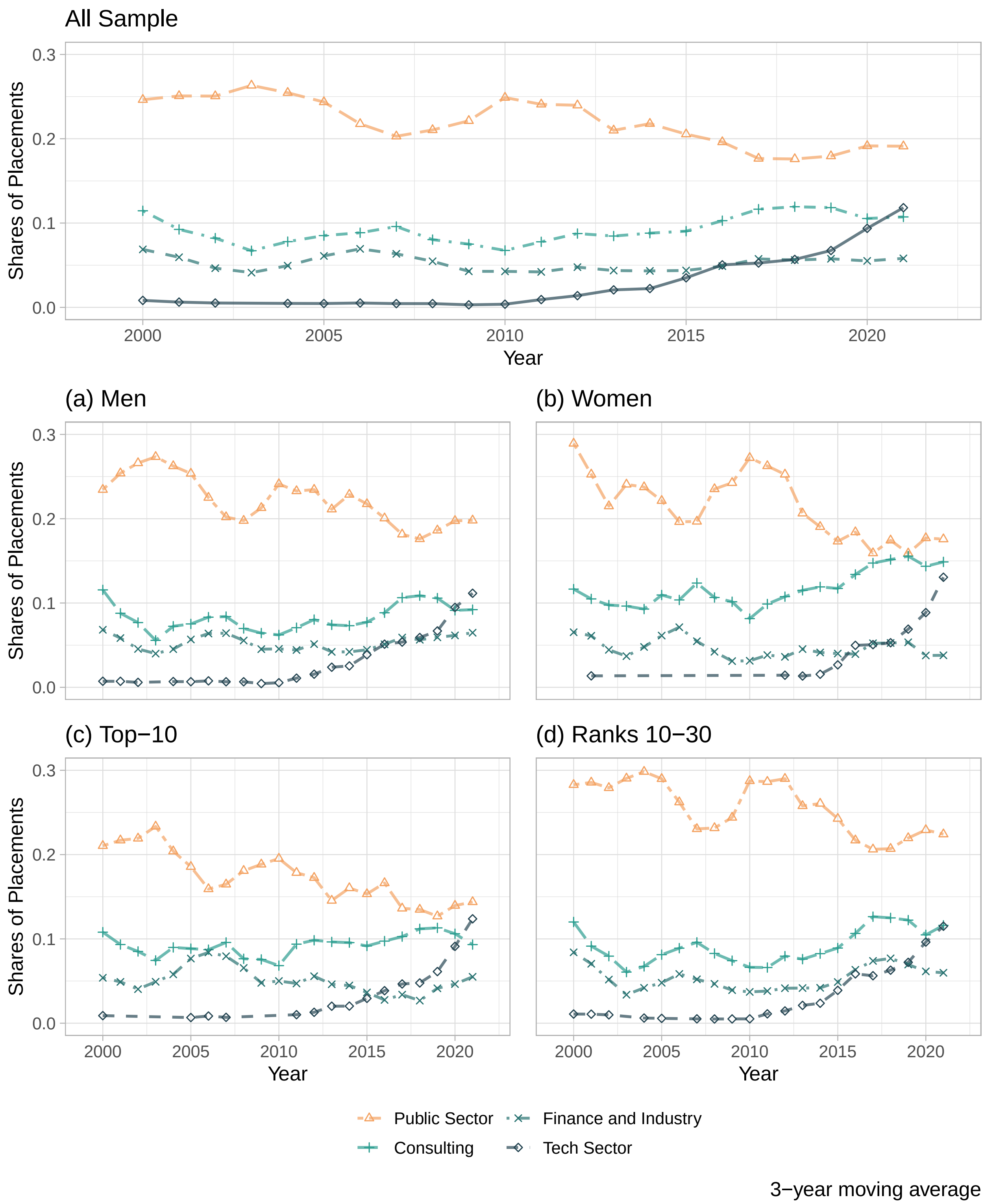
Notes: The figures plot the shares of PhD graduates securing academic jobs.

Figure 2: Geographic Trends



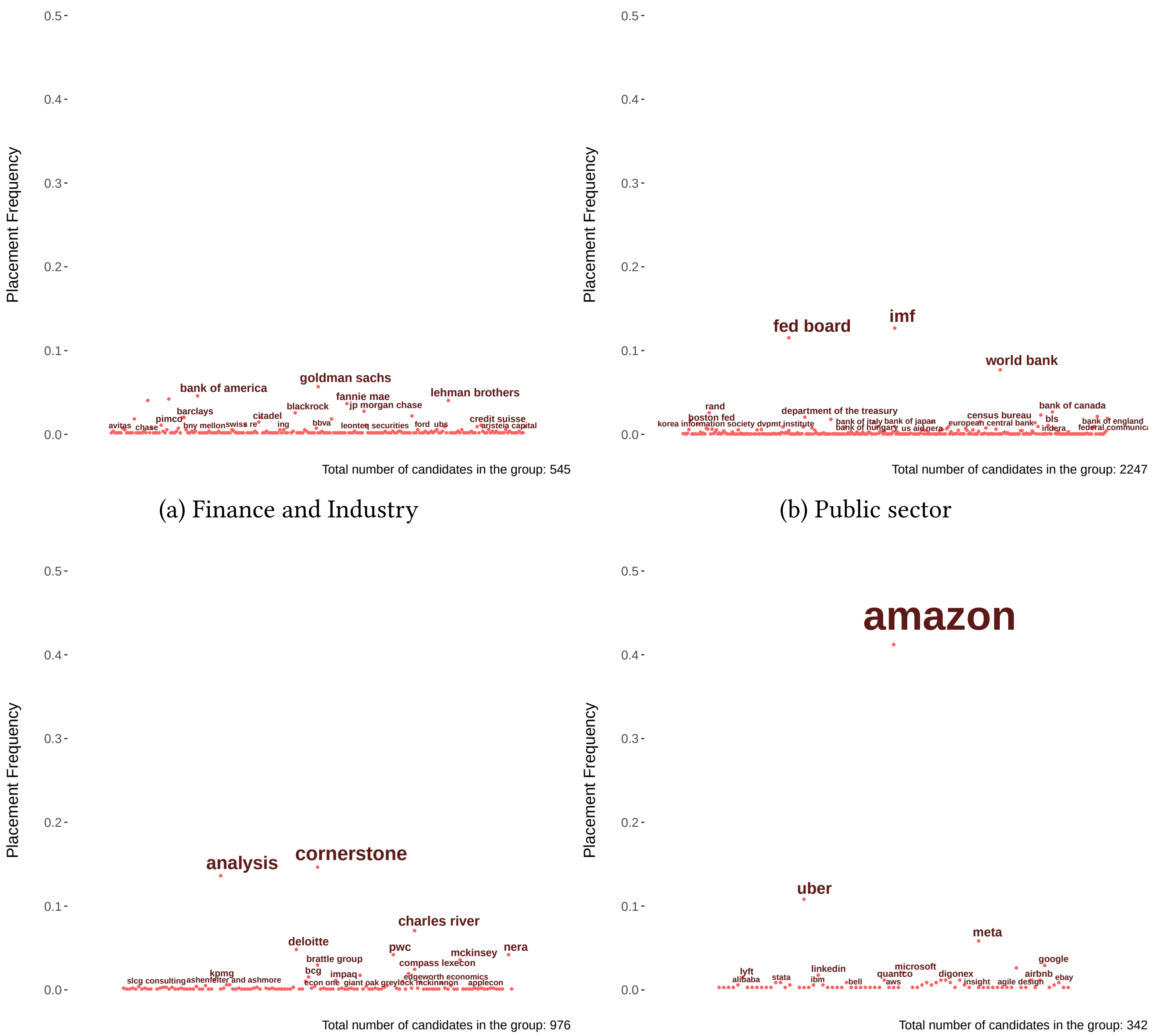
Notes: The figures plot the shares of PhD graduates securing academic jobs in different regions of the world.

Figure 3: Evolution of Non-Academic Placement



Notes: The figure plots the share of job market candidates who placed in four broad categories of non-academic jobs.

Figure 4: Frequency of Placement by Broad Sector



(a) Finance and Industry

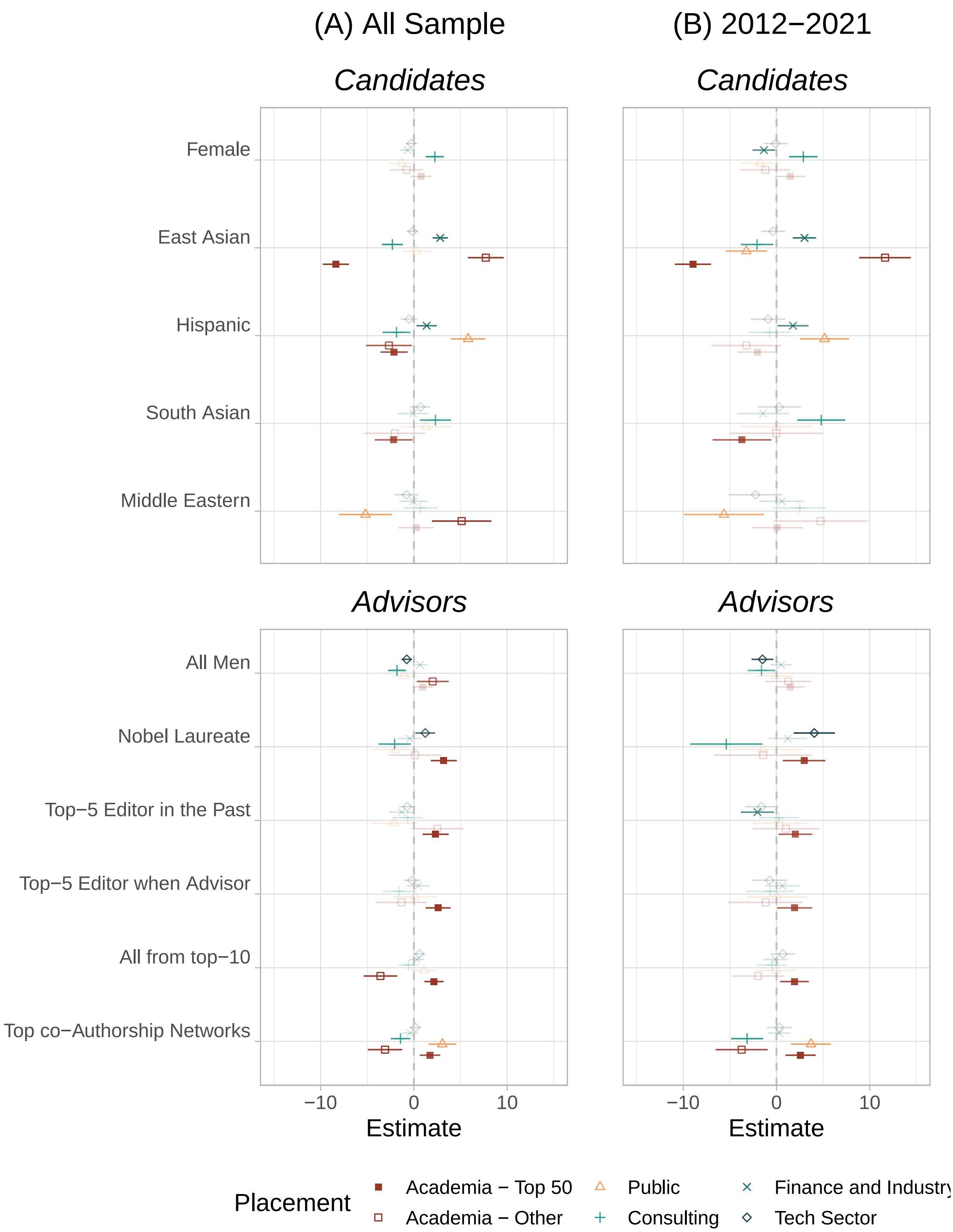
(b) Public sector

(c) Consulting

(d) Tech Sector

Notes: The figure plots the frequency of placement in each institution by broad industrial sector. The y-axis represents the frequency of placement of each institution within its respective broad sector. Label sizes are scaled according to these frequencies. For clarity, institutions are randomly positioned along the x-axis. The harmonization and classification of placements is described in Appendix section A.1.

Figure 5: Regression Results



Notes: The figure reports marginal effects, relative to the comparison group (e.g. White candidates for the different categories of ethnically minoritized candidates). See Appendix Tables D.1 and D.2 for the full results. The figure presents the results derived from two regressions: Column (A) for the full sample, and Column (B) for the period 2014-2021.

References

Joshua Angrist and Marc Diederichs. Dissertation Paths: Advisors and Students in the Economics Research Production Function. Working Paper 33281, National Bureau of Economic Research, 2024.

Catherine Ashcraft, Brad McLain, and Elizabeth Eger. *Women in tech: The facts*. National Center for Women & Technology (NCWIT), University of Colorado, Boulder, 2016.

Susan Athey, Lawrence F. Katz, Alan B. Krueger, Steven Levitt, and James Poterba. What Does Performance in Graduate School Predict? Graduate Economics Education and Student Outcomes. *American Economic Review*, 97(2):512–520, 2007.

Audinga Baltrunaite, Alessandra Casarico, and Lucia Rizzica. Women in economics: The role of gendered references at entry in the profession. *European Economic Review*, 180:105155, 2025.

Leah Boustan and Andrew Langan. Variation in women's success across PhD programs in economics. *Journal of Economic Perspectives*, 33(1):23–42, 2019.

Scott Carrell, David Figlio, and Lester Lusher. Clubs and Networks in Economics Reviewing. *Journal of Political Economy*, 132(9):2999–3024, 2024.

Tommaso Colussi. Social ties in academia: A friend is a treasure. *Review of Economics and Statistics*, 100(1):45–50, 2018.

John P. Conley and Ali Sina Ọnder. The Research Productivity of New PhDs in Economics: The Surprisingly High Non-success of the Successful. *Journal of Economic Perspectives*, 28(3):205–216, 2014.

Markus Eberhardt, Giovanni Facchini, and Valeria Rueda. Gender differences in reference letters: Evidence from the economics job market. *The Economic Journal*, 133(655):2676–2708, 2023.

Nicole Fortin, Thomas Lemieux, and Marit Rehavi. Gender Differences in Fields of Specialization and Placement Outcomes among PhDs in Economics. *AEA Papers and Proceedings*, 111:74–79, 2021.

Lucia Foster, Erika McEntarfer, and Danielle H Sandler. Early Career Paths of Economists inside and outside of Academia. *Journal of Economic Perspectives*, 37(4):231–250, 2023.

Richard B. Freeman, Danxia Xie, Hanzhe Zhang, and Hanzhang Zhou. High and Rising Institutional Concentration of Award-Winning Economists. *Mimeo*, 2024.

James J. Heckman and Sidharth Moktan. Publishing and Promotion in Economics: The Tyranny of the Top Five. *Journal of Economic Literature*, 58(2):pp. 419–470, 2020.

Christiana Hilmer and Michael Hilmer. Women Helping Women, Men Helping Women? Same-Gender Mentoring, Initial Job Placements, and Early Career Publishing Success for Economics PhDs. *AEA Papers and Proceedings*, 97(2):422–426, 2007.

Beverly Hirtle and Anna Kovner. Demographic Differences in Letters of Recommendation for Economics Ph. D. Students. Working Paper 24-11, FRB Richmond, 2024.

Alan B. Krueger and Stephen Wu. Forecasting Job Placements of Economics Graduate Students. *The Journal of Economic Education*, 31(1):81–94, 2000.

Shelly Lundberg and Jenna Stearns. Women in economics: Stalled progress. *Journal of Economic Perspectives*, 33(1):3–22, 2019.

Brooke H. McFall, Marta Murray-Close, Robert J. Willis, and Uniko Chen. Is it all worth it? The experiences of new PhDs on the job market, 2007–10. *The Journal of Economic Education*, 46(1): 83–104, 2015.

Michael E. Rose and Suraj Shekhar. Adviser connectedness and placement outcomes in the economics job market. *Labour Economics*, 84:102397, 2023.

John J. Siegfried and Wendy A. Stock. The Labor Market for New Ph.D. Economists. *Journal of Economic Perspectives*, 13(3):115–134, 1999.

John J. Siegfried and Wendy A. Stock. The Market for New Ph.D. Economists in 2002. *AEA Papers and Proceedings*, 94(2):272–285, 2004.

Valérie Smeets, Frédéric Warzynski, and Tom Coupé. Does the Academic Labor Market Initially Allocate New Graduates Efficiently? *Journal of Economic Perspectives*, 20(3):161–172, 2006.

Anna Stansbury and Kyra Rodriguez. The Class Gap in Career Progression: Evidence from US Academia. *Econometrica*, Forthcoming.

Anna Stansbury and Robert Schultz. The Economics Profession's Socioeconomic Diversity Problem. *Journal of Economic Perspectives*, 37(4):207–230, 2023.

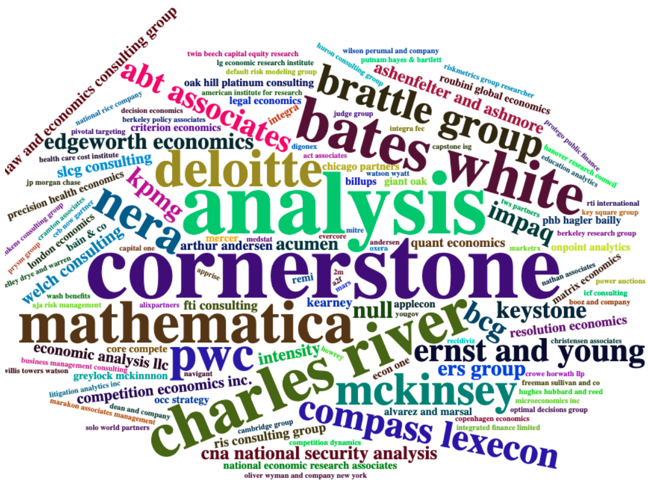
K. Hunter Wapman, Sam Zhang, Aaron Clauset, and Daniel B. Larremore. Quantifying hierarchy and dynamics in US faculty hiring and retention. *Nature*, 610:120–127, 2022.

A Data Appendix

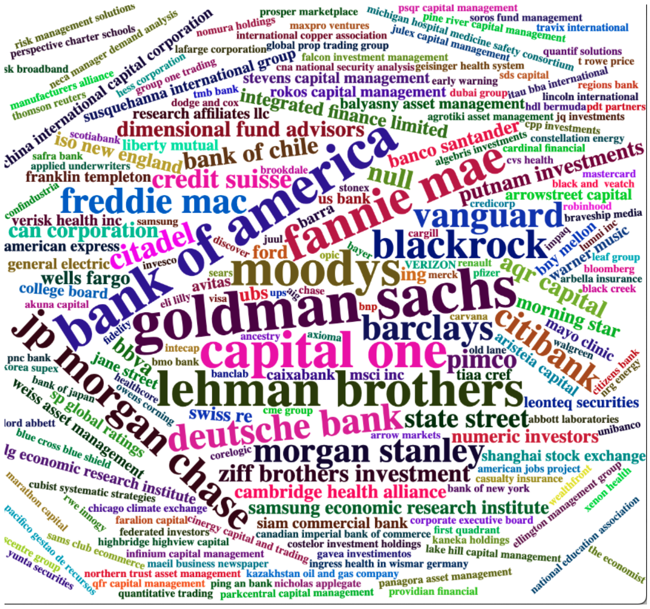
A.1 Classification of Sectors

We classify employment outside of academia into four broad categories: public sector, consulting, finance and industry, and the tech sector. To do so, we first harmonize the placement information so that placement records such as ‘analysis group inc.’ or ‘economist at analysis group’, get correctly classified into the homogeneous category ‘analysis group.’ This process was done in two stages: First, the harmonisation was done using an LLM, prompting chat-GPT to harmonise the placement records. Then, the harmonisation was entirely double-checked manually by the authors, following the alphabetical order of the classes provided by chat-GPT. The harmonization stage reduces 1,500 recorded institutions into 717 harmonized ones. Secondly, each of these institutions was manually attributed to each broad category by the authors. Figure A.1 presents word clouds of the resulting cleaned placements. In these figures, the size of the placement is monotonically related to the share of candidates who placed in these institutions. However, this relationship may not be trivial, as the size of the words is adjusted for visualisation by the algorithm. Moreover, the size of the terms is not comparable across graphs. For a transparent comparison of the importance of each placement, refer to section 4 and the figures in 4.

Figure A.1: Placement Institutions



(a) Consulting



(b) Finance and Industry

(c) Public

(d) Tech

Notes: These wordclouds show the institutions in which the candidates in our sample found jobs, across the four broad categories of placement. The size of the placement is monotonically related to the share of candidates who placed in these institutions. However, this relationship may not be trivial, as the size of the words is adjusted for visualisation. The size of the terms is not comparable across graphs. Refer to section 4 and the figures in 4 for comparable figures.

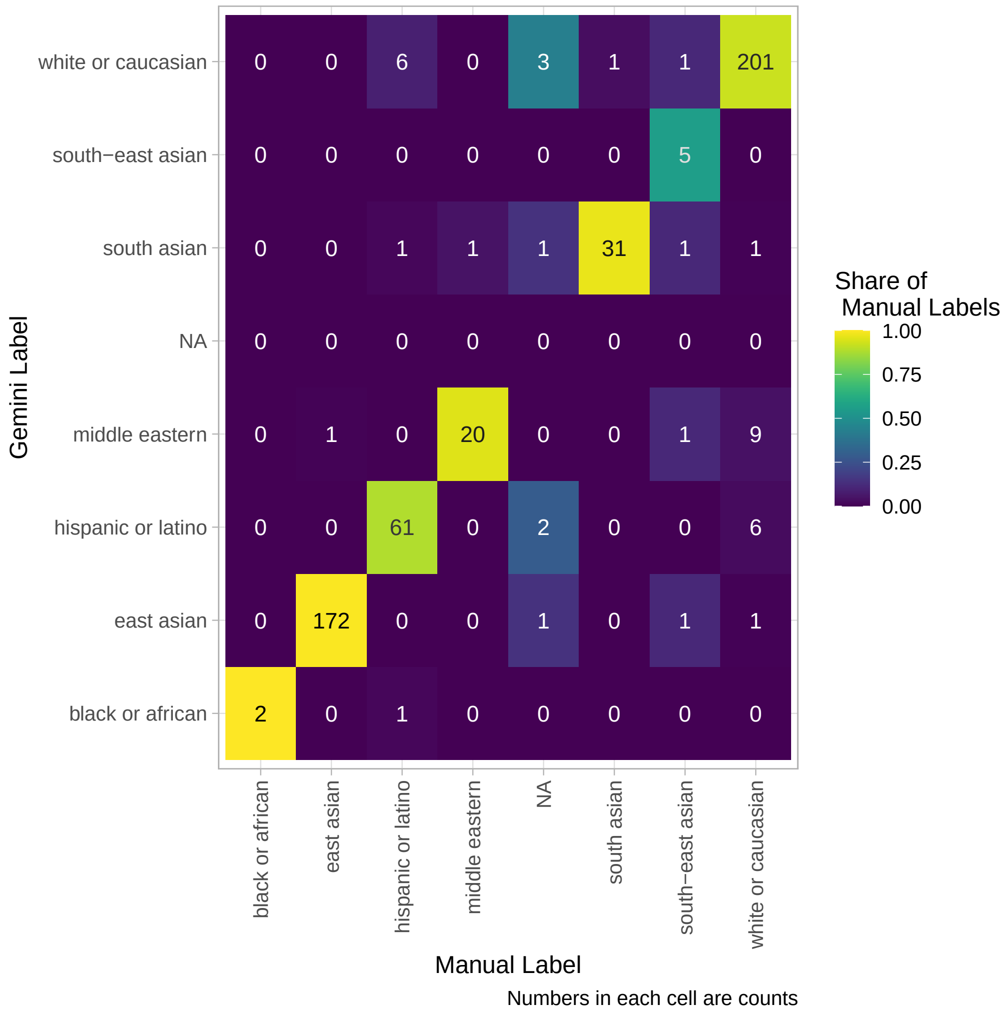
A.2 Classification of ethnicities

To attribute an ethnicity to each candidate, we asked an LLM (we use Gemini by Google for this task, as it provided strong results at a low cost). We then cross-validate the LLM's classification by comparing it to our own manual classification of an entire cohort, based on the candidate's declared ethnicity on EJM, or their name and CV information. The results of this cross-validation are summarized in the confusion matrix in Figure A.2, which compares the model's classification (Gemini Label) against the human-coded ground truth (Manual Label). Out of $N = 531$ observations, the concordance between the automated and manual labels is high across groups, providing validation for the use of the automated classifier in our analysis. Specifically, the model correctly identified 99.4% of manually-labelled 'East Asian' candidates (172/173) and achieved 91.4% accuracy for the largest group, 'White or Caucasian' (201/220). Classification agreement was also strong for 'Middle Eastern' and 'South Asian' candidates, at 95.2% (20/21) and 96.9% (31/32), respectively

The prompt used is stated below:

> "Here is a list of names of people who did a PhD in the US. Your task is for each name, tell me which of the following is the most likely ethnic origin. If there is too much uncertainty, say NA.
> Possible Origins:
>
> 1. White or Caucasian
> 2. Hispanic or Latino
> 3. East Asian
> 4. South-East Asian
> 5. South Asian
> 6. Middle-Eastern
> 7. Black or African"

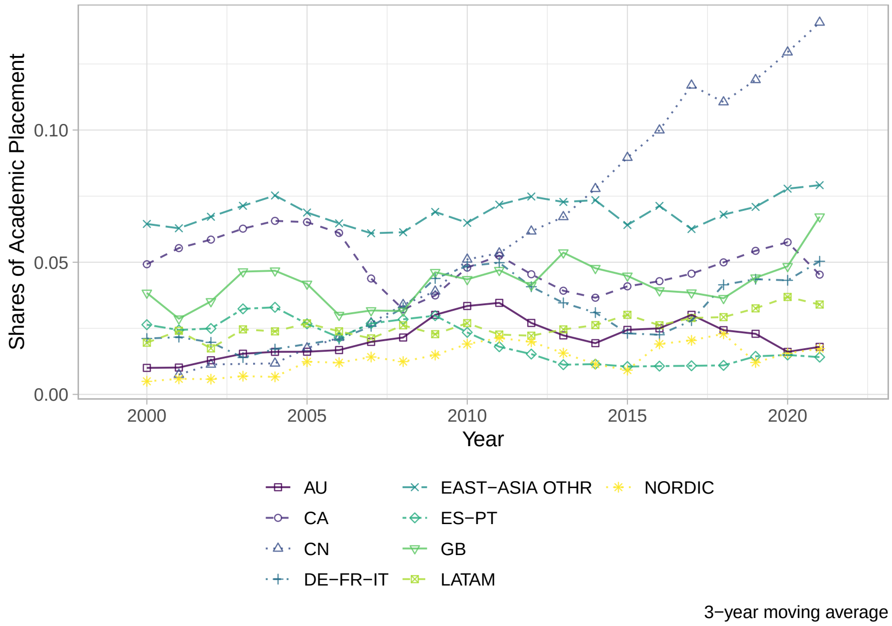
Figure A.2: Cross Validation of Ethnic Origins of Candidates



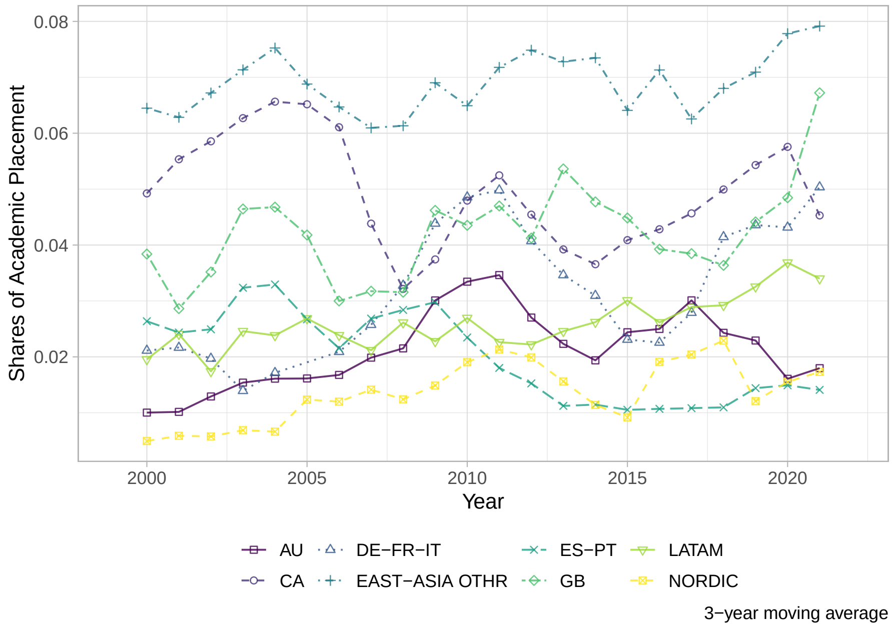
Notes: The figure displays the confusion matrix which compares the model's classification (Gemini Label, rows) against the human-coded ethnic group (Manual Label, columns).

B Figures: Additional Results

Figure B.1: Academic Placement outside of the US



(a) Top Destinations Outside the U.S.



(b) Top Destinations Outside the U.S. and China

Notes: The plot shows the share of academic placements in our sample across countries. The figure focuses on the top-10 geographic destinations, excluding the USA.

C Tables: Additional Results

Table C.1: Summary Statistics by Institution

Rank	Institution	N	Share	Share Women	Share Acad'a
1	Harvard	683	0.062	0.293	0.682
1	MIT	458	0.042	0.286	0.751
1	Stanford	422	0.039	0.249	0.637
4	Chicago	546	0.050	0.190	0.592
4	Princeton	390	0.036	0.236	0.654
4	UC Berkeley	499	0.046	0.277	0.637
4	Yale	418	0.038	0.278	0.708
8	Northwestern	469	0.043	0.186	0.706
9	Columbia	438	0.040	0.326	0.541
9	Pennsylvania	347	0.032	0.245	0.651
11	NYU	311	0.028	0.219	0.643
12	Michigan	472	0.043	0.292	0.576
12	UCLA	379	0.035	0.282	0.483
14	Caltech	120	0.011	0.300	0.775
14	Cornell	386	0.035	0.376	0.598
14	UCSD	325	0.030	0.329	0.634
14	Wisconsin Madison	428	0.039	0.290	0.575
18	Duke	276	0.025	0.322	0.525
18	Minnesota	355	0.032	0.231	0.710
20	Brown	250	0.023	0.300	0.636
21	Carnegie Mellon	126	0.012	0.278	0.556
22	Boston University	349	0.032	0.332	0.570
22	John Hopkins	178	0.016	0.320	0.472
22	Maryland	392	0.036	0.327	0.383
22	UT Austin	274	0.025	0.321	0.566
26	UC Davis	232	0.021	0.302	0.634
27	Boston College	220	0.020	0.382	0.550
27	Penn State	209	0.019	0.230	0.684
27	Rochester	200	0.018	0.215	0.745
30	University of North Carolina	237	0.022	0.287	0.498
30	University of Virginia	227	0.021	0.317	0.489
30	Vanderbilt	154	0.014	0.247	0.701
30	Washington University St Louis	172	0.016	0.233	0.733
	Total	10,942		0.280	0.615

Notes: The ranking is taken from US News (2022). The sample is made up of candidates for which we have placement information.

Table C.2: Descriptive Statistics

Variable	type	Full sample: 1998-2021 N	Mean	SD	Min	Max	Recent sample: 2012-2021 N	Mean	SD	Min	Max
Panel A: Candidate Personal Characteristics											
Female	indicator	10,942	0.280	0.449	0	1	4,892	0.278	0.448	0	1
Ethnicity: White	indicator	10,942	0.443	0.497	0	1	4,892	0.414	0.493	0	1
Ethnicity: East or SE Asian	indicator	10,942	0.283	0.451	0	1	4,892	0.325	0.469	0	1
Ethnicity: South Asian	indicator	10,942	0.064	0.244	0	1	4,892	0.061	0.239	0	1
Ethnicity: Hispanic	indicator	10,942	0.132	0.338	0	1	4,892	0.128	0.334	0	1
Ethnicity: Middle Eastern	indicator	10,942	0.068	0.253	0	1	4,892	0.061	0.240	0	1
Ethnicity: Black	indicator	10,942	0.010	0.099	0	1	4,892	0.010	0.102	0	1
Top-10 PhD Program	indicator	10,942	0.427	0.495	0	1	4,892	0.413	0.492	0	1
Number of advisors recorded	count	10,942	3.401	0.871	1	7	4,892	3.528	0.817	1	7
Panel B: Candidate Placement											
Academic Placement	indicator	10,942	0.615	0.487	0	1	4,892	0.593	0.491	0	1
Top-50 Placement	indicator	10,942	0.121	0.326	0	1	4,892	0.112	0.315	0	1
Outside Top-50	indicator	10,942	0.494	0.500	0	1	4,892	0.481	0.500	0	1
Placement outside Academia	indicator	10,942	0.385	0.487	0	1	4,892	0.407	0.491	0	1
Public institution	indicator	10,942	0.211	0.408	0	1	4,892	0.191	0.393	0	1
Consulting	indicator	10,942	0.091	0.287	0	1	4,892	0.102	0.302	0	1
Finance and Industry	indicator	10,942	0.051	0.221	0	1	4,892	0.051	0.220	0	1
Tech	indicator	10,942	0.032	0.175	0	1	4,892	0.064	0.244	0	1
Panel C: Advisor Team Characteristics (aggregated at Candidate-level)											
All advisors are male	indicator	10,942	0.655	0.475	0	1	4,892	0.595	0.491	0	1
At least one Nobel Laureate †	indicator	10,942	0.114	0.318	0	1	4,892	0.074	0.262	0	1
At least one past Top-5 Editor	indicator	10,942	0.104	0.305	0	1	4,892	0.151	0.358	0	1
At least one current Top-5 Editor	indicator	10,942	0.107	0.309	0	1	4,892	0.121	0.326	0	1
All advisors have PhD from Top-10 Program	indicator	10,942	0.299	0.458	0	1	4,892	0.270	0.444	0	1
At least one RePEc Top Co-Authorship Networks	indicator	10,942	0.316	0.465	0	1	4,892	0.299	0.458	0	1
Average years since PhD ♯	mean count	9,964	19.404	6.453	5.3	52	4,892	20.279	6.372	5.3	45
Rank: Professor	share	10,942	0.586	0.281	0	1	4,892	0.562	0.278	0	1
Rank: Associate Professor	share	10,942	0.141	0.199	0	1	4,892	0.148	0.194	0	1
Rank: Assistant Professor	share	10,942	0.160	0.203	0	1	4,892	0.166	0.199	0	1

Notes: We present descriptive statistics for the MNL regression samples for 1998-2021 and 2014-2021, respectively. There are 10,942 (4,892) candidates and 3,850 (2,595) advisors. On average, each candidate had 3.4 (3.5) advisors. Panels A and B refer to the candidate characteristics and their placement outcomes. With the exception of the advisor count these are all indicator variables. Panel C reports the characteristics of advisors teams, averaged/aggregated at the candidate-level (these are the variables entering the MNL regressions). † Any time during the entire sample period. ♯ If the year of PhD could not be established (9% of individual advisors) we coded this as zero but captured this information with an additional dummy variable indicating 'PhD age missing for at least 1 advisor' included in all MNL regressions; minimizing incidence of measurement error, all average team 'PhD ages' below 5 years as missing — hence the lower observation count.

D Tables: Main Results

Table D.1: Diversity in Placement — Full sample (1998-2021)

	(a)	(b)	(c)	(d)	(e)
Panel A: Candidates	Gender	Ethnic Origin			
Focus	Female	East Asian	South Asian	Hispanic	Middle-East
Share	0.28	0.28	0.06	0.13	0.07
Comparison Group	Male	White	White	White	White
Academia: Top 50	0.77	-8.37***	-2.17*	-2.12**	0.24
	(0.69)	(0.85)	(1.23)	(0.89)	(1.15)
Academia: outside Top 50	-0.78	7.71***	-2.05	-2.67*	5.12***
	(1.08)	(1.17)	(2.00)	(1.49)	(1.94)
Public Institution	-1.28	0.29	1.30	5.82***	-5.19***
	(0.88)	(0.95)	(1.63)	(1.13)	(1.71)
Consulting	2.24***	-2.31***	2.31**	-1.87**	0.70
	(0.59)	(0.69)	(1.01)	(0.91)	(1.10)
Finance & Industry	-0.68	2.82***	-0.07	1.37**	-0.06
	(0.48)	(0.50)	(1.00)	(0.66)	(0.93)
Tech Sector	-0.28	-0.15	0.69	-0.52	-0.81
	(0.37)	(0.38)	(0.65)	(0.54)	(0.80)

	(f)	(g)	(h)	(i)	(j)	(k)
Panel B: Advisors	Gender	1+ Nobel	1+ T5 Editor	1+ T5 Editor	Alma Mater	1+ Network
Focus	All male	Laureate	in the past	at the time	All Top 10	Top-250
Share	0.66	0.11	0.10	0.11	0.30	0.32
Comparison Group	Mixed	Not	Not	Not	Not	Not
Academia: Top 50	0.94	3.20***	2.33***	2.59***	2.15***	1.73**
	(0.66)	(0.85)	(0.85)	(0.81)	(0.63)	(0.67)
Academia: outside Top 50	2.02*	0.11	2.51	-1.34	-3.59***	-3.10***
	(1.04)	(1.73)	(1.70)	(1.68)	(1.10)	(1.12)
Public Institution	-1.02	-1.99	-2.14	0.12	1.11	3.05***
	(0.85)	(1.46)	(1.49)	(1.42)	(0.89)	(0.89)
Consulting	-1.82***	-2.07**	-0.67	-1.63	-0.59	-1.44**
	(0.58)	(1.05)	(0.97)	(1.05)	(0.64)	(0.65)
Finance & Industry	0.65	-0.46	-1.32	0.45	0.32	-0.41
	(0.49)	(0.78)	(0.81)	(0.76)	(0.48)	(0.50)
Tech Sector	-0.76**	1.21*	-0.70	-0.20	0.60	0.17
	(0.34)	(0.64)	(0.53)	(0.53)	(0.37)	(0.39)

Notes: We present marginal effects from a *single* multinomial logit (MNL) regression of candidate level sectoral placement: in academia (top-50 or not), public institutions (central banks, government, international institutions), consulting, finance & industry or the tech sector. The sample includes 10,942 candidates from the 1998-2021 job market cohorts. We include institutional FEs by tier: top-10, top-11 to 20, top-21 to 30. The Pseudo R^2 is 0.09.

Table D.2: Diversity in Placement — Recent sample (2012-2021)

	(a)	(b)	(c)	(d)	(e)
Panel A: Candidates	Gender	Ethnic Origin			
Focus	Female	East Asian	South Asian	Hispanic	Middle-East
Share	0.28	0.33	0.06	0.13	0.06
Comparison Group	Male	White	White	White	White
Academia: Top 50	1.47	-8.96***	-3.69*	-2.06	0.08
	(1.00)	(1.18)	(1.92)	(1.28)	(1.68)
Academia: outside Top 50	-1.19	11.65***	-0.02	-3.21	4.73
	(1.63)	(1.68)	(3.04)	(2.27)	(3.08)
Public Institution	-1.73	-3.23**	0.04	5.15***	-5.64**
	(1.28)	(1.35)	(2.39)	(1.60)	(2.60)
Consulting	2.88***	-2.09**	4.80***	-0.74	2.50
	(0.93)	(1.06)	(1.56)	(1.39)	(1.73)
Finance & Industry	-1.35*	3.00***	-1.43	1.77*	0.56
	(0.73)	(0.76)	(1.69)	(1.01)	(1.43)
Tech Sector	-0.08	-0.37	0.30	-0.91	-2.24
	(0.78)	(0.78)	(1.41)	(1.13)	(1.75)

	(f)	(g)	(h)	(i)	(j)	(k)
Panel B: Advisors	Gender	1+ Nobel	1+ T5 Editor	1+ T5 Editor	Alma Mater	1+ Network
Focus	All male	Laureate	in the past	at the time	All Top 10	Top-250
Share	0.60	0.07	0.15	0.12	0.27	0.30
Comparison Group	Mixed	Not	Not	Not	Not	Not
Academia: Top 50	1.48	2.96**	2.03*	1.95*	1.93**	2.58***
	(0.92)	(1.39)	(1.10)	(1.14)	(0.93)	(0.98)
Academia: outside Top 50	1.26	-1.42	1.02	-1.17	-1.97	-3.74**
	(1.49)	(3.18)	(2.18)	(2.43)	(1.69)	(1.70)
Public Institution	-0.14	-1.42	0.34	0.02	-0.03	3.69***
	(1.17)	(2.57)	(1.79)	(1.99)	(1.33)	(1.30)
Consulting	-1.61*	-5.39**	0.25	-0.69	-0.51	-3.15***
	(0.89)	(2.36)	(1.31)	(1.56)	(1.01)	(1.05)
Finance & Industry	0.50	1.21	-2.05*	0.62	-0.11	0.29
	(0.68)	(1.26)	(1.08)	(1.11)	(0.78)	(0.75)
Tech Sector	-1.50**	4.06***	-1.59	-0.73	0.68	0.33
	(0.72)	(1.34)	(1.10)	(1.13)	(0.79)	(0.80)

Notes: We present marginal effects from a *single* multinomial logit regression of candidate sectoral placement: in academia (top-50 or not), public institutions (central banks, government, international institutions), consulting, finance & industry or the tech sector. The sample includes 4,892 candidates from 2012-2021. We include institutional FEs by tier: top-10, top-11 to 20, top-21 to 30. For all other details, see Table **??**. The Pseudo R^2 is 0.09.