Competing for Scientific Talent: Industry vs. Academia*

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Abstract

How is highly-skilled labor allocated across sectors and is there misallocation? In this paper, I study the allocation of scientists at graduation between Industry and Academia and the extent of misallocation through the lens of the publication-wage relationship. Using an administrative dataset covering more than 40 cohorts of Ph.D. graduates with information about their earnings and their scientific production, I first estimate the causal impact of joining the private sector vs Academia on earnings and publication output. I account for selection and heterogeneity through a step-wise approach. I first rely on variation in sorting across individuals in the same department. I then use an instrumental variable that exploits variation over time in firms' vs universities' demand for PhDs in the same major. I show that scientists who start their career in the private sector publish about 71% less than scientists who start their career in Academia. They also earn about 69% more in the early-stage of their career, but this gap disappears with seniority. In order to study heterogeneity in treatment effects, I extend my analysis to the estimation of Marginal Treatment Effects which shows a substantial amount of heterogeneity across individuals, both for earnings and publications. I then use the reduced-form estimates in a simple model of social returns. Findings indicate that about 10% of individuals are misallocating, primarily within the private sector. This misallocation has increased over time and is primarily driven by PhDs in Engineering entering Management and Professional Services positions.

Keywords: *Sorting*, *Allocation*, *Heterogeneity*, *Spillovers*, *Innovation*, *Human capital*

*The use of NSF data does not imply NSF endorsement of the research methods or conclusions contained in this report.

1 Introduction

When he started his Ph.D. program in Computer Engineering at a renowned American university, James was convinced that he wanted to become a professor. While the papers written with his advisor during his doctoral studies were received quite favorably by the scientific community, James decided to leave Academia and joined a robotic company. "I am in the R&D team, working on new technologies that aim to completely change the way warehouse operations are currently performed. I think I fit much better in the private sector than in Academia. That's probably also why the firms I applied to were willing to offer me such a high salary. Of course, I could have had a broader impact if I had stayed in Academia and had been able to publish my work... but honestly, I am not sure I would have been extremely productive there". Though I changed his name to protect his privacy, James' story is illustrative of the tension that lies at the intersection of Industry and Academia. How much higher are James' earnings in the private sector compared to those he would have received if he had stayed in Academia? How many more or less publications would he have produced? And what can we infer from James' publication-wage relationship in Industry vs Academia regarding the sector where he would have the highest social value?

This example is part of a broader phenomenon affecting the population of highly-skilled workers, who play a central role in advanced economies by generating scientific discoveries and technological innovations that drive firms' outcomes and overall economic growth (Romer, 1990). While the literature shows that markets do not necessarily direct R&D to areas with highest social value (Arrow, 1972; Budish et al., 2015), most existing work has examined this question at the firm, industry or macroeconomic level. Although there is a growing body of work studying the supply of individuals who are part of the research and innovation labor force (Bell et al., 2017), less is known about the *allocation* of scientists across sectors and its consequences for firms, science and the economy. In this paper, I focus on the choice of joining Industry vs Academia after PhD graduation. Scientists can generate value in Academia by pushing forward the frontier of fundamental knowledge, or they can generate value in Industry by helping develop new product innovations. Because individuals are heterogeneous in skills and some occupations have greater potential of generating significant spillovers than others, the matching between jobs and individuals is of critical importance. Increasingly, concerns have been raised regarding potential misallocation of scientists across sectors. On one hand, some critics argue that Industry's for-profit orientation allows firms to offer salaries that universities cannot compete with in order to recruit scientists for positions that do not fully leverage the specialized human capital they have accumulated during their training (Jiang et al., 2023). On the other hand, some argue that the unique resources and technologies available to scientists in Industry allow them to conduct valuable projects that would otherwise be impossible (Ahmed et al., 2023).

How many scientists that enter Industry could have been more productive had they worked in Academia, and vice versa? Answering this question is not straightforward for three main reasons: (i) it requires individual-level information about scientists' productivity; (ii) it requires an approach that accounts for the endogenous forces that steer scientists to enter one sector or the other; (iii) it

requires an approach that can handle the significant heterogeneity across scientists in terms of how productive they may be in either sector.

I make progress on all three of these dimensions and provide new answers to this question of scientific talent allocation across Industry and Academia through the lens of the publication-wage relationship. To understand scientists' productivity, I make use of an administrative dataset that matches demographics and earnings information about doctorate holders who graduated between 1970 and 2013 to their publication output. I use earnings as a proxy for private returns and publications as a proxy for spillovers. To understand endogeneity, I first model the choice of sector at graduation, incorporating heterogeneity in individuals' ability which creates selection into sector of employment. I then handle the endogeneity that arises from selection in several ways. I first use a fixed-effects model relying on variation in sorting for individuals in the same university department, defined as the combination of doctoral institution and PhD major (e.g., Economics at Harvard). Under the identifying assumption that unobservable determinants of individuals' outcomes within a department are uncorrelated with their unobserved productivity in Industry vs Academia, I find that joining Industry vs Academia at graduation increases earnings by about 35% over the career and decreases publications by about 60%. In order to account for selection at the individual-level, I then use an instrumental variable strategy that exploits variation over time in firms' vs universities' demand for PhDs in the same major. Under the identifying assumption that average ability within a major does not differ across years, the results imply that the population of individuals affected by my instrument earn about 69% more during the first part of their career and publish about 71% less by joining the private sector vs Academia. Finally, in order to handle heterogeneity across individuals, I extend my framework to the estimation of Marginal Treatment Effects (MTE). This allows me to calculate treatment effects for individuals with the same latent propensity of choosing Industry vs Academia at graduation. Results show evidence of heterogeneity in treatment effects, both for earnings and publications. In particular, individuals who appear more likely to join the private sector vs Academia based on their observed and unobserved characteristics experience a higher boost in earnings and a lower publication decrease than others.

In order to shed light on how the increase in earnings compares with the decrease in publications, I use these reduced-form estimates in a simple model of returns where I proxy private returns with earnings and spillovers with publications. Under this simplified framework and using a conservative estimate to convert publications to dollars, I find that about 10% of individuals would have higher returns in the sector they did not join, a result primarily driven by individuals misallocating to the private sector. I show that misallocation has increased in over time and is primarily characteristic of individuals in the field of Engineering entering Management and Professional Services positions. I then discuss the sensitivity of these results to the consideration of spillovers from patents and the inclusion of sector-specific prices.

This paper is linked to the literature that examines the relationship between talent, innovation and economic growth. Classical models of endogenous growth highlight the central role of ideas in the production function. Because ideas are embodied by individuals, it is critical to understand

the frictions that could give rise to productivity losses. Bell et al. (2017, 2019) show that parental background and exposure to innovation influence who becomes an inventor, while Akcigit et al. (2020) show that financial frictions may reduce the propensity of individuals to enter the research market and Celik (2023) shows that this misallocation of talent between the production and the innovation sectors leads to substantial economic losses. Related in idea to this paper is Akcigit and Goldschlag (2023) which examines the allocation of inventors between large, incumbent firms vs young firms and shows that inventors hired by incumbents earn 13% more and innovate by 6% to 11% less than inventors at young firms. I contribute to this literature by highlighting the critical role of another type of friction related to the allocation of scientists (i.e., individuals who are already part of the research market) across sectors of employment. I focus specifically on the sorting decision of doctorate holders at graduation between Industry and Academia. Because one sector - Academia - has a relatively constrained capacity, my work allows to link the extensive margin - how many people are part of the innovative capacity overall - to the intensive margin - how many people want or can be absorbed by each sector. In doing so, I also build a bridge between the micro-behavior of individuals and the macro consequences of such choices.

This work is also related to resource allocation within organizations and its consequences for performance. Because the vast literature on general and firm-specific human capital shows that individuals are the microfactors that drive competitive advantage (Coff and Kryscynski, 2011), the *matching* of individuals and organizations that is at the core of my paper tackles a central strategic question. I specifically focus on a major input of organizations' production function - highly-skilled labor - and highlight the importance of heterogeneity across individuals in thinking about this allocation. While research has showed that some specific shocks can play a significant role in the decision of which sector to join Roche (2023), I specifically focus on how this heterogeneity influences individuals' selection into sector of employment. Shu (2016) shows that MIT students who select into finance have different skills than those who specialize in Science and Engineering. My model uses a similar idea by relating selection to heterogeneity in individual productivity in both Academia and Industry that I leverage through a Generalized Roy Model framework.

By relating heterogeneity to differences in individuals' preferences (Agarwal and Ohyama, 2013; Roach and Sauermann, 2010) and institutional norms between both sectors (Dasgupta and David, 1994), this work also speaks to the broad literature that looks at the role of Industry and Academia in the production of knowledge and innovation (Stephan, 2012). A large number of papers has highlighted the institutional differences between these two sectors and the different drivers of their demand for scientists. Academia would focus primarily on more fundamental research and would promote non-pecuniary motives such as priority for discovery and recognition (Merton, 1973). In contrast, the private sector would be seeking scientists for their capacity to innovate and transform new knowledge into profitable products (Aghion et al., 2008) as well as for the spillovers between fundamental and applied research (Bikard et al., 2019). Most works are primarily interested in the determinants of the choice of joining Industry vs Academia (Roach and Sauermann, 2010, 2024). While I build on the selection effect they identify, I primarily focus on post-sorting productivity

outcomes, leveraging information about earnings and publications. Closely related to this paper is Agarwal and Ohyama (2013), which studies the mechanisms behind the earnings gap between Industry/Academia and highlights the role of preferences for non-pecuniary returns and differences in human and physical capital investments. Stern (2004) focuses primarily on Industry, differentiating between firms that allow vs do not allow to publish, and shows that scientists with higher 'taste for science' are willing to accept a compensating wage differential to work for science oriented firms. However, study of the different frictions arising at the intersection of firms and universities is complicated by the difficulty to identify plausibly exogenous variation. Stern (2004) estimates the relationship between earnings and firms' involvement in Open Science for a relatively small sample of Ph.D. in biology by using individuals' fixed-effects in order to control for unobserved ability. To make progress on that front, I use an instrumental variable strategy inspired by earlier work (Oyer, 2006) that exploits variation in firms' vs universities' demand for PhD majors over time. While the validity of my instrument cannot be proved, two other supplementary instruments find similar results, providing some reassurance. I also improve on the external validity front by using data covering more than 40 cohorts of graduation and a broad range of fields.

Finally, a related literature has been concerned by the estimation of the wedge between private and social returns. Focus has mainly been on spillovers arising from firms' own R&D to other firms (Bloom et al., 2013) or from the public funding of corporate R&D (Azoulay et al., 2019; Myers and Lanahan, 2022). I bring a complementary analysis by focusing on private and social returns at the individual level, building on previous work that highlighted the role of universities in the production of public research and the spillovers that ensue (Nelson, 2004; Sorenson and Fleming, 2004). The estimation of private and social returns is often challenging because of the necessity to access individual level data. The dataset I use that allows me to link earnings and publication output for individuals coming from a wide range of cohorts and fields is an interesting new resource for follow-on research on that topic.

2 Data

In this section, I describe the data sources and define the key variables.

2.1 Data sources and sample construction

I use individual-level data from three restricted files: (i) the Survey of Earned Doctorates (SED), (ii) the Surveys of Doctorate Recipients (SDR) and (iii) the 2015 Survey of Doctorate Recipients Bibliometric Research Data (SDR15-WoS). These surveys are conducted by the National Center for Science and Engineering Statistics (NCSES) and cover individuals who received a Ph.D. from an American institution.[1]

The SED is an annual census of all individuals who graduated from a Ph.D. in a given academic

[1]These data are restricted-use and were accessed remotely from the National Opinion Research Center (NORC) data enclave.

year (e.g., the SED 2010 is sent to all individuals who earned their doctoral degree in 2010). The SED is therefore a *within-cohort* dataset which gives information about PhDs *at the time of graduation*. The response rate is about 90%. The SED contains demographic and background information including Ph.D. field of study and institution ; previous education ; place of birth, gender, race, parental education, citizenship status and the sector that students join or plan to join after their PhD. Starting in 2008, the SED added a question about the salary associated with this first job.

The SDR is a biennal panel survey of doctorate holders which contains longitudinal data about individuals' employment at the time of survey such as sector of employment, principal job activity and earnings. For each survey, the sample consists of both individuals who were surveyed in previous SDR editions (as long as they are less than 76 years old) as well as new doctoral graduates who earned their Ph.D. since the last cycle. The SDR is therefore an *across-cohorts* dataset and gives information about individuals *during the career*. The response rate is about 65%. I use all the SDR surveys to which I have access to (years 2003, 2006, 2008, 2010, 2013, 2015, 2017, 2019 and 2021). Note that individuals can be surveyed several times during their career and hence might appear in several SDR waves.

In the years 2022/2023, the NCSES launched a new Research Data Infrastructure with the goal of creating new linkages with external data. I take advantage of this effort by using a newly created dataset that matches each individual surveyed in the SDR 2015 to her research output from graduation until 2017, using information from Web of Science. This gives me individual-level information about (public) research production between graduation and 2017 such as publications, top publications and average number of citations in the first 2 or 5 years after publication. For each of these measures and for each individual, I have access to *aggregate* values up to 2017 as well as more granular information by bins of experience (e.g., publications produced during the PhD, publications produced during the first 5 years post-graduation and so on).[2]

I match the SDR 2015 and the SDR15-WoS to gather earnings and research output information for individuals surveyed in the SDR 2015. In order to retrieve information about these individuals at the time of graduation, I then match this sample to the SED. This is my primary sample when studying the impact of sorting at graduation on the *stock* of publications. I also match this sample to the other editions of the SDR to gather additional earnings information for individuals surveyed several times during their career.

The initial sample contains 57,811 individuals. I drop PhDs in Humanities, Education, Business and Health for whom I have little observations and focus on STEM fields (Computer and Mathematical Sciences, Life Sciences, Physical Sciences, Social Sciences and Engineering). I keep cohorts that graduated in or after 1970 because of several changes in the way the SDR answers are coded before that year. In order to assign individuals to a sector of employment when they start their career, I keep students with definite postgraduate commitments at graduation at the time of sur-

[2]I have counts of these measures for the 5 years before graduation and for bins of 5 years after graduation, starting for bin of years 1 to 5 after graduation up to bin of years 46 to 50 after graduation.

vey and exclude individuals who declare starting an internship, traineeship, clinical residency or military service. I exclude individuals who do not start their career in the United States (12.6%). I also exclude individuals for whom I do not have information about publications, gender, father education, mother education, race PhD field and earnings. This leaves me with 21,406 observations. Because the earnings outcome is a flow and doctorate holders can be surveyed several times, the earnings regressions will be estimated on a sample of 80,282 observations, meaning that I observe on average 3.7 earnings values per individual.

2.2 Dependent Variables

Earnings - From these datasets, I primarily have access to information about earnings *during* the career. Earnings correspond to the total earned income before deductions in the previous year. This includes wages, bonuses, overtime, consulting fees and summertime teaching or research. I use the number reported by respondents across the several SDR surveys they have taken so that I may have several earnings observations per individual corresponding to different levels of experience. I transform all values in 2015 US dollars. The SED has information about salary *at graduation* for cohorts who graduated in or after 2008. I will also exploit this variable for the subs-sample of individuals for whom it is available since it gives me information about earnings right after graduation, but it is not my preferred variable given that it highly restricts the number of observations available. I winsorize observations below the 1^{st} percentile and above the 99^{th} percentile.

Publications - I calculate the number of publications published after Ph.D. graduation by subtracting the number of publications published before graduation from the total number of publications published by the individual until 2017.[3] I winsorize observations below the 1^{st} percentile and above the 99^{th} percentile.

2.3 Defining the sector joined at graduation

I first assign each individual to three potential sectors: Industry (business for-profit), Academia (2-year and 4-year college or university and university-affiliated research institute) or Government (US or foreign government).[4] My preferred treatment variable is an indicator variable equal to 1 for individuals joining Industry and 0 for individuals joining any other sector, i.e., Academia or Government (in the rest of the paper, I will loosely refer to this treatment variable as joining Industry vs Academia).[5] Note that about 50% of individuals in my sample start their career in a postdoc position. In theory, a postdoc could be performed in the private sector or in Academia. Individuals who graduated between 1969 and 2003 and started their career with a postdoc were

[3] I only include publications that were articles, reviews or conference proceedings.

[4] I follow the classification provided by the NCSES. I exclude individuals working in non-profit and U.S. preschool, elementary and middle school

[5] This is motivated by my informal conversations with doctorate holders, but my results are robust to excluding the Government category.

not asked questions about their employer type as part of the SED. The question started to be asked to individuals in 2004 onwards. Hence, I cannot directly assign a sector of employment after graduation for individuals starting a postdoc between 1970 and 2003. However, looking at cohorts graduating in or after 2004, 82% of them do their postdoc in Academia, 11% in the government and only 2% in Industry. I therefore take the stand of assigning postdocs to the academic sector. Among the 21,406 unique individuals in my sample, 17% are joining Industry.[6]

Note that my treatment corresponds to the sector where individuals *start* their career, but individuals may change sector between graduation and the time of survey. As a consequence, I might, for example, have individuals who started their career in Academia but for whom I observe earnings while they are in Industry (and vice-versa). Similarly, the stock of publications observed in 2017 might include publications produced while in Academia and others produced while in Industry. This is not an issue for my empirical analysis as I am interested in the causal impact of *starting* one's career in Industry vs Academia, which also incorporates the probability of changing sector. But if the reader were to be interested in the causal impact of *working* in Industry vs Academia, my estimates are likely to represent lower bounds. Indeed, most of individuals in my sample who changed sector between graduation and survey moved from Academia to Industry. For these individuals, their earnings value is therefore attributed to the academic sector while they correspond to a position in Industry (which likely pays more), hence decreasing the earnings gap between Industry and Academia. Similarly, their stock of publication is attributed to Academia while part of their career was spent in Industry (where individuals tends to publish less). This decreases the publication difference between Industry and Academia.

2.4 PhD fields and majors

I refer to Ph.D. *major* as the most granular group I have access to for each individual (e.g., Biology, Genetics, Biochemistry, Astronomy, Computer Engineering etc.). This is what students choose to study. My dataset includes 57 distinct PhD majors. I refer to PhD *field* as a way to categorize these majors. I focus my study on 5 fields: Computer Sciences and Mathematics, Life Sciences, Physical Sciences, Social Sciences and Engineering.

3 Descriptive analysis

In this section, I further describe the sample and present the main characteristics of individuals joining Industry vs Academia at graduation.

3.1 Supply

Figure 1 shows the number of Ph.D. by cohort of graduation and Ph.D. field in my sample. The number of individuals increases with cohort of graduation, reflecting the increase in the number of

[6] 17% are joining Industry, 72% are joining Academia and 10% are joining Government.

PhD over time. Figure A.1 shows an important increase in the share of international students over time, from about 10% in the 80s to 30% in 2013, with a peak at about 40% in 2006. Overall, 72% of individuals in my sample are born in the United States. Interestingly, Figure A.2 shows that this increase is primarily concentrated in the fields of Computer Sciences and Engineering, where the share of international students rose from about 30% in the 80s to 50% in 2013. The share of female increased linearly from about 25% in the 80s to about 45% in 2013. This increase is characteristic of all fields though it seems to be relatively flat in the field of Computer Sciences and Mathematics.

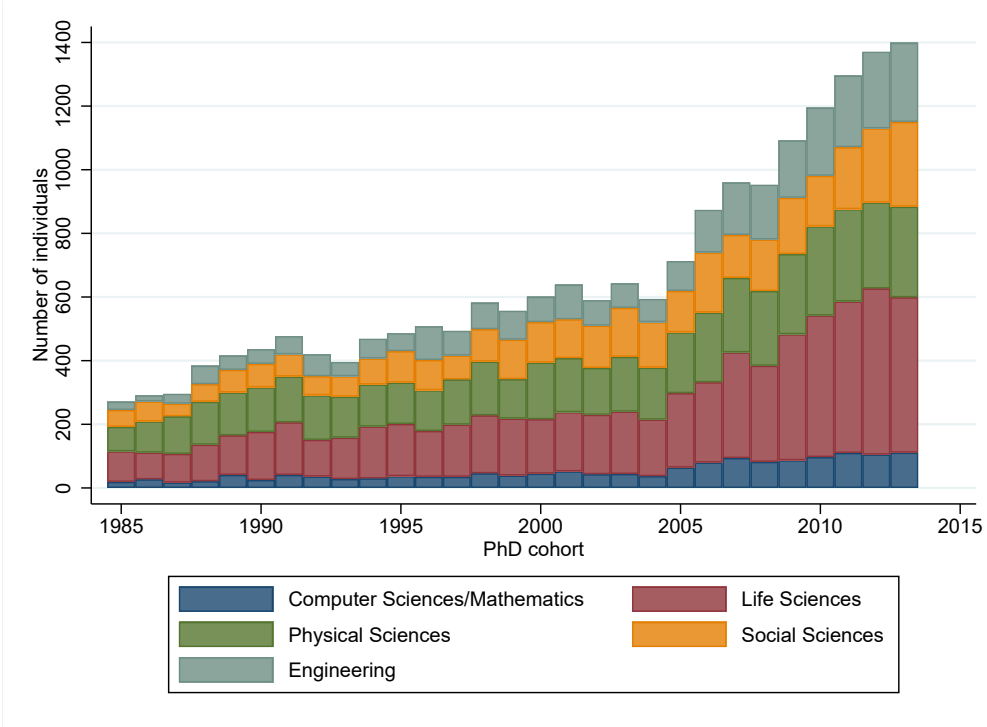


Figure 1: Number of individuals by PhD cohort of graduation

3.2 Sorting

Figure 2 shows the sorting pattern between Industry and Academia. The blue (resp. red) bar shows the number of people who join the academic (resp. private) sector after graduation. The black lines translates this sorting into a share by showing the percentage of individuals joining the private sector at graduation, which fluctuates around 20% but remains relatively constant over time. Interestingly, the share of individuals joining the private sector at graduation peaks and then decreases around the major macro-economic shocks: in 1981/1982, 1990, 2000/2001 and 2007/2008.

Figure 3 shows that there is variation across fields regarding the share of individuals joining the private sector, with Engineering being the most Industry-oriented field. Of note is the increase of the share of individuals in Computer Sciences/Mathematics joining the private sector starting around 2005. Importantly, most of the variation seems to be *within* field. I will leverage this idea to construct an instrumental variable. Figure A.3 shows that starting in the 90s, international students

are more likely than Americans to join the private sector.

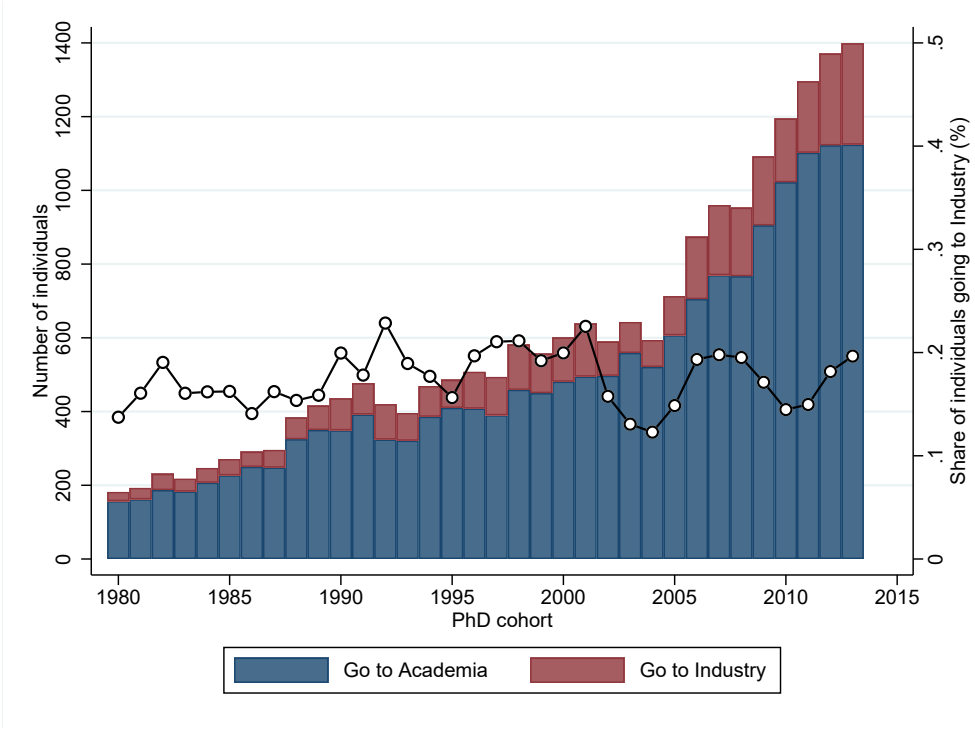


Figure 2: Sector joined at graduation

3.3 Summary statistics

Table 1 shows some summary statistics for my sample as a function of the sector joined at graduation. Individuals who *started* their career in Industry earn on average 47k more per year than individuals who started their career in Academia. The salary gap at graduation is about 44k. They also published on average 11 fewer publications between graduation and the time of survey.[7] On average, individuals graduated in 2001, representing about 13 years of experience at the time of survey. 42% of individuals in Academia are female in Academia, vs only 26% in Industry. In both sectors, a majority of individuals are white and this share is higher Academia. On average and in both sectors, 49% (62%) of individuals have a mother (father) who has at least a bachelor degree. As highlighted before, more international students tend to join the private sector at graduation than Academia. There is no apparent significant differences between sectors regarding the number of publications before graduation.

[7] While this difference might seem low compared to what we would expect from the difference in publications between Industry and Academia over the career, remember that my treatment variable is defined by individuals' sorting decision *at graduation*, not by the sector that employs them at the time of survey. This tends to make the publication difference between individuals who *started* in Industry and individuals who *started* in Academia lower than the publication difference we would expect between individuals *working* in Industry and individuals *working* in Academia.

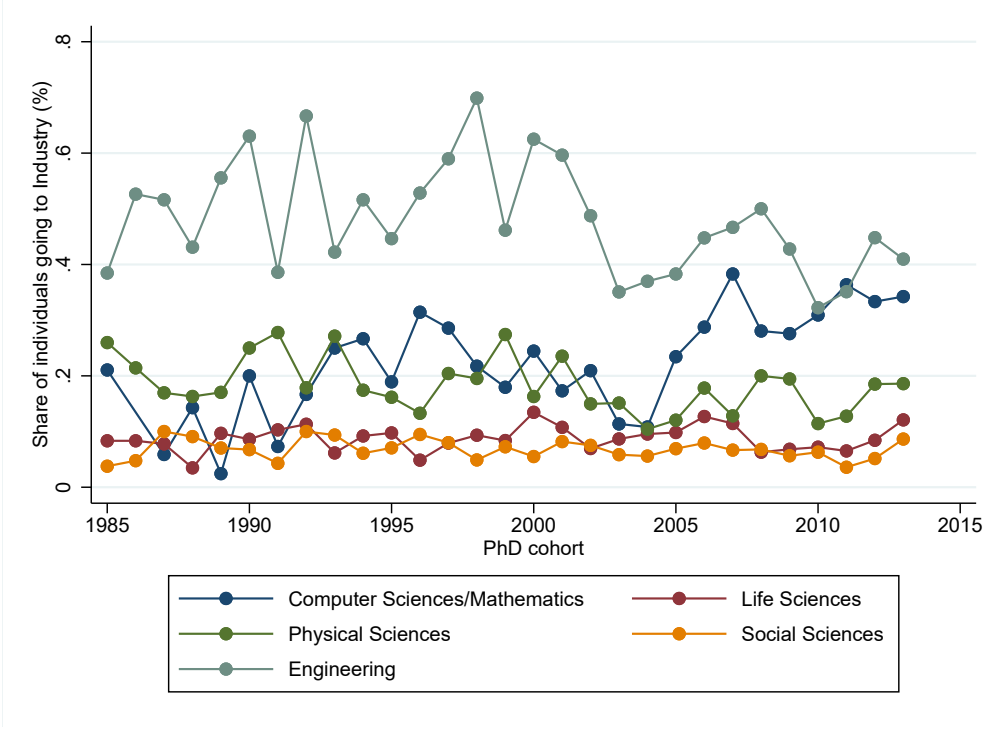


Figure 3: Share of individuals joining the private sector by PhD field of study and PhD cohort of graduation

Table 1: Summary Statistics

	Academia (1)		Industry (2)		(1)-(2)
	Mean	S.d.	Mean	S.d.	Diff.
Earnings (2015 USD th.)	99.6	69.3	147.1	98.3	-47.5***
Publications (stock)	18.8	28.7	8.0	18.8	10.8***
PhD cohort	2,000	10	2,001	10	-1**
White (0/1)	0.7	0.5	0.6	0.5	0.1***
Female (0/1)	0.4	0.5	0.3	0.4	0.2***
Experience (years)	13	10	12	10	1***
Mother at least undergrad. (0/1)	0.5	0.5	0.5	0.5	-0.01
Father at least undergrad. (0/1)	0.6	0.5	0.6	0.5	-0.02*
American (0/1)	0.7	0.4	0.6	0.5	0.1***
Publications during PhD	2.2	5.3	2.3	4.1	-0.1
Observations	17,697		3,709		21,406

The survey asks respondents to report their "primary job activity", which corresponds to the activity they spend most of their time on. Figure 4 shows that in both sectors, a vast majority of individuals report 'Research and Development' as their main activity (about 70% in Academia and about 80% in Industry). As expected, a bit more than 20% of individuals in Academia report 'Teaching' as their primary activity. Figure A.4 shows the results in 2015, i.e., during individuals' career. As expected, the share of individuals reporting 'Research and Development' as their main activity decreases to about 50% in both sectors in favor of 'Management'. Figure A.5 in Appendix shows that 'Research and Development' performed within Academia is split equally between 'Basic Research' and 'Applied Research', while 'Research and Development' performed within Industry is primarily 'Applied Research' and 'Development' (Agarwal and Ohyama, 2013).

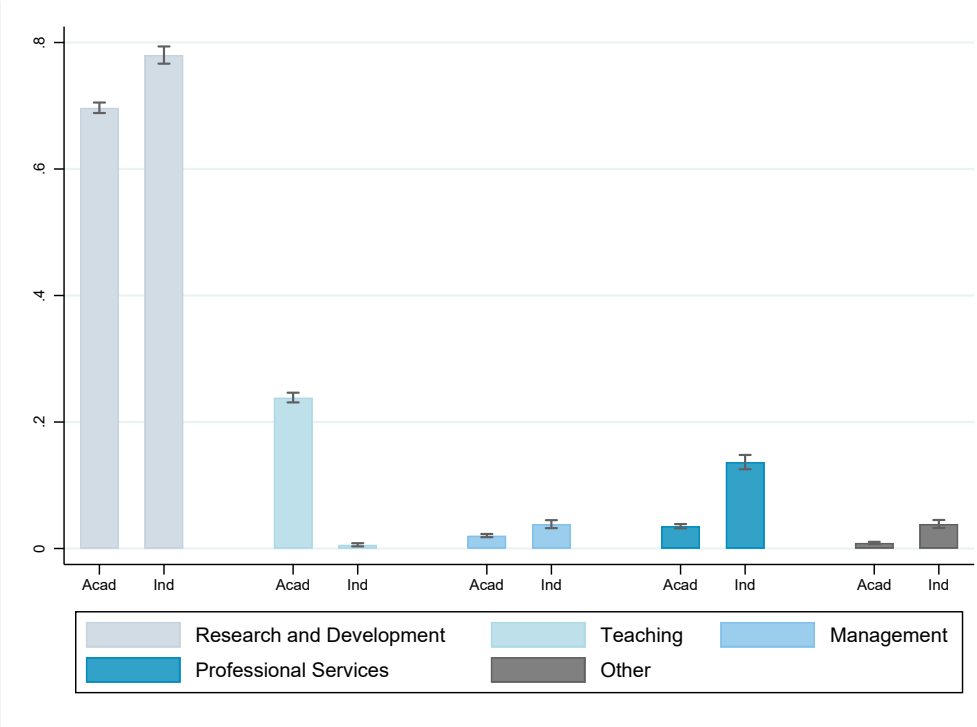


Figure 4: Primary job activity, by sector joined at graduation

In the survey, individuals are also asked to report the *importance* they give to and the *satisfaction* they have with 9 job attributes on a scale from 1 (very important) to 4 (not important at all): opportunities for advancement, job benefits, challenge, independence, location, responsibility, salary, security and contribution to society. For each variable (18 in total), I create an indicator equal to 1 when the attribute is declared as very important and 0 otherwise. Individuals are also asked to report their *overall job satisfaction* and I create an indicator for this variable too which I take as my best proxy for *sector taste*. Figure 5 shows the 9 job attributes, each associated with 4 bars. The first two bars with the black outline denote the average *importance* of the job attribute among individuals observed in Academia (A) and Industry (I). The subsequent two bars represent

the average *satisfaction* with the job attribute for individuals in Academia and Industry. Finally, the last two bars, colored in black, summarize overall job satisfaction. Analyzing the first two bars for each attribute reveals that individuals entering Industry tend to place less importance on Independence, Security, and impact on Society, while prioritizing Salary more. Satisfaction for each attributes appear roughly similar across sectors except for Challenge, Independence, Security and Impact on Society (where individuals in Industry appear less satisfied) and Salary (where individuals in Industry appear more satisfied). Interestingly, the gap in overall job satisfaction appears rather small between both sectors. This is likely to be due to the fact that individuals in Industry put more weight on the Salary attribute than on the Challenge, Security and Society ones.

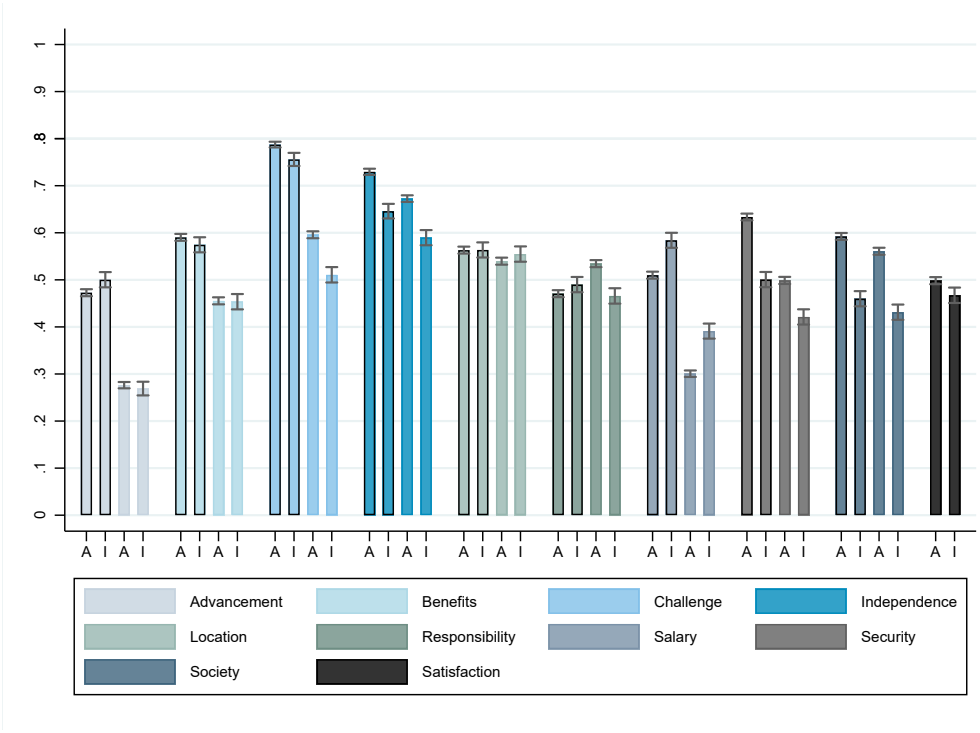


Figure 5: Job-attributes: importance and satisfaction by sector joined at graduation

Finally, Figures 6 and 7 show the two main outcomes of interest as a function of career experience. The difference in publication stock appears to be increasing over time. The earnings curve in Industry has a higher intercept but is less steep, so that earnings in both sectors look roughly similar in the raw data towards the end of the career.

While the raw data suggests important differences in earnings and publications between individuals who start their career in Industry and those who start their career in Academia, these numbers do not reflect causal estimates because they are likely to be biased by *selection*, as individuals can be expected to choose their sector at graduation based on their private returns. In what follows, I present a simple of model of selection and highlights the endogeneity it entails.

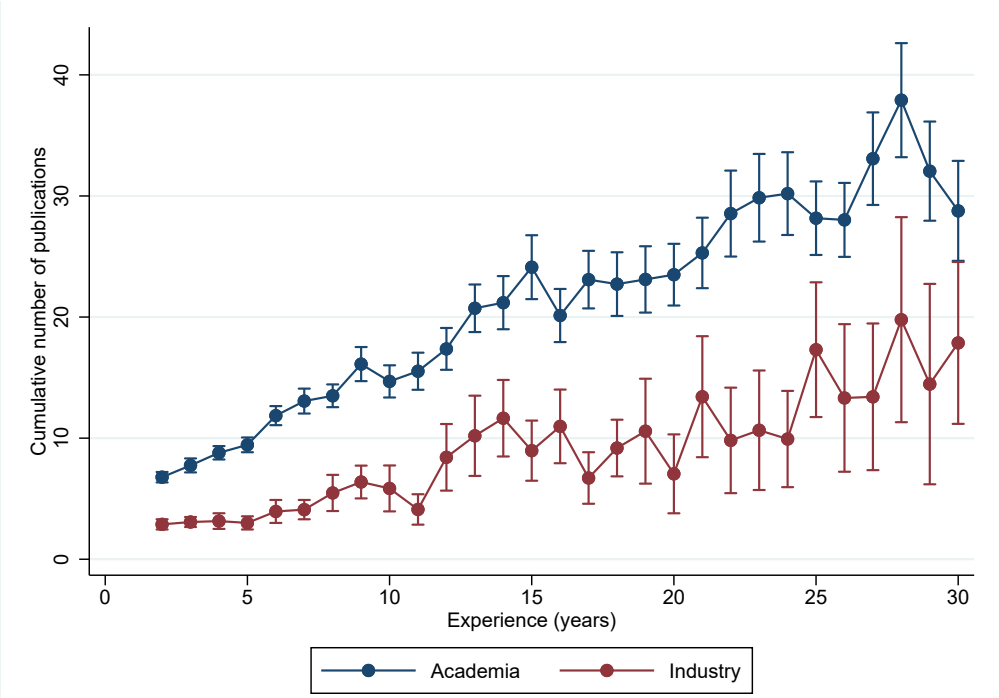


Figure 6: Mean publications (stock) as a function of experience and sector joined at graduation

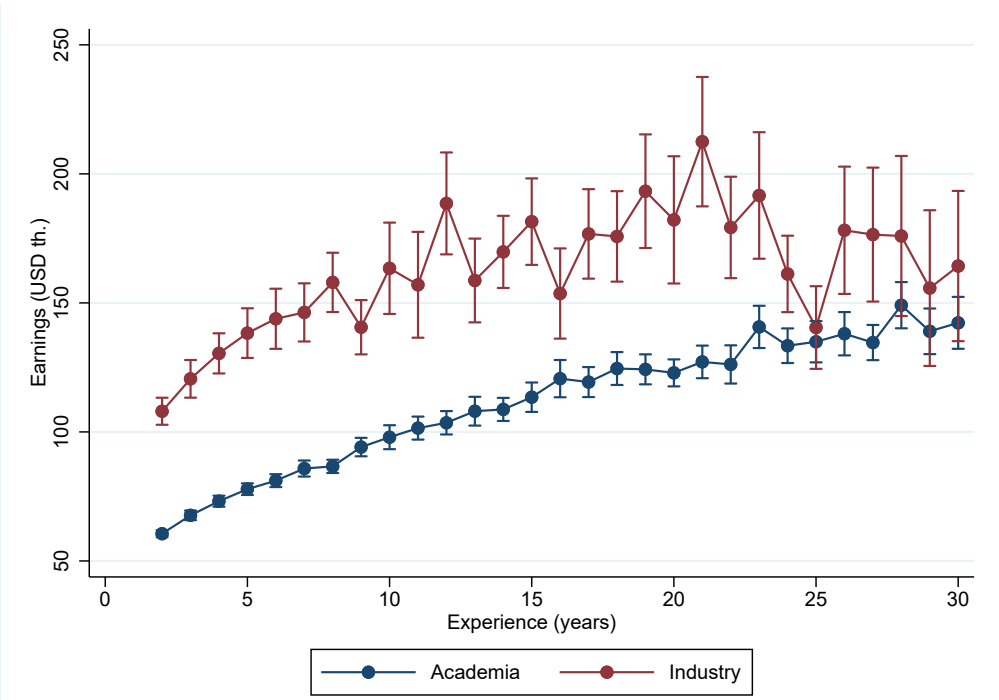


Figure 7: Mean earnings as a function of experience and sector joined at graduation

4 Model of selection

Let individuals be indexed by i and time be indexed by $t \in [0, T]$. Let $j(i)$ denote the sector that individual i joins after graduating from her Ph.D. at time $t = 0$. Individuals can join one of two sectors in the economy: Industry ($j(i) = I$) or Academia ($j(i) = A$). I assume that I observe a unique generation of individuals so that t can also be conceptualized as years of experience. I also assume for simplicity and because it does not impact the selection mechanism I want to highlight that individuals do not change sector during their career (Appendix C presents the full model allowing for transitions across sectors).

Each individual receives two endowments at birth: an individual-specific productivity parameter in Industry δ_i^I and an individual-specific productivity parameter in Academia δ_i^A. These parameters capture how more/less productive individual i is in Industry and Academia compared to the average. δ_i^I represents general skills that are common to both Industry and Academia, such as overall ability or creativity, as well as Industry-specific skills, such as social and communication skills, taste for teamwork, a greater concern for salary and access to resources, a stronger interest in downstream work and the ability to work on problems and find solutions which are relevant for the firm (Roach and Sauermann, 2010). Similarly, δ_i^A represents general skills that are common to both sectors, as well as Academia-specific skills, such as work independence, taste for publishing, importance given to peer recognition, ability to formulate research questions, self-criticism, as well as writing and teaching skills (see Ballesteros-Rodríguez et al. (2022) for a review of the literature).

Assuming that earnings proxy for productivity,[8] we can write the potential earnings of individual i at time t if she started her career in sector $j \in (I, A)$ as:

$$W_{it}^j \equiv \overline{W_t^j} + \delta_i^j \tag{1}$$

with $\overline{W_t^j}$ the average earnings at time t of individuals who started their career in sector j and δ_i^j individual's i productivity parameter in sector j.

At the micro level, W_{it}^j is the sum of pecuniary returns related to research output and pecuniary returns related to non-research output. Research output can be further decomposed into a public and a private component. Public research relates to research that is publicly disclosed through publications or patents, while private research relates to research that is not disclosed outside of the boundaries of the organization. Depending on individual i's sector and job in sector j, earnings could be a function of (i) public research, private research, and other activities (e.g., if i has a position in Academia or works in a firm that engages in public research), (ii) private research and other activities (e.g., if i has a research position in a firm that does not publicly disclose its results) or (iii) other activities only (e.g., if individual i has a job that is not related to research, such as supply-chain manager). Calling P_{it}^j, R_{it}^j and O_{it}^j respectively the public research output, private research output and output related to other activities produced at time t by individual i who started

[8] The fact that other things enter the earnings component does not change the selection mechanism I want to highlight.

her career in sector j, we can write W_{it}^j as:

$$W_{it}^j = p^j P_{it}^j + r^j R_{it}^j + o^j O_{it}^j = p^j(\overline{P_t^j} + \theta_{p,i}^j) + r^j(\overline{R_t^j} + \theta_{r,i}^j) + o^j(\overline{O_t^j} + \theta_{o,i}^j) \tag{2}$$

with p^j, r^j and o^j the sector-specific prices that convert these outputs into dollars, $\overline{P_t^j}$, $\overline{R_t^j}$, $\overline{O_t^j}$ the mean outputs by activity type in each sector and $\theta_{p,i}^j$, $\theta_{r,i}^j$ and $\theta_{o,i}^j$ the individual-specific unobservables associated with each output type in each sector. By construction:

$$\overline{W_t^j} = p^j \overline{P_t^j} + r^j \overline{R_t^j} + o^j \overline{O_t^j} \tag{3}$$

and

$$\delta_i^j = p^j \theta_{p,i}^j + r^j \theta_{r,i}^j + o^j \theta_{o,i}^j \tag{4}$$

Define the utility u_{it}^j of individual i at time t in sector j as being equal to:

$$u_{it}^j = W_{it}^j + \varepsilon_i^j \tag{5}$$

with ε_i^j individual i's non-pecuniary returns in sector j. Individual i's utility of *starting* her career in sector $j \in (I, A)$, denoted by U_i^j, is then equal to the sum of the discounted utilities over the career:[9]

$$U_i^j = \sum_{t=0}^{T} \rho^t u_{it}^j = \sum_{t=0}^{T} \rho^t \, \overline{W_t^j} + \frac{1-\rho^{T+1}}{1-\rho} \, (\delta_i^j + \varepsilon_i^j) \tag{6}$$

with ρ^t the discount factor at time t.

Individual i *starts* her career in Industry iff :

$$\begin{aligned} j(i) = I \iff & U_i^I - U_i^A > 0 \\ \iff & \sum_{t=0}^{T} \rho^t \, (\overline{W_t^I} - \overline{W_t^A}) + \frac{1-\rho^{T+1}}{1-\rho} \, (\delta_i^I - \delta_i^A) + \frac{1-\rho^{T+1}}{1-\rho} \, (\varepsilon_i^I - \varepsilon_i^A) > 0 \end{aligned} \tag{7}$$

Equation 7 shows that individuals select on the difference in private gains $\delta_i^I - \delta_i^A$.[10] Because we allow for heterogeneous effects, this selection on gains is allowed to be correlated with a selection on level so that the difference in unobservables $\delta_i^I - \delta_i^A$ can be correlated with the levels of δ_i^I and δ_i^A (see Appendix D for the formal proof).

My two outcomes of interest are earnings W_{it}^j and publications P_t^j. This creates endogeneity issues since the error term of these outcomes is likely to be correlated with the difference in unobservables $\delta_i^I - \delta_i^A$ that enters the selection equation. This is easily visible for the earnings outcome which is a function of δ_i^j: if individuals who tend to select into the private sector (their difference $\delta_i^I - \delta_i^A$ is high) also tend to be particularly skilled in Industry (their δ_i^I is high), the earnings we observe

[9] Working with expected utilities does not change the main selection mechanism I want to highlight.
[10] Directly through $\delta_i^I - \delta_i^A$ and also potentially indirectly since $\varepsilon_i^I - \varepsilon_i^A$ is allowed to be correlated with $\delta_i^I - \delta_i^A$.

in the private sector will be biased upwards. Similarly for publications, if those who tend to stay in Academia (their difference in unobservables $\delta_i^I - \delta_i^A$ is low) also tend to be particular skilled in (public) research (high $\theta_{p,i}^A$), the publication output observed in Academia will be biased upwards. In general, the sense of the bias will depend on the correlation between $\delta_i^I - \delta_i^A$ and the error term of the outcome considered.

5 Estimation Strategy and Results

In this section, I present the several estimation strategies I use to estimate the causal impact of joining Industry vs Academia at graduation on earnings and publications. My first strategy relies on variation *within PhD major* × *doctoral institution* (hereafter 'department') in order to estimate an Average Treatment Effect (ATE). My second strategy uses an instrumental variable that allows me to estimate a Local Average Treatment Effect (LATE). I then explore heterogeneity on observable and unobservable characteristics using Marginal Treatment Effects (MTE).

5.1 Within department variation

One strategy to solve the selection issue consists in controlling for ability. This is not easy to do in my context as the usual variables used in the literature do not vary in my sample (e.g., education) or are simply not available (previous wages). Instead, I follow recent work that uses the quality of PhD students' university department by using department ranking as a linear control (Agarwal and Ohyama, 2013; Cohen et al., 2020; Roach and Sauermann, 2023, 2024). I extend this idea by using PhD major × doctoral institution fixed effects in a cross-section regression. Note that this is a more stringent version than linearly controlling for PhDs' department ranking, since I only use variation across individuals *within* a department. Under the identifying assumption that the difference in unobserved productivities between Industry and Academia does not vary within a department, using variation in sorting across individuals pertaining to the same department recovers the ATE of joining Industry vs Academia at graduation. My main specification is the following:

$$Y_i = \alpha_0 + \alpha_1 \text{Industry}_i + \delta_{mu} + \alpha_2 \mathbf{X_i} + \varepsilon_i \tag{8}$$

with m indexing PhD major, u indexing university. δ_{mu} represents PhD major × university fixed effects and $\mathbf{X_i}$ a vector of control variables which includes an indicator equal to 1 if the individual reports being a female, an indicator equal to 1 if the individual reports being white, an indicator equal to 1 for American (vs International) students, an indicator equal to 1 if the individual's father has at least a bachelor degree, an indicator equal to 1 if the individual's mother has at least a bachelor degree. I control for experience using a linear and quadratic terms for experience, but results are similar using variation within PhD major × doctoral institution × PhD cohort. In one specification, I also proxy for sector-specific preferences that could be correlated with the outcomes by using information about the 9 job attributes presented in Figure 5. More precisely, I control for the importance given to job independence, salary, security and impact on society by including

4 indicators equal to 1 if the attribute is judged 'very important'.[11] Note however that because these these preferences are observed during employment, they might have been influenced by the treatment variable itself.

Publications - Results for the (log) publication outcome are presented in Table 2, with robust standard errors clustered at the doctoral institution level. Column (1) only includes the main demographics controls (gender, race, parental education and nationality). Column (2) adds PhD major fixed effects in order to control for field-specific differences in publication norms. Column (3) adds doctoral institution fixed effects. Column (4) adds doctoral institution × PhD major fixed effects so that the effect is identified by using granular variation *within* universities' departments. This is my preferred specification. Column (5) adds controls for sector-specific preferences. Overall, the coefficient on the treatment variable *Industry* remains stable and equal to about -0.9, implying that going to Industry vs Academia decreases the total number of publications by about 60%, representing a loss of about 10 publications.[12] Table B.1 reiterates the analysis on the sub-sample of individuals with strictly positive publications and finds similar results. Table B.2 uses citations-weighted publications as the main outcome and finds more negative coefficients, implying that publications produced in Academia also gather more citations.

Table 2: Within department specification - OLS Publications (stock)

	Log(1+Publications)				
	(1)	(2)	(3)	(4)	(5)
Industry	-0.911***	-0.943***	-0.936***	-0.942***	-0.900***
	(0.0200)	(0.0255)	(0.0255)	(0.0278)	(0.0296)
Demographics	Yes	Yes	Yes	Yes	Yes
Experience	Yes	Yes	Yes	Yes	Yes
PhD major FE		Yes	Yes	Yes	Yes
Doct. Inst. FE			Yes	Yes	Yes
PhD major x Doct. Inst. FE				Yes	Yes
Taste					Yes
Observations	21,406	21,406	21,406	21,406	21,406
R-sq	0.167	0.197	0.226	0.327	0.349

Notes: This table reports the OLS estimates for publications using within department (defined as PhD major × doctoral institution) variation. Experience controls include a linear and a quadratic terms. Standard errors (in parentheses) are clustered at the doctoral institution level.

Earnings - Table 3 Panel A shows results for the earnings outcome, with the same controls as before. I first consider for each individual the earnings observation closest to graduation. Once all controls are included, the estimate is about 0.32, implying that the earnings premium is equal to about

[11] The other attributes are highly correlated with these 4 ones.
[12] The mean of (winsorized) publications is 16.9.

35%, representing about USD 39k. Using the sub-sample of individuals who graduated after 2008 and for whom I have earnings observations at graduation, the earnings premium is higher, at about 86% or USD 52k. Table 3 Panel B shows the result using all the earnings observations linked to an individual. Once all controls are included, the coefficient of 0.27 implies an earnings premium of about 31%, representing a premium of USD 38k.[13] This suggests that the earnings gap is primarily characteristic of the early-stage of the career.

Table 3: Within department specification - OLS Earnings

	Log(1+Earnings)				
	(1)	(2)	(3)	(4)	(5)
Panel A: First observation					
Industry	0.367***	0.296***	0.295***	0.302***	0.302***
	(0.0121)	(0.0134)	(0.0135)	(0.0149)	(0.0169)
Observations	21,406	21,406	21,406	21,406	21,406
R-sq	0.166	0.196	0.218	0.315	0.325
Panel B: All observations					
Industry	0.350***	0.279***	0.278***	0.274***	0.268***
Observations	80,282	80,282	80,282	80,282	80,282
R-sq	0.127	0.158	0.179	0.281	0.298
Demographics	Yes	Yes	Yes	Yes	Yes
Experience	Yes	Yes	Yes	Yes	Yes
PhD major FE		Yes	Yes	Yes	Yes
Doct. Inst. FE			Yes	Yes	Yes
PhD major x Doct. Inst. FE				Yes	Yes
Taste					Yes

Notes: This table reports the OLS estimates for earnings. Panel A uses the observation closest to PhD graduation and Panel B uses all observations linked to an individual. I use within department (defined as PhD major × doctoral institution) variation. Experience controls include a linear and a quadratic terms. Standard errors (in parentheses) are clustered at the doctoral institution level.

Note that the coefficients do not vary much once the PhD field fixed-effects are included. This implies limited selection on ability from the supply-side (at least within the context of this model) and echoes findings from Roach and Sauermann (2024).

Despite this list of controls which follows the state of the literature, we might still be concerned that some unobservable individual characteristics that are correlated with both sector choice and outcomes vary across individuals, even within a department. Hence, I also implement an instrumental variable (IV) strategy to estimate the causal impact of joining Industry vs Academia on earnings and publications. This allows me to estimate a local average treatment effect (LATE), i.e., the causal effect of joining Industry vs Academia for individuals on the margin of going to Industry.

[13]The mean of (winsorized) earnings is USD 121.6.

5.2 Instrumental Variable

As depicted in Figure 3, there is considerable variation across cohorts within each PhD major in the proportion of individuals opting for the private sector upon graduation. To leverage this variation, I construct an instrumental variable based on the fluctuating macroeconomic conditions experienced by different cohorts of PhD graduates. For example, the demand for PhDs in Aerospace Engineering from firms might surge in 2009 due to specific industry needs, while shifts in undergraduate enrollments could affect faculty demands in Biomedical Engineering in different years. Within each PhD major, these fluctuations create year-to-year variations in the likelihood of individuals choosing Industry over Academia upon graduation. Building upon Oyer (2006), who focused on the Economics major, I extend this approach to encompass all PhD majors within my sample. Empirically, one can think of the instrument as a vector of PhD major × PhD cohort fixed effects, controlling for PhD major fixed effects. In practice, I show later how I construct a continuous leave-one out version of this instrument.

To be valid, the instrument: (i) should not be correlated with individuals unobservable productivities in Industry vs Academia $\delta_i^I - \delta_i^A$ and (ii) should not impact earnings/publications directly (i.e., other than through its impact on sector joined at graduation). This implies that individuals that are more/less productive in Industry vs Academia do not time their decision of when to go on the market based on macroeconomic conditions. Said differently, the average quality of individuals within a major is not systematically related to the state of the economy. In order to make this assumption more plausible, I include doctoral institution fixed effects as well as an indicator variable equal to 1 if the individual has already published at least once before graduating. This also partly controls for the fact that some majors could become more Industry-oriented over time which would change who selects into it over time.

Empirically, one can think of this instrument as a vector of PhD major × PhD cohort fixed effects, controlling for PhD major fixed effects, which exploits variation *across cohorts within PhD majors.*[14] In practice, I follow the literature and create a leave-one out continuous equivalent of the interaction term to reduce the risk of bias.[15] For each individual, the instrument Z_i is therefore equal to:

$$Z_i = \frac{\sum_{i'} Ind_{i'} \times \mathbf{1}\{m(i') = m(i)\} \times \mathbf{1}\{c(i') = c(i)\} - Ind_i}{\sum_{i'} \mathbf{1}\{m(i') = m(i)\} \times \mathbf{1}\{c(i') = c(i)\} - 1} \tag{9}$$

with i' indexing individuals, Ind_i an indicator equal to 1 if i starts her career in Industry, $m(i)$ representing individual i's PhD major and $c(i)$ representing individual i's PhD cohort of graduation. In Appendix , I also present results using another instrument that relies on variation across undergraduate majors close in the knowledge space for individuals with similar sector-specific preferences, and for which I find very similar results. *[Awaiting export approval]*

[14] I only keep PhD major × PhD cohort fixed effects for which I have at least 10 observations.
[15] Dobbie et al. (2018)Sampat and Williams (2019)

First Stage - The first-stage estimates are presented in Table 4, which shows variants of the following regression:

$$Ind_i = \gamma_0 + \gamma_1 Z_i + \gamma_2 \mathbf{X_i} + \nu_i \tag{10}$$

Ind_i is an indicator equal to 1 if the individual joins Industry at graduation and 0 otherwise. Z_i is the instrument for individual i. X_i include PhD major fixed effects so that I rely on variation *across years within PhD major*, as well as controls for experience with a linear and quadratic terms and demographics controls (an indicator for being female, an indicator for being white, an indicator for father's education being at least an undergraduate degree, an indicator equal to 1 for mother's education being at least an undergraduate degree, an indicator equal to 1 for being American vs International). Column (1) includes controls for experience and demographic characteristics. Column (2) adds doctoral institution fixed effects. Column (3) adds an indicator equal to 1 if the individual has published at least once before graduating. Standard errors are clustered at the PhD major and PhD cohort level to account for intra-group correlation.[16]

Table 4: First-stage estimates

	Industry		
	(1)	(2)	(3)
Z_i	0.220***	0.214***	0.214***
	(0.0385)	(0.0390)	(0.0389)
Demographics	Yes	Yes	Yes
Experience	Yes	Yes	Yes
PhD major FE	Yes	Yes	Yes
Doct. inst. FE		Yes	Yes
Publ. bef. grad.			Yes
F-stat	32.48	30.17	30.18
Observations	21,406	21,406	21,406
R-sq	0.163	0.185	0.185

Notes: This table reports the first-stage estimates. Standard errors (in parentheses) are two-way clustered at the PhD major and PhD cohort level.

All columns show a first-stage with a F-statistic above 30. As expected, graduating in a year where macroeconomic shocks increase firms' demand for PhDs (as reflected in higher values of the instrument) increases individuals probability to enter the private sector.

2SLS Publications - Table 5 presents the 2SLS estimates for the publication outcome. Using the preferred specification in column (3), the LATE estimates imply that the marginal individual starting her career in Industry generates 71% less publications than if she would have stayed in Academia,

[16] Results clustering at the PhD major level only give similar results.

representing about 12 publications less.[17] Table B.4 uses citations-weighted publications as an outcome and finds more negative magnitudes, implying that publications in Academia also receive more citations.

Table 5: 2SLS - Publications

	Log(1+Publications)		
	(1)	(2)	(3)
Industry	-1.203***	-1.225***	-1.227***
	(0.440)	(0.463)	(0.476)
Demographics	Yes	Yes	Yes
Experience	Yes	Yes	Yes
PhD major FE	Yes	Yes	Yes
Doct. Inst. FE	No	Yes	Yes
Publ. bef. grad.	No	No	Yes
F-stat	32.48	30.14	30.15
Observations	21,406	21,406	21,406
R-sq	0.191	0.220	0.231

Notes: This table reports the 2SLS results for publications. Standard errors (in parentheses) are two-way clustered at the PhD major and PhD cohort level.

2SLS Earnings - Table 6 columns (1) to (3) repeats this exercise for the earnings outcome, considering the earnings observation closest to graduation for each individual. The preferred specification in column (3) implies that joining Industry at graduation leads to a 69% earnings premium, or USD 75k. Table 6 columns (4) to (6) repeats this exercise by considering all earnings observations linked to an individual. The magnitude decreases and becomes insignificant, suggesting that the earnings gap is most relevant at the earlier stage of the career. Unfortunately, I am under-powered to run the regression on the sub-sample of individuals with earnings observations at graduation. While studying the micro-factors behind this earnings gap is beyond the scope of this paper, the literature suggests that it may stem from differences in non-pecuniary factors as well as differences in human and physical capital investments (Agarwal and Ohyama, 2013; Roach and Sauermann, 2010; Stern, 2004).

While the 2SLS estimates get us closer to a causal effect, they also present several limitations. In particular, they identify the effect for a very specific group of individuals - the compliers - and do not allow to study heterogeneity in treatment effects as well as the pattern of selection. I now proceed to the analysis of heterogeneity along observable and unobservable dimensions.

[17] Table B.3 in Appendix shows the results when restricting the sample to individuals with at least one publication. Results are unchanged.

Table 6: 2SLS - Earnings

	Log(1+Earnings)					
	First observation			All observations		
	(1)	(2)	(3)	(4)	(5)	(6)
Industry	0.497*	0.526**	0.527**	0.283	0.309	0.313
	(0.264)	(0.267)	(0.267)	(0.252)	(0.248)	(0.248)
F-stat	33.11	30.72	30.73	25.82	24.55	24.59
Observations	21,406	21,406	21,406	80,282	80,282	80,282
R-sq	0.186	0.206	0.206	0.158	0.179	0.179
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Experience	Yes	Yes	Yes	Yes	Yes	Yes
PhD major FE	Yes	Yes	Yes	Yes	Yes	Yes
Doct. Inst. FE	No	Yes	Yes	Yes	Yes	Yes
Publ. bef. grad.	No	No	Yes	No	No	Yes

Notes: This table reports the 2SLS results for earnings using the observation closest to PhD graduation. Standard errors (in parentheses) are two-way clustered at the PhD major and PhD cohort level.

5.3 Heterogeneity on observable characteristics

I focus on two main margins of observable heterogeneity: gender (female vs non-female) and nationality (American vs non-American) using my instrument. Table 7 shows results for the publications (columns (1) and (2)) and earnings (columns (3) and (4)) outcomes. Columns (1) and (3) focus on heterogeneity across genders. Results show that female students joining the private sector tend to publish more and earn less than male students, though this last result is not statistically significant. Columns (2) and (4) shed light on heterogeneity across nationalities. Results show that Americans publish less and earn less than International ones. One reason for the higher earnings premium received by International students could be that those individuals who select into leaving their country are of higher ability than Americans on average. In order to shed more light on differences between American and International students, I restrict the sample to individuals joining the private sector at graduation and run a regression of the form:

$$Y_i = \gamma_0 + \gamma_1 Z_i + \gamma_2 Z_i \times \text{American} + \gamma_3 \mathbf{X_i} + \nu_i \tag{11}$$

where the coefficient of interest is γ_2, which shows the differential effect of joining Industry on the outcome Y_i for Americans vs Internationals. I explore 3 different outcomes (i) occupations (ii) firms' size (iii) mobility and (iv) location. I find no difference with regards to occupation, with Americans and Internationals being equally likely to be observed in a R&D or managerial position. I find that Internationals are more mobile, defined as working on a different state than the state of doctoral

institution, more likely to work in California and more likely to be observed in large firms with more than 25k employees.

Table 7: 2SLS Heterogeneity

	Log(1+Publications)		Log(1+Earnings)	
	(1)	(2)	(3)	(4)
Industry	-1.316***	-0.964**	0.349	0.433*
	(0.456)	(0.432)	(0.236)	(0.214)
Industry × Female	0.289*		-0.124	
	(0.166)		(0.0848)	
Industry × American		-0.393***		-0.181**
		(0.140)		(0.0748)
Demographics	Yes	Yes	Yes	Yes
Experience	Yes	Yes	No	No
PhD major FE	Yes	Yes	Yes	Yes
Doct. Inst. FE	Yes	Yes	Yes	Yes
Publ. bef. grad.	Yes	Yes	Yes	Yes
F-stat				
Observations	21,406	21,406	80,282	80,282
R-sq	0.251	0.244	0.196	0.198

Notes: This table reports the 2SLS results looking at heterogeneity across genders (columns (1) and (3)) and nationality (columns (2) and (4)). Standard errors (in parentheses) are two-way clustered at the PhD major and PhD cohort level.

5.4 Heterogeneity on observables and unobservables

Equation 7 from the initial model suggests that individuals select on gains, i.e., based on the difference $\delta_i^I - \delta_i^A$. However, the LATE estimate gives us a limited overview of selection and hence of the heterogeneity in unobservables it relates to. Indeed, the LATE averages the treatment effect for a specific part of the population (the compliers) and does not allow us to examine how treatment effect varies for individuals with different values of $\delta_i^I - \delta_i^A$ (Andresen, 2018). I therefore extend the 2SLS framework to a Marginal Treatment Effects (MTE) analysis (Björklund and Moffitt, 1987; Heckman and Vytlacil, 1999, 2007). The MTE analysis relates treatment effect heterogeneity to observed (i.e., related to observable characteristics) and unobserved (i.e., related to $\delta_i^I - \delta_i^A$) propensities to join the private sector. The MTE represents the treatment effect for individuals with a specific propensity of entering treatment, and we can recover the LATE (and other key estimands such as the ATE or the ATT) by computing weighted-averages of the MTEs. The MTE can be modelled as part of the generalized Roy Model that I present in Appendix G. I give here the main intuition.

Model - Each individual is characterized by observables X and Z (which represents the instrument) and unobserved characteristic U_D that is usually interpreted as the unobserved resistance or distaste for treatment.[18] Importantly for the interpretation, individuals with lower values of U_D are more likely to join the private sector for unobservable reasons while individuals with higher values of U_D are less likely to enter the private sector (i.e., more likely to enter Academia) for unobservable reasons. Individuals join Industry if:

$$Ind_i = \mathbf{1}\{P(Z_i, X_i) > U_{D_i}\}$$

with $P(Z, X)$ the propensity score. In this setup, the *marginal treatment effect* for individuals with observables $X = x$ and disutility for treatment $U_D = u$ is:

$$\text{MTE}(X = x, U_D = u) = \mathbb{E}[Y^I - Y^A | X = x, U_D = u] \tag{12}$$

with Y the outcome of interest (i.e. earnings and publications). This is the ATE for groups of individuals who have the same latent propensity to be treated. The MTE formula makes it clear that treatment effect heterogeneity may result from both observed and unobserved characteristics. For instance, for individuals with observables X that make them more likely to enter the private sector, I can test whether they have smaller or higher treatment effects than others. Similarly, considering individuals with lower U_D that make them more likely to enter the private sector, I can test whether they have smaller or higher treatment effects than others. A common way to present the results is to plot the MTE as a function of U_D for average values of X. If the slope of the curve is flat, then $\mathbb{E}[Y_1 - Y_0 | X = x, U_D = u]$ is constant so that there is no heterogeneity in treatment effect across individuals with different propensities for joining the private sector vs Academia (or equivalently for individuals with different distaste for joining the private sector vs Academia). If the slope is upward or downward sloping, there is heterogeneity in treatment effect across individuals with different propensities for joining the private sector vs Academia.

The assumptions needed for the calculation of the MTE are the same as for the IV framework, with in particular a valid exclusion restriction which can be written as $(U^A, U^I, V) \perp\!\!\!\perp Z | X$ where $\perp\!\!\!\perp$ denotes conditional independence and (U^A, U^I) are the error terms of the outcomes.[19] In practice, provided my previous instrument is valid, I can use it to estimate the MTE. In practice, it is possible to estimate the MTE with no further assumption. However, this requires full support of the propensity score in both the treated and untreated states for all values of X which is rarely feasible (Andresen, 2018). Following the literature, I further assume additive separability between the observed and unobserved components. This allows me to write the MTE as:

$$\text{MTE}(X = x, U_D = u) = x(\beta_1 - \beta_0) + \mathbb{E}[U_1 - U_0 | U_D = u] \tag{13}$$

[18] Given Equation 7, U_D is a function of $\delta_i^I - \delta_i^A$ and $\varepsilon_i^I - \varepsilon_i^A$.

[19] Omitting individual subscript, $U^A = \delta^A$ and $U^I = \delta^I$ when the outcome is earnings. When the outcome is publications, $U^A = \theta_p^A$ and $U^I = \theta_p^I$.

It also implies that treatment affect heterogeneity coming from observed characteristics affects the intercept of the MTE curve (plotted as a function of U_D) but not its slope (Cornelissen et al., 2016). While this MTE framework is more restrictive than the 2SLS one, it allows me to bring more nuance into treatment heterogeneity and the pattern of selection.[20]

Results - Figure 8 shows histograms of the propensity score estimates (i.e., predicted probabilities to go to Industry vs Academia), for individuals who started their career in Industry and those who started their career in Academia. The common support ranges between 0 and about 0.9. In what follows, I trim the thinnest tails of support and keep observations between the two dashed red lines.[21]

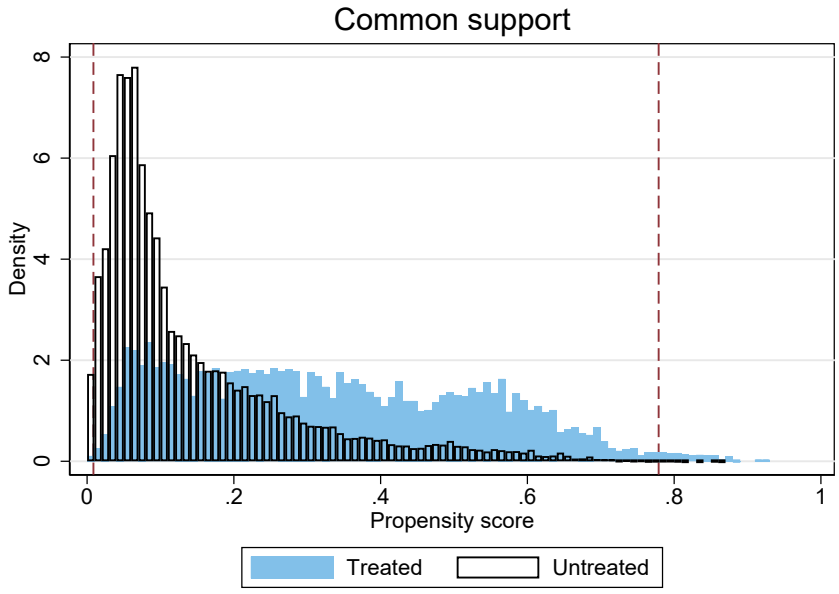


Figure 8: Common support

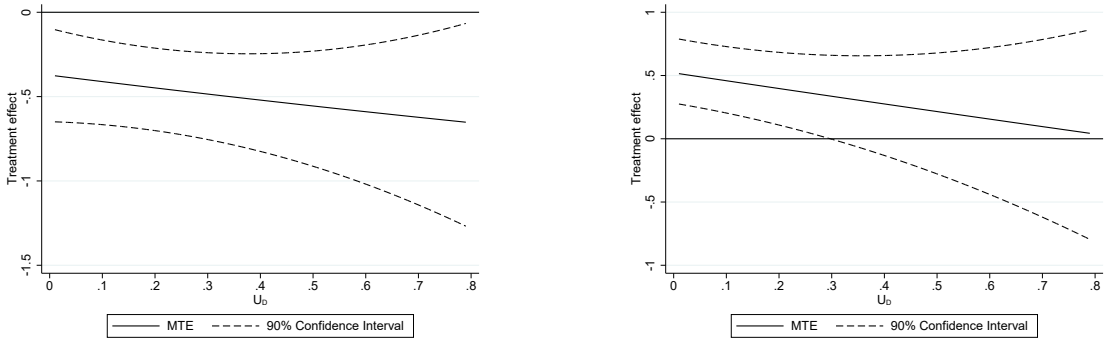
Figures 9a and 9b show the MTE curves for publications and earnings respectively, estimated at the mean values of the covariates and with bootstrapped standard errors.[22] These curves relate the unobserved components of the treatment effect on earnings (i.e., $\delta_i^I - \delta_i^A$) and publications (i.e., $\theta_{p,i}^I - \theta_{p,i}^A$) and the unobserved component of treatment choice U_D, i.e., the *resistance* (or disutility) to join the private sector. The left figure shows a downward sloping curve: at the 10^{th} percentile of unobserved resistance (i.e., individuals who are very likely to go to the private sector), the decrease in publications associated with joining the private sector vs Academia is approximately equal to 60%. For individuals at the 70^{th} percentile of unobserved resistance (i.e., individuals that

[20] Note that the separability assumption remains much less restrictive than a joint normal distribution of (U^A, U^I, V) as assumed by traditional selection models (Andresen, 2018).

[21] Note that the fact that the common support does not range entirely from 0 to 1 is not an issue for the analysis given that I am not looking to estimate the ATE or ATT.

[22] I use the separate method with a polynomial of degree 1.

are less likely to go to the private sector), this decrease is approximately equal to 85%.[23] The earnings curve is also downward sloping: earnings gains are approximately equal to 65% at the 10^{th} percentile of unobserved resistance and approximately equal to 11% at the 70^{th} percentile of unobserved resistance.[24] Overall, this shows evidence of positive selection: those who go to Industry are the ones who have the most to earn, but they are not the ones who would have experienced the highest decrease in publications.



(a) Publications (b) Earnings

Figure 9: MTE Curves

5.5 Postestimation

An advantage of the MTE estimation approach is that the estimates can be combined with the data (i.e., individuals' observables and realized sector) to derive the expected response to treatment $\mathbf{E}[Y^I - Y^A|X, D, p]$ for any observation in the data. Figure 10 shows the histogram of the expected treatment effects for the publications (left panel) and earnings (right panel) outcomes, separately for individuals who join Industry (green) vs those who join Academia (red). This is just another graphical way to display the previous MTE: those who go to Industry have higher earnings gains of joining the private sector vs Academia and a lower decrease in publication output.

(a) [Awaiting export approval] (b) [Awaiting export approval]

Figure 10: Expected treatment effects for earnings, by sector joined

Differences in MTE across individuals could stem from differences in the outcomes in the 'treated' state (Industry) or the 'untreated' state (Academia) or both. One advantage of the separate approach that I use to estimate MTE is that I can calculate the values of the potential outcomes in each state. This allows me to investigate where differences in treatment effect come from.

Figure 11 shows the potential outcomes separately in Industry and in Academia for publications. Interestingly, those joining the private sector have a similar publication potential in Academia

[23] The test of heterogeneity on observable characteristics is significant at the 1% level. The test of heterogeneity on unobservable characteristics is not significant at the 10% level.

[24] The tests of heterogeneity on observable and unobservable characteristics are both significant at the 10% level.

as those who don't, but their publication potential in Industry is higher. Figure 12 repeats this exercise for earnings. Individuals who join the private sector have a lower earnings potential in Academia than those who don't. Combined with the previous result that publication potential in Academia is on average similar across individuals irrespective of the sector they join, this suggests that individuals who start their career in Industry either (i) lack non-publication related skills that are valued in Academia (*productivity mechanism*) or (ii) have higher non-pecuniary returns in Academia than those who join the academic sector at graduation (*compensating differential mechanism*). In order to disentangle these 2 mechanisms, I construct a measure of non-pecuniary returns by averaging the 7 indicators that capture individuals' satisfaction with non-money related job attributes (i.e., I exclude individuals' satisfaction with salary and with benefits). I then run a MTE analysis, similar as before. I find that those who start their career in the private sector would have lower non-pecuniary returns in Academia compared to individuals who start their career in the academic sector. This suggests that mechanism (i) is more likely: individuals who start their career in Industry lack non-publication-related skills that are valued in Academia.

(a) [Awaiting export approval] (b) [Awaiting export approval]

Figure 11: Potential outcomes, Publications

(a) [Awaiting export approval] (b) [Awaiting export approval]

Figure 12: Potential outcomes, Earnings

The fact that individuals who start their career in Industry publish more in this sector than individuals who start their career in Academia suggests that individuals who start their career in Industry either (i) join a different type of firms than individuals who start their career in Academia (i.e., firms more engaged in Open Science, which allow workers to publish) or (ii) they join the same type of firms that the ones individuals who start their career in Academia would join, but they are more productive (in terms of publications) in this sector and so publish more. If (i) was the main mechanism, we would expect individuals who start in the private sector to earn less in Industry than individuals who start their career in Academia (Stern, 2004). However, Figure 12 shows that the earnings potential in Industry of those who start their career in the private sector is higher than the earnings potential in Industry of those who start their career in Academia. This suggests that individuals would start their career in the private sector tend to be relatively more productive there than would be those who started their career in Academia.

[Consequences for firms and universities - in progress]

6 (Mis)allocation

The MTE analysis shows that there is substantial heterogeneity across individuals regarding their returns in Industry vs Academia with respect to earnings and publications. I this section, I use these individual-level reduced-form estimates in order to shed light on (mis)allocation of individuals across sectors. I start with a simple model of social returns. I then empirically estimate misallocation. My goal is not to pinpoint exact magnitudes, as I cannot capture the entirety of externalities that individuals generate as part of their employment and I cannot estimate complementarity between research performed in Industry and research performed in Academia (i.e., my discussion is intrinsically limited to the *rate* rather than the *direction* of innovation). Rather, the main point of the exercise is to highlight trends and patterns.

6.1 A Model of misallocation

Individuals sort based on their private returns according to Equation 7. However, the maximization objective for individuals, driven by private returns, may not align with the maximization objective of a social planner, which considers both private returns and the spillovers generated by individuals:

$$\text{Social returns}_i^j = \text{Private Returns}_i^j + \text{Spillovers}_i^j$$

In this framework, the private returns of individual i going to sector j correspond to i's utility of joining j, while the social returns of individual i going to sector j include both i's utility of joining j *and* the externalities that individual i generates by joining sector j. In the baseline results, I use earnings to proxy for private returns. For spillovers, I take the transparent assumption of proxying the bulk of their value using publication output. While this is obviously a simplified version of the reality, it allows to draw interesting insights about the order of magnitude of the friction between private and social returns. First, note that it has long been established that publications generate positive externalities because they are a public good that can be used as input for follow-on work (Arrow, 1972; Dasgupta and David, 1994; Nelson, 2009; Stephan, 2012). Second, while many spillovers related to Academia and Industry might counterweight each other, the role played by publications differs significantly between both sectors. Academia is characterized by a specific reward system that encourages scientists to publicly disclose their research, while firms usually operate in a market-based system that tends to preclude the disclosure of knowledge (Gans and Stern, 2010). Hence, we can expect differences in publication output (and so differences in the spillovers that ensue from them) between both sectors. Note that in this model, any private research performed by a scientist in the private sector is assumed to be priced in earnings and hence is captured in social returns through individual's private returns. While I do not have access to patent information for all individuals in my sample, I will use a sub-sample of the data to show that their omission does not seem to significantly impact the conclusions. I will also show in robustness how my results change when I assign sector-specific prices for earnings and publications.

In the main specification, the social returns generated by individual i who starts her career in

sector j are then defined as:

$$V_i^j = U_i^j + \lambda \sum_{t=0}^{T} Pub_{it}^j = \sum_{t=0}^{T} \rho^t \, W_{it}^j + \lambda \sum_{t=0}^{T} Pub_{it}^j \tag{14}$$

with Pub_{it}^j the flow of publications at time t generated by individual i who started her career in sector j and λ the parameter that maps publications to dollars. Note that because individuals are already compensated for their publications through earnings, λ only includes the "public" price of publications.[25] Empirically, one can think of λ as the price a major federal research agency, such as the National Institutes of Health, would be willing to pay for a publication. With this definition, the social returns of joining Industry vs Academia for individual i equals:

$$V_i = V_i^I - V_i^A = \sum_{t=0}^{T} \rho^t \left(W_{it}^I - W_{it}^A\right) + \lambda \sum_{t=0}^{T} (Pub_{it}^I - Pub_{it}^A) \tag{15}$$

Importantly, high social returns in a sector could come from either high earnings or high spillovers (or both). Hence, even if individual i wasn't publishing at all (e.g., because she is working in a firm in a non-research related job), her social returns in Industry could be higher than in Academia if her earnings in the private sector are particularly high.

In this model, the friction between private and social returns that leads to misallocation can arise from two situations. First, if individual i joins the industrial sector while her social returns in Academia would be higher than the ones she has in Industry:

$$\begin{cases} Ind_i = 1 \\ V_i^A > V_i^I \end{cases} \tag{16}$$

Second, if individual i stays in Academia while her social returns in Industry would be higher:

$$\begin{cases} Ind_i = 0 \\ V_i^A < V_i^I \end{cases} \tag{17}$$

Figure 13 shows a simplified example of the difference between private and social returns and how one can think about misallocation across sectors. Assume that all estimates are causal. The top left graph plots the marginal treatment effects of joining Industry vs Academia on earnings. Individuals at the left of point A go to Industry because their earnings there are higher than in Academia, while individuals at the right of A stay in Academia. The top right graph shows the spillover part of social returns proxied with publications, with individuals ordered similarly as before. Individuals at the left of point B tend to generate more publications in Industry than in Academia. We can then sum the earnings and publications in order to get the difference in social returns between Industry and

[25] I assume that individuals are small compared to the total pool of scientists so that the additional utility they could receive from their own publications - aside from getting remunerated for it - is negligible.

Academia for each individual. This is showed in the bottom picture. The black and blue lines are summed in order to get the orange line, which represents social returns. Interestingly now, the social returns are positive for all individuals at the left of point C. According to this model, individuals between points A and C are 'misallocating', in the sense that they join the private sector while their social returns would have been higher in Academia. In practice, we may expect misallocation to happen in both sectors.

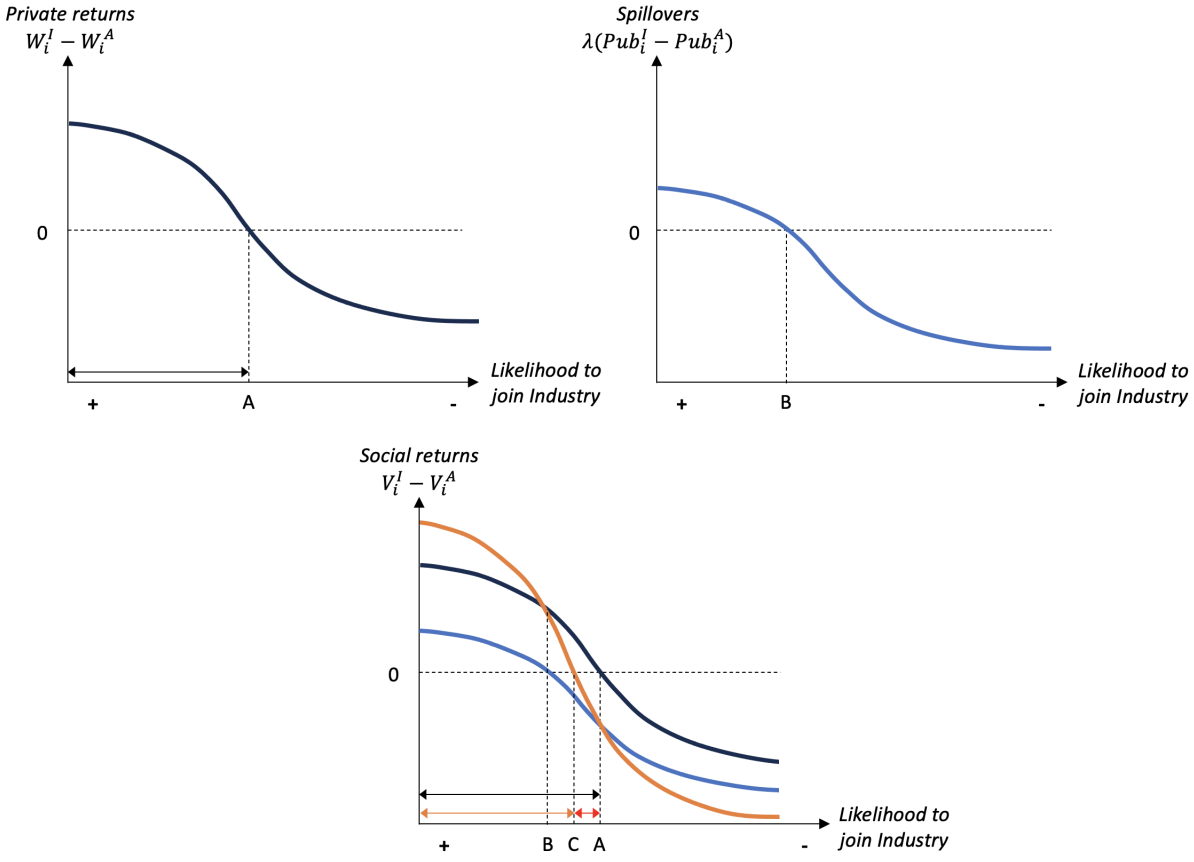


Figure 13: Private vs Social returns and Misallocation

In the ideal reallocation case, individuals in Industry with $V_i < 0$ would be reallocated to Academia while individuals in Academia with $V_i > 0$ would be reallocated to Industry. However, one specific characteristic of my set-up is that the capacity of the academic sector is often considered as constrained. Therefore, any reallocation exercise should take this constraint into account.

Call κ_t Academia's capacity in year t, with $t \in (1, ..., T)$.[26] Rank individuals in ascending order of V_i so that individual with rank 1 has the highest social return of going to Academia vs Industry. Call r_i the rank of individual i. For each cohort, individuals with $r_i \leq \kappa_t$ should be (re)allocated to Academia and individuals with $r_i > \kappa_t$ should be (re)allocated to Industry. Importantly, this

[26] Results are unchanged if I rather consider Academia's capacity by *field* over time.

implies that some individuals who were 'correctly' allocating to Academia (resp. Industry) because their V_i value was negative (resp. positive) might be 'pushed-out' from their initial sector because the gains from reallocating someone else from Industry (resp. Academia) to the academic sector (resp. private sector) is higher than the loss of pushing-out these individuals to the other sector.

6.2 Empirical estimation

Empirically, I calculate the MTE of starting a career in Industry vs Academia on social returns:

$$\begin{aligned} MTE(V_i) &= \mathbb{E}[V_i^I - V_i^A | X_i = x_i, U_{Di} = u_i] \\ &= \mathbb{E}\left[\sum_{t=0}^{T} \rho^t (W_{it}^I - W_{it}^A) + \lambda \sum_{t=0}^{T} (Pub_{it}^I - Pub_{it}^A) | X_i = x_i, U_{Di} = u_i\right] \end{aligned} \tag{18}$$

Rescaling as a flow rather than as a stock, this is equivalent to estimating:

$$MTE(V_i) = \mathbb{E}\left[\frac{\sum_{t=0}^{T} \rho^t (W_{it}^I - W_{it}^A)}{T} + \lambda \frac{\sum_{t=0}^{T} (Pub_{it}^I - Pub_{it}^A)}{T} | X_i = x_i, U_{Di} = u_i\right] \tag{19}$$

Empirically I have estimated:

$$MTE(\ln(W_{i,t(i)})) = \mathbb{E}[\ln(W_{i,t(i)}^I) - \ln(W_{i,t(i)}^A) | X_i = x_i, U_{Di} = u_i] \tag{20}$$

and

$$MTE(\ln(\sum_{t=0}^{t(i)} Pub_i)) = \mathbb{E}[\ln(\sum_{t=0}^{t(i)} Pub_{it}^I) - \ln(\sum_{t=0}^{t(i)} Pub_{it}^A) | X_i = x_i, U_{Di} = u_i] \tag{21}$$

with $t(i)$ individual i's year of experience at the time of survey.

I cannot directly exponentiate the MTE estimates for the logged outcomes in order to recover the MTE in levels since $exp(ln(a) - ln(b)) \neq (a - b)$. However, the use of the separate method for the estimation of the MTE allows me to recover the potential outcomes in the treated and untreated states separately. I can then exponentiate these potential outcomes separately for each individual and calculate their difference in order to recover $MTE[W_{i,t(i)}] = \mathbb{E}[W_{i,t(i)}^I - W_{i,t(i)}^A | X, U_D]$ and $MTE(\sum_{t=0}^{t(i)} Pub_i) = \mathbb{E}[\sum_{t=0}^{t(i)} Pub_{it}^I - \sum_{t=0}^{t(i)} Pub_{it}^A | X_i = x_i, U_{Di} = u_i]$. The next step consists in dividing $MTE(\sum_{t=0}^{t(i)} Pub_i)$ by the number of years between PhD graduation and the year of collection of the publication data. I then calculate for each individual $MTE(V_i)$ as $MTE[W_{i,t(i)}] + \lambda \frac{MTE[\sum_{t=0}^{t(i)} Pub_i]}{t(i)}$.

The estimation of social returns requires me to make an assumption about the value of λ which maps publications to dollars. Conceptually, this parameter can be thought of as the price a major federal research agency, such as the National Institutes of Health, would be willing to pay for a publication. Estimates of the returns to NIH funding in terms of publications are hard to calculate

because (i) endogeneity issues abound, (ii) publication output needs to be observed over a sufficiently long period of time following funding and (iii) we need variation in the intensive margin of funding. To the best of my knowledge, there is no consensus on this estimate. Payne et al. (1999) finds that a $1 million in federal research funding to a university results in about 14.5 publications.[27] Boyack and Börner (2003) reports 434 publications for $35.3million awarded over the period 1993-1997. Converting funding into 2015 dollars, these estimates represents a price per publication that ranges between $113k and $126k. Myers (2020) reports a much higher price per publication of $344k for RFA grants and $665k for open grants. I use the value of $113k for the baseline results as a conservative estimate of spillovers and will show how results vary when changing the value of λ. Using this value, I can then calculate the MTE of V_i for individuals falling at different margins of the disutility parameter and compare it to the sector they actually joined.

Figure 14: [Awaiting export approval]

Figure 14 shows the histogram of MTE(V_i) as a function of sector joined. Individuals with positive MTE(V_i) values have a higher social value in Industry than in Academia so that individuals in green at the right of the black dashed line are misallocating to the academic sector. Similarly, individuals with negative MTE(V_i) values have a higher social value in Academia so that individuals in red at the left of the black dashed line are misallocating to Industry.

Using the previous value for λ, I find that 10% of individuals are misallocating. 43% of the individuals who joined the private sector would have had higher social returns in Academia, while 3% of the individuals who joined the academic sector would have had higher social returns in Industry.[28] Figure A.7 shows how the share of misallocation varies as a function of how we value publications (i.e., the value of λ). As expected, the higher the value of spillovers associated with publications, the higher the share of individuals misallocating in Industry and the lower the share of individuals misallocating in Academia, up to the point where the overall share of misallocation equals the share of individuals in the private sector.

6.3 Characterizing misallocation

In this part, I focus on the trends regarding misallocation. Figure 15 shows the share of misallocation over time. This share was relatively stable until the 90s, after which it increased to reach its highest point in 2013. Figure A.8 shows trends by field. Engineering is the field with the highest share of misallocation. Interestingly, the increase in recent years is also driven by an increase in the share of misallocation in the Computer Sciences and Mathematics field. Figure 16 shows the share of misallocation within each sector and highlights that the increase in the last 20 years has been

[27] Estimates range between 11 and 18 publications. From the paper, it is unclear what fields of science are included in the analysis

[28] Weighting publications with citations by multiplying publications and citations and use this as an outcome has little consequences on the results.

primarily driven by an increase in the share of individuals misallocating to the private sector.[29]

Figure 15: [Awaiting export approval]

Figure 16: [Awaiting export approval]

In order to dig deeper on the roots of misallocation within the private sector (which drives most of the misallocation results), Figure A.9 explores changes in earnings gap and publication gap between Industry and Academia for individuals identified as misallocating in Industry. The publication gap is divided by the number of years since graduation so that it represents the yearly difference in publications generated within Industry vs Academia and accounts for differences in experience. The earnings difference between Industry and Academia for individuals misallocating is quite stable since the 90s. However, the publication difference between Industry and Academia has become linearly more negative. This suggests that individuals who misallocate are increasingly joining firms that are less engaged in Open Science that before.

But is misallocation driven by individuals joining firms engaged in R&D (but not openly publishing their findings), or by individuals joining firms that are not primarily engaged in innovative activities? I classify individuals into 2 categories depending on their job activity at graduation. For this, I use the answer to the question that asks 'what will be your primary work activity?', with answers being (i) Research and development (ii) Teaching (iii) Management or administration (iv) Professional services (such as health care, counseling, financial services, legal services, consulting) and (v) Other. Note that given that I focus on STEM fields, (iv) is likely heavily represented by consulting and financial services. In order to make this readable, I group R&D/Teaching together (Teaching being marginal for individuals misallocating to the private sector) and Management/Professional services together and ignore the 'Other' category for which I have little information. Figure 17 shows the share of individuals in each category who misallocate to the private sector as a function of cohort of graduation. While there is misallocation within both job activities, a clear change is visible starting in the years 2000s, where an increasing share of individuals who start their career in Management or Professional services positions are identified as misallocating. This shows changes in allocation on the intensive margin (conditional on entering a Management/Professional services position, individuals tend to misallocate more). Figure A.10 explores the role of the extensive margin and shows that share of individuals entering Industry at graduation with a position identified as Management/Professional services also increased, particularly in the Engineering field. This suggests that misallocation within the private sector is a result of both (i) more individual entering this activity at graduation (extensive margin) and (ii) more individuals misallocating within this activity (intensive margin).

Figures A.11 and A.12 show trends by gender and nationality respectively. Male tend to misallo-

[29] Note that my dataset stops before the rise of Tech firms and their involvement in Open Science. It is possible that the misallocation within the Computer Sciences field is actually higher now in Academia than in Industry.

Figure 17: $< - - -$ Insert about here $- - - >$

cate more and this has increase in the last 20 years. Internationals tend to misallocate more though patterns in this two groups look similar.

6.4 Reallocation

In order to estimate the gains of reallocating individuals, I use the initial number of individuals I observe in the academic sector (i.e., prior to any reallocation exercise) to proxy for Academia's capacity in each cohort, 79% of individuals who were misallocating to the private sector can be reallocated to Academia. 80% of this reallocation 'pushes out' individuals with higher social returns in Academia than in Industry. 95% of individuals who were misallocating to the academic sector can be reallocated to Industry. I find a gain in social value representing 11% of the initial social value. Note that almost the entirety of this gain comes from reallocating individuals who misallocate to the private sector to Academia.

While giving precise policy recommendations is beyond the scope of this paper, especially given the caveats of the exercise previously acknowledged, one important question is whether individuals who misallocate to the private sector do so because Academia's capacity is limited, or because they do not want to enter this sector. If individuals misallocating to Industry are 'pushed out' from Academia, we might expect them to exhibit higher preferences for academic job attributes compared to those who choose industry. Similarly, we might expect them to exhibit similar preferences for academic job attributes compared to those in Academia.

I first compare individuals who misallocate in Industry with individuals in Academia. For each of the 9 job attributes, I run a regression using as dependent variable an indicator equal to 1 if the attribute is reported as being 'very important' and as independent variable an indicator equal to 1 if the individual is identified as misallocating to Industry and 0 if she starts her career in Academia. I include the usual controls for experience, demographic characteristics and PhD major $\times$ doctoral institution fixed-effects. This allows me to compare individuals who misallocate in Industry with individuals in Academia regarding their preference for sector-specific job attributes. I find that individuals who misallocate to Industry give less importance to challenge, independence, job security and impact on society and more importance to location and salary, compared to individuals in Academia. I then reiterate this exercise but this time comparing individuals identified as misallocating to Industry with individuals identified as 'correctly' allocating to Industry, I find no difference regarding preferences for job attributes. This suggests that simply expanding Academia's capacity might not necessarily be the best solution to reallocate individuals identified as misallocating to Industry to the academic sector.

7 Robustness and Limitations

Spillovers from patenting - So far, I have proxied spillovers with publications. Patents are another main form of spillovers. Individuals surveyed in 2015 (who constitute the basis of my sample) were not asked any questions about patenting. However, previous waves (1995, 2001, 2003, 2008) had questions about patenting activity. In particular, respondents were asked *"over the last 5 years, how many applications for US patents have named you as an inventor"*. Among individuals in my sample, 2,256 have been surveyed at least once during one of the previous waves with patenting information. I keep this sub-sample for what follows. Figures A.13, A.14, A.15 show the MTE curves for the earnings, publications and patent outcome. By definition, individuals in this sample tend to be disproportionately from older cohorts. Hence, the MTE curve for earnings tends to show less heterogeneity than in the main sample. The curve for publications is similar to what I found the main sample. The curve for patents is downward slopping too. As before, I need to make an assumption about the dollar value of spillovers from patents, which is not a straightforward exercise. As a first approximation, I use Kogan et al. (2017), which reports the *private* value of a patent. On average, they find that a patent is worth \$10 million with a median equal to \$3 million. When including non-listed firms, Kline et al. (2019) find a lower average of \$5 million and a median of \$2 million. I do not know whether firms in the sample are publicly listed or not. 50% of individuals are observed in firms that have less than 25k employees and 40% of them have less than 500 employees. This is way lower than the average employment in their sample of 45k. I use \$10 million as baseline. Given that Kline et al. (2019) report that employees capture 61% of this value in their earnings, I use \$10 million $\times$ (1-0.61)=\$3.9 million as my baseline for the social value of a patent. I will show how results vary when varying this price. With this number in hand, I can now compare the extent of misallocation in this sample with and without considering patents. I find that without considering patents, 23% of individuals are misallocating (12% within the academic sector and 60% within the private sector). Including patents decreases the share of misallocation in Industry to 34% and increases the share of misallocation in Academia to 25%. The overall share of misallocation is equals to about 27%. Figure 18 shows how these results change when varying the price of a patent. The third dot from the left on the x-axis shows the previous results. If the price of a patent increases, the share of misallocation increases, driven by a higher misallocation in Academia. Note that as the price of a patent increases, the share of misallocation in Academia starts to plateau. This is because about 2/3 of individuals in Academia wouldn't patent more if they were in Industry (e.g., they would not join firms involved in patenting). Similarly, the share of individuals misallocating in the private sector does not fall to 0 because about 1/3 of individuals in Industry would be good patenters in Academia. This highlights that while patents are often considered as a spillover generated by the private sector, the patenting potential of individuals is not necessarily higher in the private sector than in Academia.

Sector-specific prices - In what follows, I explore whether the previous misallocation results I found are sensitive to different pricing of earnings and publications in Industry vs Academia. Because the

Figure 18: < − − − Insert about here − − − >

value from earnings might be differently appropriated by individuals in Industry vs in Academia, one could argue that earnings should not be priced equally in Industry and Academia. Similarly, one could argue that the spillovers coming from publications in the private sector should not be priced equally as the spillovers coming from publications in Academia. Hence, in the more general case where we allow prices to differ for both outcomes, the calculation of social returns of individual i in sector j equals:

$$\begin{aligned} V_i^j &= U_i^j + \lambda \sum_{t=0}^{T} Pub_{it}^j \\ &= \sum_{t=0}^{T} \rho^t \left(\mathbf{E} \left[p_w^j W_{it}^j \right] \right) + \lambda \sum_{t=0}^{T} p_p^j Pub_{it}^j \end{aligned} \tag{22}$$

with p_w^j the sector-specific earnings multiplier and p_p^j the sector-specific publications multiplier. Consider earnings first. The change in my previous conclusions depends on how p_w^I compares with p_w^A. Figure 7 shows that the earnings profile is flatter in Academia, suggesting that it is less easy to appropriate value in this sector and implying that $p_w^I < p_w^A$. This could for instance be due to monopsony power of universities (Goolsbee and Syverson (2019)). While I do not have information about employer size at the start of the career, most of the individuals who started their career in the private sector are working within large firms when they got surveyed in 2015. Hence, one could also argue that there is monopsony power in the private sector too, which would tend to decrease p_w^I with respect to p_w^A.

Now consider publications. While my dataset does not give me information at the publication level, research conducted in Academia is typically more fundamental compared to research carried out in Industry (Nelson (1959), Arrow (1972), Aghion et al. (2008)). In that case, we can expect $p_p^A > p_p^I$, which would tend to increase the value of spillovers generated in Academia. This would likely increase the share of individuals previously found to be misallocating in Industry and decrease the previous share of individuals misallocating to Academia.

In order to see how the share of individuals misallocating depends on the assumptions surrounding prices, I normalize $p_w^A = p_p^A = 1$ and write the difference in social returns between Industry and Academia (standardized as a flow) as:

$$\begin{aligned} \frac{V_i}{t_i} &= \frac{U_i^I - U_i^A}{t_i} \\ &= p_w^I W_{i,t(i)}^I - W_{i,t(i)}^A + \lambda \frac{\sum_{t=0}^{t(i)} p_p^I Pub_{it}^I - Pub_{it}^A}{t(i)} \end{aligned} \tag{23}$$

Figure 19 shows the result when varying p_w^I and p_p^I (see Figure **??** for the share of misallocation by sector). With $p_w^I = p_w^A = 1$ and $p_p^I = p_p^A = 1$, the share of misallocation replicates the results previously found (10%). The share of misallocation tend to be more dependent on the pricing of

the earnings component.

Figure 19: [Awaiting export approval]

8 Conclusion

Through the lens of a new dataset covering more than 40 cohorts of doctorate holders with information about their earnings and their publication output, this paper studies the allocation of scientists at graduation between Industry vs Academia.

Using a quasi-experimental strategy, I show that scientists who start their career in the private sector generate about 71% less publications and earn about 69% more, compared to scientists who start their career in a university. The estimation of Marginal Treatment Effects shows substantial heterogeneity across individuals with regards to their productivity in both sectors, suggesting that talent *allocation* should be an important concern for organizations. Embodying the reduced-form estimates into a simple model of social returns suggests that there is significant misallocation across sectors, both in Industry and in Academia. This misallocation has increased over time and is primarily characteristic of individuals misallocating to Management and Professional Services positions after a PhD in Engineering. While I remain cautious about suggesting formal policy proposals given that my model does not capture all the spillovers generated by individuals through their employment nor the complementarities between research performed within firms and the one done by universities, simply expanding Academia's capacity is unlikely to substantially affect this misallocation.

Understanding better the role of labor allocation in organizations' performance and overall economic growth is a fertile ground for future research. While this paper focuses on the allocation of highly-skilled individuals across two main sectors of employment that are Industry and Academia, my framework can be applied to other settings characterized by heterogeneity across individuals and non-random sorting into treatment. One avenue for future research could be to study the allocation of labor *within* a firm *across* diverse activities, such as R&D vs operation activities. The research presented here can also be extended to include a more nuanced analysis about the *direction* of research performed by firms and universities. Existing evidence indicates distinct trajectories in their research pursuits, each contributing complementary elements through their mutual interaction. Unfortunately, limitations in my dataset preclude a detailed exploration of these nuances. Finally, further work could add heterogeneity across firms and investigate its interaction with heterogeneity across individuals.

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Appendix A Figures



Figure A.1: Share of International vs American students by PhD cohort of graduation

Notes: This figure shows the share of international students as a function of PhD cohort of graduation

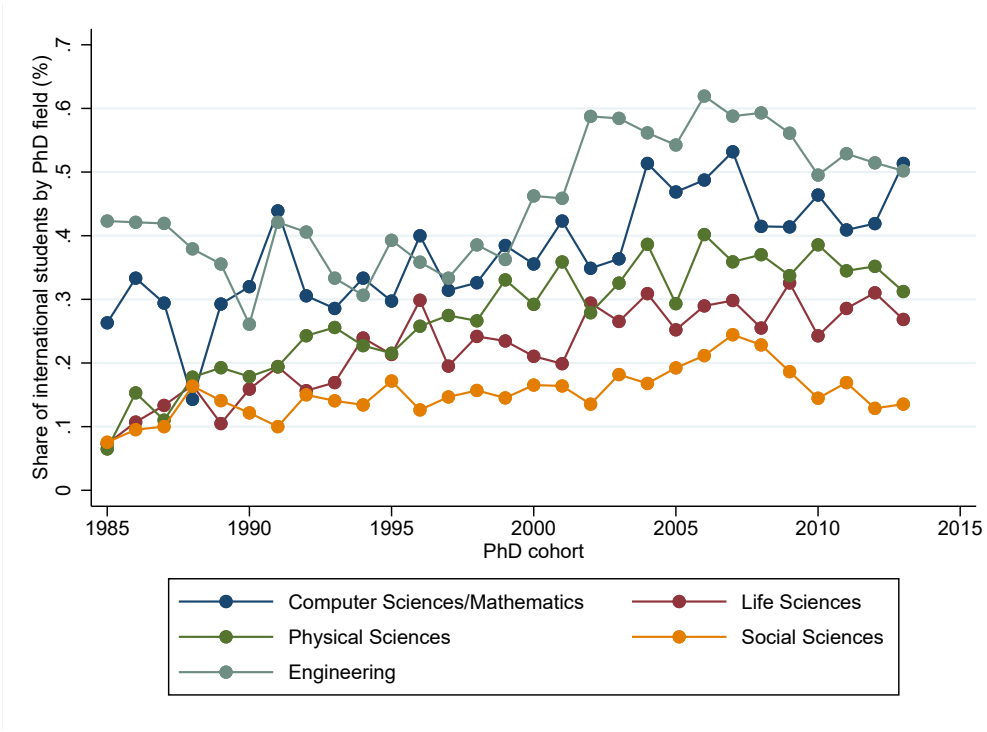


Figure A.2: Share of International vs American students by PhD field and PhD cohort of graduation

Notes: This figure shows the share of international students by PhD field as a function of PhD cohort of graduation

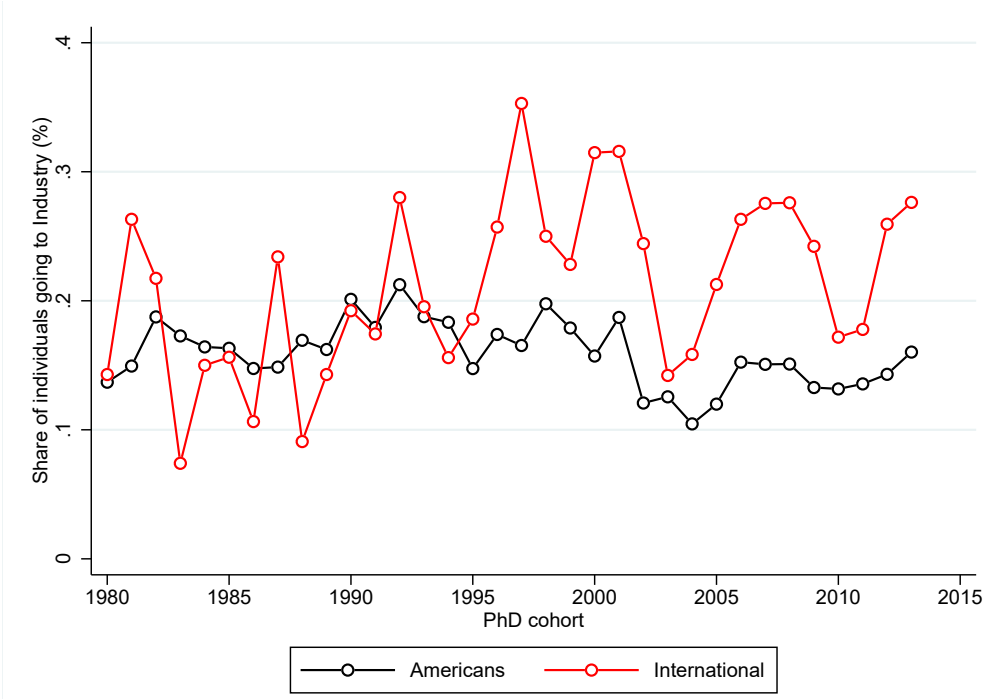


Figure A.3: Share of International and American students joining the private sector by PhD cohort of graduation

Notes: This figure shows the share of international and American students who join the private sector as a function of PhD cohort of graduation

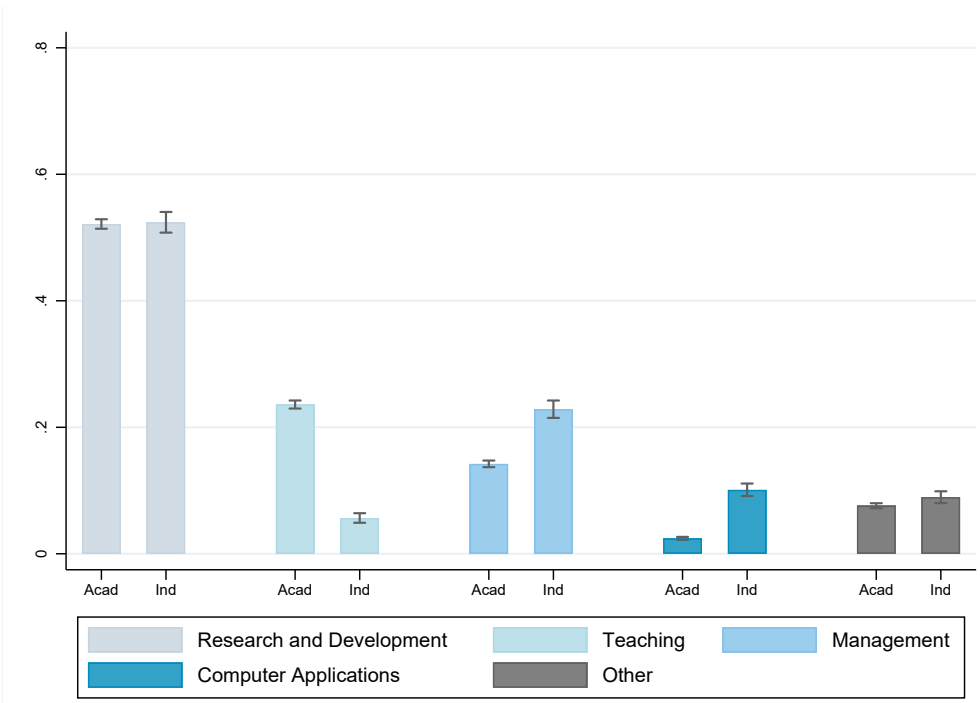


Figure A.4: Main activity during employment, by sector joined at graduation

Notes: This figure shows the main activity performed by individuals as part of their employment when surveyed as part of the SDR (i.e., during their career)

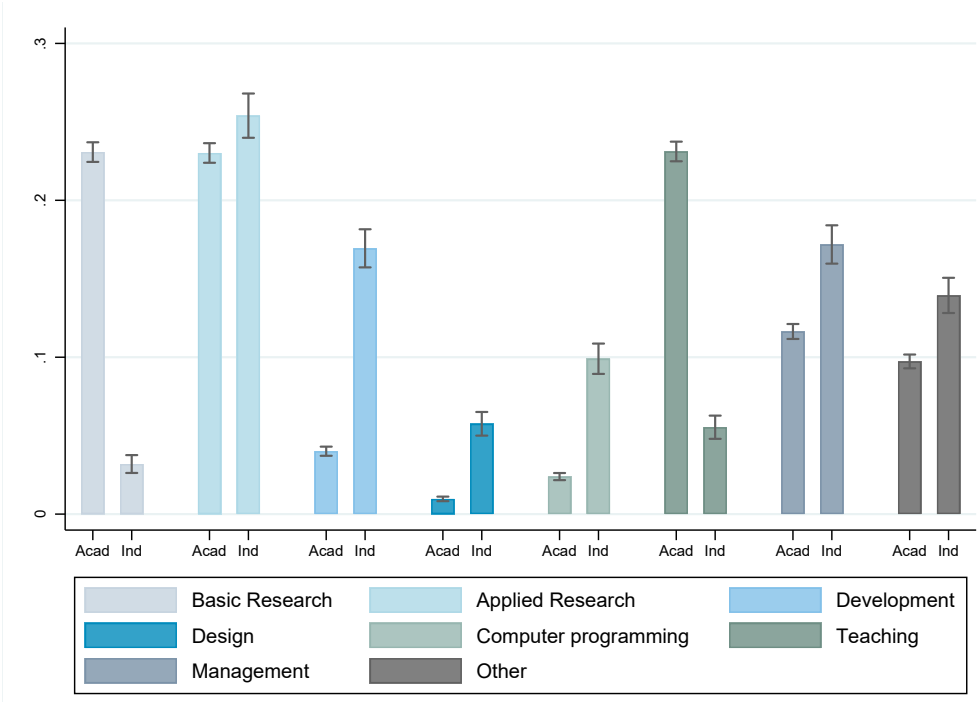


Figure A.5: Main detailed activity during employment, by sector joined at graduation

Notes: This figure shows the main activity performed by individuals as part of their employment when surveyed as part of the SDR (i.e., during their career) at a more granular level

Figure A.6: < − − − Insert about here − − − >

Figure A.7: Share of misallocation as a function of the value of a publication

Figure A.8: < − − − Insert about here − − − >

Figure A.9: < − − − Insert about here − − − >

Figure A.10: < − − − Insert about here − − − >

Figure A.11: < − − − Insert about here − − − >

Figure A.12: < − − − Insert about here − − − >

Figure A.13: < − − − Insert about here − − − >

Figure A.14: < − − − Insert about here − − − >

Figure A.15: < − − − Insert about here − − − >

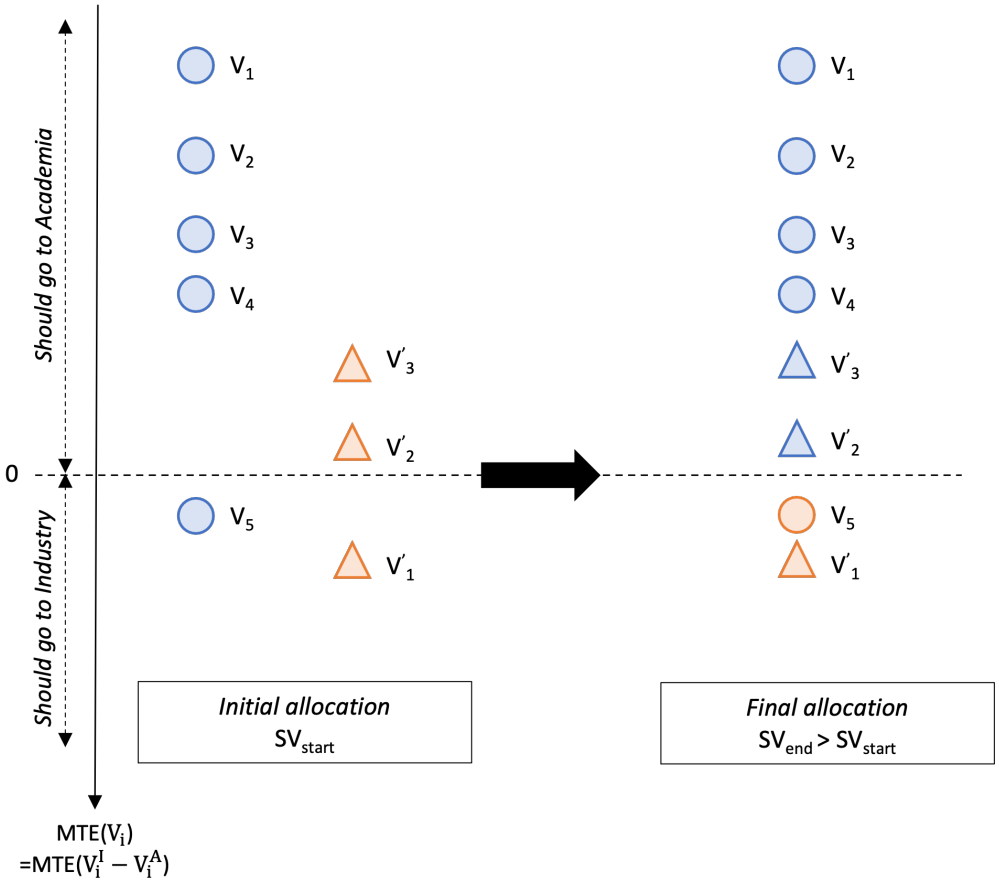


Figure A.16: Allocation and reallocation under no constraint

Notes: This figure shows the reallocation exercise under no capacity constraint. The blue circles represent individuals who went to Academia. The orange triangles represent individuals who went to Industry. The y-axis shows the value of MTE(V_i) in descending order. Individuals who went to Industry (orange triangles) joined the sector where their social returns are the highest if they are located below the dotted line representing the null value (MTE($V_i > 0$)). Individuals who went to Academia (blue circles) joined the sector where their social returns are the highest if they are located above the dotted line representing the null value (MTE($V_i < 0$). Hence, individuals V_2', V_3' and V_5 are misallocating. In that case, we can easily increase aggregate social returns by moving V_3' and V_2' to Academia and V_5 to Industry. In the final situation, 6 people are in Academia (blue color) and 2 individuals are in Industry (orange color).

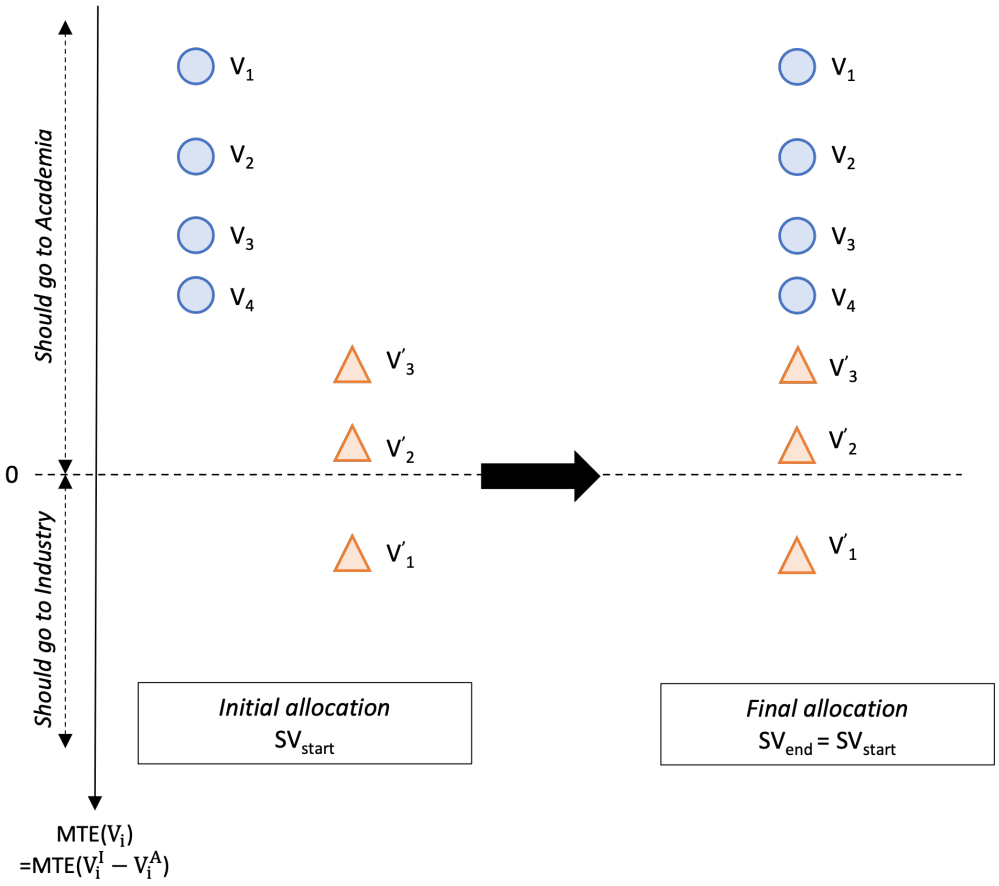


Figure A.17: Constrained reallocation - Case 1

Notes: This figure shows the reallocation exercise under capacity constraint. The blue circles represent individuals who went to Academia. The orange triangles represent individuals who went to Industry. The y-axis shows the value of MTE(V_i) in descending order. Individuals who went to Industry (orange triangles) joined the sector where their social returns are the highest if they are located below the dotted line representing the null value (MTE($V_i > 0$)). Individuals who went to Academia (blue circles) joined the sector where their social returns are the highest if they are located above the dotted line representing the null value (MTE($V_i < 0$). Assume for simplicity that no one in Academia misallocated. Assume that only 4 people can enter the academic sector because of its limited capacity. In that case, the best action is to keep the status quo and not reallocate anyone.

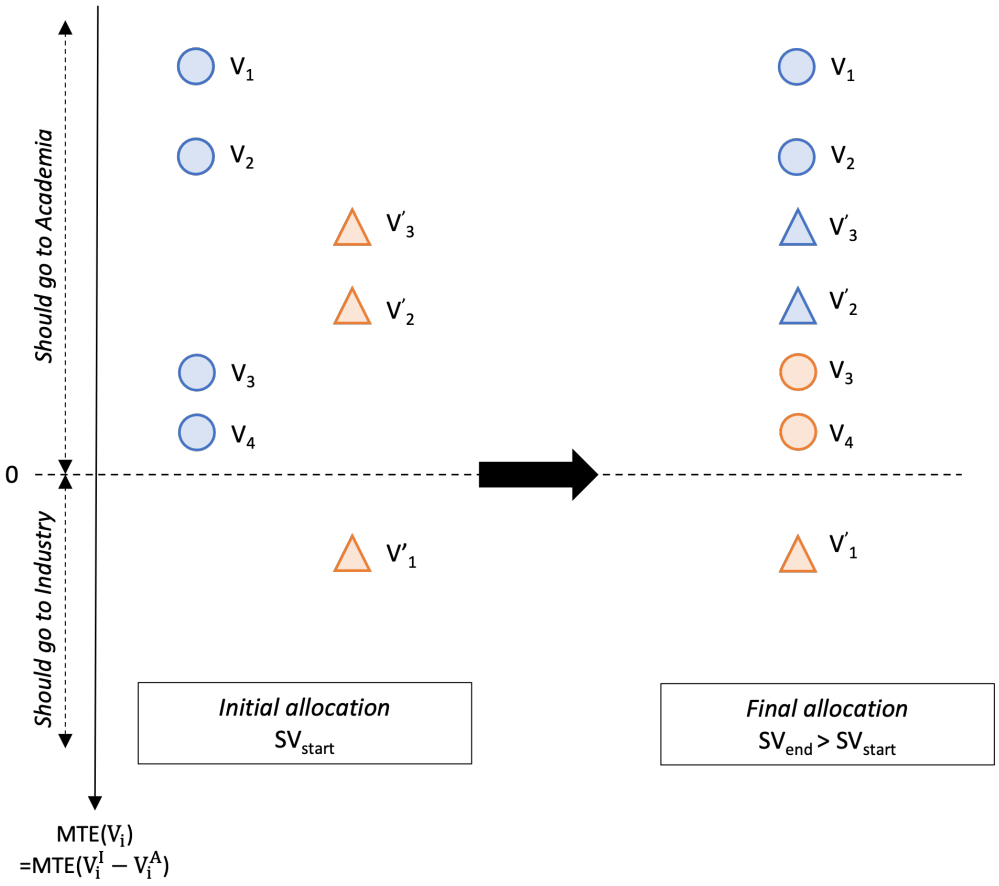


Figure A.18: Constrained reallocation - Case 2

Notes: This figure shows the reallocation exercise under capacity constraint. The blue circles represent individuals who went to Academia. The orange triangles represent individuals who went to Industry. The y-axis shows the value of MTE(V_i) in descending order. Individuals who went to Industry (orange triangles) joined the sector where their social returns are the highest if they are located below the dotted line representing the null value (MTE($V_i > 0$)). Individuals who went to Academia (blue circles) joined the sector where their social returns are the highest if they are located above the dotted line representing the null value (MTE($V_i < 0$). Assume for simplicity that no one in Academia misallocated. Assume that only 4 people can enter the academic sector because of its limited capacity. In that case, because V_3' and V_2' are higher than V_3 and V_4, we are better off by reallocating the two individuals with values V_3' and V_2' to Academia while transferring the two individuals with values V_3 and V_4 to Industry. The net gain will be $V_3' + V_2' - V_3 - V_4 > 0$.

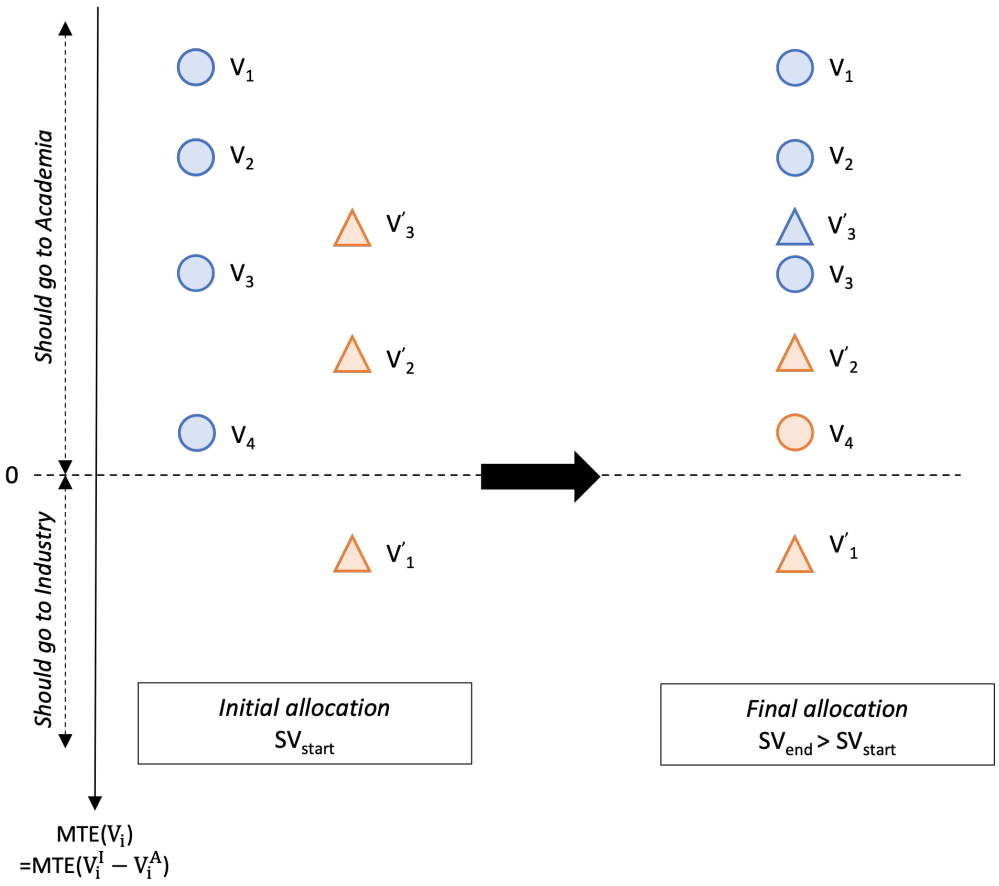


Figure A.19: Constrained reallocation - Case 3

Notes: This figure shows the reallocation exercise under capacity constraint. The blue circles represent individuals who went to Academia. The orange triangles represent individuals who went to Industry. The y-axis shows the value of MTE(V_i) in descending order. Individuals who went to Industry (orange triangles) joined the sector where their social returns are the highest if they are located below the dotted line representing the null value (MTE($V_i > 0$)). Individuals who went to Academia (blue circles) joined the sector where their social returns are the highest if they are located above the dotted line representing the null value (MTE($V_i < 0$). Assume for simplicity that no one in Academia misallocated. Assume that only 4 people can enter the academic sector because of its limited capacity. In that scenario, we are better off by moving the individual with value V_3' to Academia even if this comes at the expense of the individual with value V_4 who has to move to the private sector. The net gain will be $V_3' - V_4 > 0$.

Appendix B Tables

Table B.1: OLS pub estimates, Publications> 0

	Log(1+Publications (stock)				
	(1)	(2)	(3)	(4)	(5)
Industry	-0.776***	-0.817***	-0.807***	-0.819***	-0.777***
	(0.0186)	(0.0241)	(0.0239)	(0.0263)	(0.0290)
Constant	1.653***	1.631***	1.630***	1.631***	1.641***
	(0.0240)	(0.0237)	(0.0243)	(0.0288)	(0.0303)
Demographics	Yes	Yes	Yes	Yes	Yes
Experience	Yes	Yes	Yes	Yes	Yes
PhD major FE		Yes	Yes	Yes	Yes
Doct. Inst. FE			Yes	Yes	Yes
PhD major x Doct. Inst. FE				Yes	Yes
Taste					Yes
Observations	19,945	19,945	19,920	18,405	16,084
R-sq	0.149	0.183	0.210	0.314	0.338

Notes: This table reports the OLS estimates for publications using within department (defined as PhD major × doctoral institution) variation, keeping individuals with at least one publication. Standard errors (in parentheses) are clustered at the doctoral institution level.

Table B.2: OLS citations estimates

	Log(1+Cites-weighted Publications)				
	(1)	(2)	(3)	(4)	(5)
industry	-1.731***	-1.477***	-1.463***	-1.470***	-1.409***
	(0.0418)	(0.0437)	(0.0441)	(0.0479)	(0.0524)
Constant	3.750***	3.665***	3.699***	3.711***	3.757***
	(0.0550)	(0.0568)	(0.0445)	(0.0501)	(0.0490)
Demographics	Yes	Yes	Yes	Yes	Yes
Experience	Yes	Yes	Yes	Yes	Yes
PhD major FE		Yes	Yes	Yes	Yes
Doct. Inst. FE			Yes	Yes	Yes
PhD major x Doct. Inst. FE				Yes	Yes
Taste					Yes
Observations	21,024	21,024	20,999	19,488	17,081
R-sq	0.108	0.219	0.261	0.363	0.375

Notes: This table reports the OLS estimates for cites-weighted publications using within department (defined as PhD major × doctoral institution) variation. Standard errors (in parentheses) are clustered at the doctoral institution level.

Table B.3: 2SLS - Publications, Publications>0

Log(1+Publications)			
	(1)	(2)	(3)
Industry	-0.940**	-0.971**	-0.964**
	(0.455)	(0.480)	(0.491)
Demographics	Yes	Yes	Yes
Experience	Yes	Yes	Yes
PhD major FE	Yes	Yes	Yes
Doct. Inst. FE	No	Yes	Yes
Publ. bef. grad.	No	No	Yes
F-stat	30.52	28.17	28.15
Observations	19,945	19,945	19,945
R-sq	0.182	0.209	0.231

Notes: This table reports the 2SLS results for publications using individuals with at least one publication. Standard errors (in parentheses) are two-way clustered at the PhD major and PhD cohort level.

Table B.4: 2SLS - Cites-weighted Publications

	Log(1+Cites-weighted Publications)		
	(1)	(2)	(3)
industry	-2.684***	-2.738***	-2.749***
	(0.806)	(0.837)	(0.850)
Demographics	Yes	Yes	Yes
Experience	Yes	Yes	Yes
PhD major FE	Yes	Yes	Yes
Doct. Inst. FE	No	Yes	Yes
Publ. bef. grad.	No	No	Yes
F-stat	30.31	28.12	28.15
Observations	21,024	21,024	21,024
R-sq	0.182	0.223	0.230

Notes: This table reports the 2SLS results for cites-weighted publications. Standard errors (in parentheses) are two-way clustered at the PhD major and PhD cohort level.

Appendix C Sector Choice

I present here the full model of sector choice that allows individuals to change sector over their career.

Let individuals be indexed by i and time be indexed by $t \in (0, T)$. There are 2 sectors in the economy: Industry, indexed as I and Academia, indexed as A. I assume for simplicity that I observe a unique generation of individuals so that t can also be conceptualized as years of experience. Each individual receives two endowments at birth: an individual-specific productivity parameter in Industry δ_i^I and an individual-specific productivity parameter in Academia δ_i^A. These parameters capture how more/less productive individual i is in Industry and Academia compared to the average. δ_i^I is composed of skills that are common to both Industry and Academia, as well as skills that are specific to the private sector. Similarly, δ_i^A is composed of skills that are common to both Industry and Academia, as well as skills that are specific to the academic sector. Each individual works between $t = 0$ and $t = T$ and is characterized by a vector $j(i)$ representing the sectors she works in during each time period: $j(i) = (j_0(i), j_1(i), ..., j_T(i))$. For clarity, I will use j instead of $j(i)$ in the equations that follow, but the reader should keep in mind that j is individual-specific. $j = (I, I, ..., I)$ for individuals who spend their whole career in Industry and $j = (A, A, ..., A)$ for individuals who spend their whole career in Academia, but individuals are allowed to change sector during their career. I am interested in j_0, the sector where individuals *start* their career after graduating form their PhD.

Define $W_i^{j_t}$ the potential earnings of individual i at time t if she works in sector $j_t \in (I, A)$ at time t. We can decompose $W_{it}^{j_t}$ into a sector-mean and an individual-specific component:

$$W_i^{j_t} = \overline{W_t^{j_t}} + \delta_i^{j_t} \tag{24}$$

with $\overline{W_t^{j_t}}$ the average earnings in sector j_t for individuals with experience t and $\delta_i^{j_t}$ an individual-specific component.
The utility $u_i^{j_t}$ of individual i at time t who works in sector j_t equals:

$$u_i^{j_t} = (W_i^{j_t} + \chi_i^{j_t}) + \varepsilon_i^{j_t} + \sigma_i^{j_t}$$

with $\chi_i^{j_t}$ a random shock to earnings at time t, $\varepsilon_i^{j_t}$ individual i's taste for sector j_t and $\sigma_i^{j_t}$ some noise. I model individual i's utility of *starting* her career in sector $j_0 \in (I, A)$, called $U_i^{j_0}$, as a function of the sum over her career of her expected (discounted) earnings and an error term $\varepsilon_i^{j_0}$:

$$\begin{aligned}
U_i^{j_0} &= \sum_{t=0}^{T} \rho^t \ \mathbf{E}\left[u_i^{j_t} \mid j_0\right] \\
&= \sum_{t=0}^{T} \rho^t \ \mathbf{E}\left[W_i^{j_t} + \chi_i^{j_t} + \varepsilon_i^{j_t} + \sigma_i^{j_t} \mid j_0\right] \\
&= \sum_{t=0}^{T} \rho^t \ \left(\mathbf{E}\left[W_i^{j_t} \mid j_0\right] + \mathbf{E}\left[\varepsilon_i^{j_t} \mid j_0\right]\right) \\
&= \sum_{t=0}^{T} \rho^t \ \left(\mathbf{E}\left[\overline{W_t^{j_t}} + \delta_i^{j_t} \mid j_0\right] + \mathbf{E}\left[\varepsilon_i^{j_t} \mid j_0\right]\right) \\
&= \sum_{t=0}^{T} \rho^t \ \Big(p(j_t = I|j_0)(\overline{W_t^I} \ + \delta_i^I) + p(j_t = A|j_0)(\overline{W_t^A} \ + \delta_i^A) + \mathbf{E}\left[\varepsilon_i^{j_t} \mid j_0\right]\Big) \\
&= \sum_{t=0}^{T} \rho^t \ \Big(p(j_t = I|j_0)(\overline{W_t^I} \ + \delta_i^I) + (1 - p(j_t = I|j_0))(\overline{W_t^A} \ + \delta_i^A) + \mathbf{E}\left[\varepsilon_i^{j_t} \mid j_0\right]\Big) \\
&= \sum_{t=0}^{T} \rho^t \ \Big(p(j_t = I|j_0)(\overline{W_t^I} \ + \delta_i^I - \overline{W_t^A} \ - \delta_i^A) + \overline{W_t^A} \ + \delta_i^A + \mathbf{E}\left[\varepsilon_i^{j_t} \mid j_0\right]\Big)
\end{aligned} \tag{25}$$

with $p(j_t = I|j_0)$ (resp. $p(j_t = A|j_0)$) being the probability that individual i works in Industry (resp. Academia) at time t given that i started her career in sector j_0.

Individual i *starts* her career in Industry iff :

$$\begin{aligned} j_0(i) = I \iff & U_i^I - U_i^A > 0 \\ \iff & \sum_{t=0}^{T} \rho^t \Big((p(j_t = I|j_0 = I) - p(j_t = I|j_0 = A))(\overline{W_t^I} + \delta_i^I - \overline{W_t^A} - \delta_i^A) \\ & + \mathbf{E}\left[\varepsilon_i^{j_t} \mid j_0 = I\right] - \mathbf{E}\left[\varepsilon_i^{j_t} \mid j_0 = A\right] \Big) > 0 \end{aligned} \tag{26}$$

Because this equation includes the difference in unobserved productivity parameters $\delta_i^I - \delta_i^A$, the sorting of individuals at graduation is not random.

Appendix D Selection on gains vs selection on level

I detail here the difference between selection on level and selection on gains and how they might be correlated with each other.

The first selection mechanism is selection on *gains* which refers to the value of the difference $\delta_i^I - \delta_i^A$ and influences which sector individuals choose at graduation. Individuals with higher values of $\delta_i^I - \delta_i^A$ have more to gain by going to the private sector and are thus more likely to select into that sector. The second selection mechanism refers to selection on *level* which is linked to the values of δ_i^I and δ_i^A. Consider two individuals identical on observable characteristics and with the same gains $\delta_i^I - \delta_i^A$, but assume that individual 1 has higher level values of δ_i^I and δ_i^A compared to individual 2. Because earnings are the sum of a sector-mean (common to individuals 1 and 2) and an individual-specific component (higher for individual 1), individual 1's potential earning outcomes are higher than individual 2's potential earning outcomes. While the sector selection equation is only linked to $\delta_i^I - \delta_i^A$, this difference might be correlated with the levels δ_i^I and δ_i^A except if we assume constant treatment effects. To see that, let's derive the conditions under which the difference and the levels are uncorrelated:

$$
\begin{gathered}
Cov(\delta_i^I - \delta_i^A, \delta_i^I) = 0 \\
Cov(\delta_i^I - \delta_i^A, \delta_i^A) = 0 \\
\iff \\
Var(\delta_i^I) - Cov(\delta_i^A, \delta_i^I) = 0 \\
Cov(\delta_i^I, \delta_i^A) - Var(\delta_i^A) = 0 \\
\iff \\
Cov(\delta_i^A, \delta_i^I) = Var(\delta_i^I) = Var(\delta_i^A) \\
\iff \\
\frac{Cov(\delta_i^A, \delta_i^I)}{\sqrt{Var(\delta_i^I)Var(\delta_i^A)}} = \frac{Var(\delta_i^I)}{\sqrt{Var(\delta_i^I)Var(\delta_i^A)}} = 1
\end{gathered}
$$

This implies a linear relationship between δ_i^I and δ_i^A:

$$\delta_i^I = a + b\delta_i^A$$

with a and b some constant. Plugging back into the initial conditions:

$$
\begin{gathered}
Cov(\delta_i^I - \delta_i^A, \delta_i^I) = 0 \\
Cov(\delta_i^I - \delta_i^A, \delta_i^A) = 0 \\
\iff \\
Cov(a + b\delta_i^A - \delta_i^A, \delta_i^I) = 0 \\
Cov(a + b\delta_i^A - \delta_i^A, \delta_i^A) = 0 \\
\iff \\
Cov(a + (b-1)\delta_i^A, \delta_i^I) = 0 \\
Cov(a + (b-1)\delta_i^A, \delta_i^A) = 0 \\
\iff \\
(b-1)Cov(\delta_i^A, \delta_i^I) = 0 \\
(b-1)Var(\delta_i^A) = 0
\end{gathered}
$$

which implies that $b = 1$ or δ_i^I and δ_i^A being constant. In both cases, this implies that the difference $\delta_i^I - \delta_i^A$ is a constant.

Appendix E Micro-foundations of the sector choice equation

Set-up: Each individual i is characterized by (i) a state of birth s_i with $s_i \in S = \{s^1, s^2, ..., s^S\}$ and (ii) an unobservable productivity parameter in Industry δ_i^I and an unobservable productivity parameter in Academia δ_i^A that are part of the error term of the earnings equation and describe how much more/less productive individual i is in Industry and Academia compared to the average

State of birth s_i is assumed to be uncorrelated with δ_i^I and δ_i^A. This is equivalent to assuming that more or less productive people in Industry (or Academia) are equally likely to be born in one of the 50 American states. In the empirical analysis, I condition on parental education to make this assumption more plausible.

Individuals make two successive choices about their education[30]: (i) first, they choose a bachelor field b_i with $b_i \in B = \{b^1, b^2, ..., b^B\}$; (ii) then, they choose a doctoral institution l_i and a Ph.D. field f_i, with $l_i \in L = \{l^1, l^2, ..., l^L\}$ and $f_i \in F = \{f^1, f^2, ..., f^F\}$. I call c_i the year in which individual i graduates from her doctoral studies. l_i and f_i are allowed to be correlated with δ_i^I and/or δ_i^A, which introduces selection into Ph.D. field of study and doctoral institution. For instance, this allows individuals with a higher unobservable productivity in the private sector δ_i^I (who can be expected to be more likely to select into Industry) to choose Ph.D. fields of study and doctoral institutions that have a higher propensity to lead them to the private sector after Ph.D. graduation.

Supply-side: individual-specific components influencing sector choice after Ph.D. graduation: The individual-specific components that influence individual i's desire to join Industry are (i) f_i (some fields are more likely to lead to the private sector) (ii) l_i (some doctoral institutions are more likely to lead to the private sector) (iii) δ_i^I (a higher unobserved productivity parameter in Industry is more likely to lead to the private sector) and (iv) c_i (individuals from different cohorts have different propensities to join the private sector). Similarly, individual i's desire to join Academia is a function of f_i, l_i, δ_i^A, t_i^A and c_i. Individual i's propensity to "desire" the private sector vs Academia will therefore depend on the difference between his propensity to supply herself to the private sector and the propensity to supply herself to Academia. Assuming very simple linear forms and additivity, the sector that individual i joins after Ph.D. graduation, $j(i)$, is therefore a function of $(f_i, l_i, \delta_i^I - \delta_i^A, c_i)$.

Demand-side: sector-specific components influencing sector choice: Firms' demand for hiring individual i, D_i^I, is a function of δ_i^I and an exogenous demand-shock for field f_i and cohort c_i, called $\phi_{f_i c_i}^I$, that is common to all individuals sharing the same field $\times$ cohort variable. For example, $\phi_{f_i=CS;c_i=2010}^I$ could be some exogenous technological shock that increases the demand for computer scientists in 2010. Similarly, Academia's demand for hiring individual i, D_i^A, is a function of δ_i^A and an exogenous demand-shock for field f_i and cohort c_i, called $\phi_{f_i c_i}^A$, that is common to all individuals sharing the same field $\times$ cohort variable. For example, $\phi_{f_i=LS;c_i=2005}^A$ could be a 2005 specific demand for professors in Life Sciences, potentially driven by a high number of retirements that year or an increased amount of undergraduate students enrollments. As before, $j(i)$ will therefore be a function of the difference between firms' and universities' demand for individual i, so that $j(i)$ will be a function of $(\phi_{f_i c_i}^I - \phi_{f_i c_i}^A, \delta_i^I - \delta_i^A)$.

Combining the supply- and demand-side factors that influence individual i's sector of employment after Ph.D. graduation, we have:

$$j(i) = f(\phi_{f_i c_i}^I - \phi_{f_i c_i}^A, f_i, l_i, \delta_i^I - \delta_i^A, c_i) \tag{27}$$

Micro-founding Ph.D. field and doctoral institution: f_i, the Ph.D. field of individual i and l_i, the doctoral institution of individual i are micro-founded with other variables of the model.

Individuals are more likely to study in the state they are born[31] so I model l_i as a function of s_i. In addition, I allow individuals who are more productive in Industry vs Academia to be more likely to study in specific doctoral institutions, so I model l_i as a function of $\delta_i^I - \delta_i^A$.

[30] Of course, there are other major important choices that I could detail, but I focus on those that are relevant for the choice of sector after Ph.D. graduation.

[31] This follows the literature that uses distance to e.g., college to instrument for schooling - see Card (1993), Toivanen and Väänänen (2016), Aghion et al. (2023)

The choice of Ph.D. field f_i is a function of: (i) individuals' expectations of firms' vs universities' demand for their future supply of labor for each potential field they could choose, represented by the vector $\{E_{c_i-5}[D_i^I - D_i^A | f_i = f_l], l = 1...F\}$[32] (ii) bachelor field b_i (individuals are more likely to choose a Ph.D. field that is close to their undegraduate degree) and (iii) δ_i^I and δ_i^A, since individuals with a higher unobservable productivity parameter in Industry vs Academia are more likely to choose an industry-oriented Ph.D. field.

Hence, we can write l_i and f_i as:

$$\begin{aligned} l_i &= L(s_i, \delta_i^I - \delta_i^A) \\ f_i &= F(\{E_{c_i-5}[D_i^I - D_i^A | f_i = f_l]\}_{l=1...F}, b_i, \delta_i^I - \delta_i^A) \end{aligned}$$

Remember that D_i^j is a function of $\phi^j_{f_i c_i}$ and δ_i^j. Assuming for simplicity a linear and additive form for D_i^j so that $D_i^j = \phi^j_{f_i c_i} + \delta_i^j$, f_i can be rewritten as:

$$\begin{aligned} f_i &= F(\{E_{c_i-5}[\phi^I_{f_l c_i} + \delta_i^I - \phi^A_{f_l c_i} - \delta_i^A]\}_{l=1...F}, \delta_i^I - \delta_i^A) \\ &= F(\{E_{c_i-5}[\phi^I_{f_l c_i} - \phi^A_{f_l c_i}] + \delta_i^I - \delta_i^A\}_{l=1...F}, b_i, \delta_i^I - \delta_i^A) \end{aligned}$$

We can thus rewrite Equation 27 as:

$$\begin{aligned} j(i) &= f(\phi^I_{f_i c_i} - \phi^A_{f_i c_i}, f_i, l_i, \delta_i^I - \delta_i^A, c_i) \\ &= f(\phi^I_{f_i c_i} - \phi^A_{f_i c_i}, \{E_{c_i-5}[\phi^I_{f_l c_i} - \phi^A_{f_l c_i}]\}_{l=1...F}, b_i, s_i, \delta_i^I - \delta_i^A, c_i,) \end{aligned} \tag{28}$$

Figure E.20 summarizes graphically this equation. Remember that considering one time period only, the choice of sector can be written as:

$$j(i) = I \iff (\overline{W^I} - \overline{W^A}) + (\delta_i^I - \delta_i^A) + (\varepsilon_i^I - \varepsilon_i^A) > 0$$

Linking both equations highlights how we can micro-found each of the terms involving differences. In particular, calling g and h some general functions, we have:

$$\begin{aligned} \overline{W^I} - \overline{W^A} &= g(\{E_{c_i-5}[\phi^I_{f_l c_i} \phi^A_{f_l c_i}]\}_{l=1...F}, \phi^I_{f_i c_i} - \phi^A_{f_i c_i}) \\ \varepsilon_i^I - \varepsilon_i^A &= h(b_i, s_i, c_i) \end{aligned}$$

[32] I assume that a Ph.D. lasts on average 5 years but this assumption has no impact on the conclusions of the model

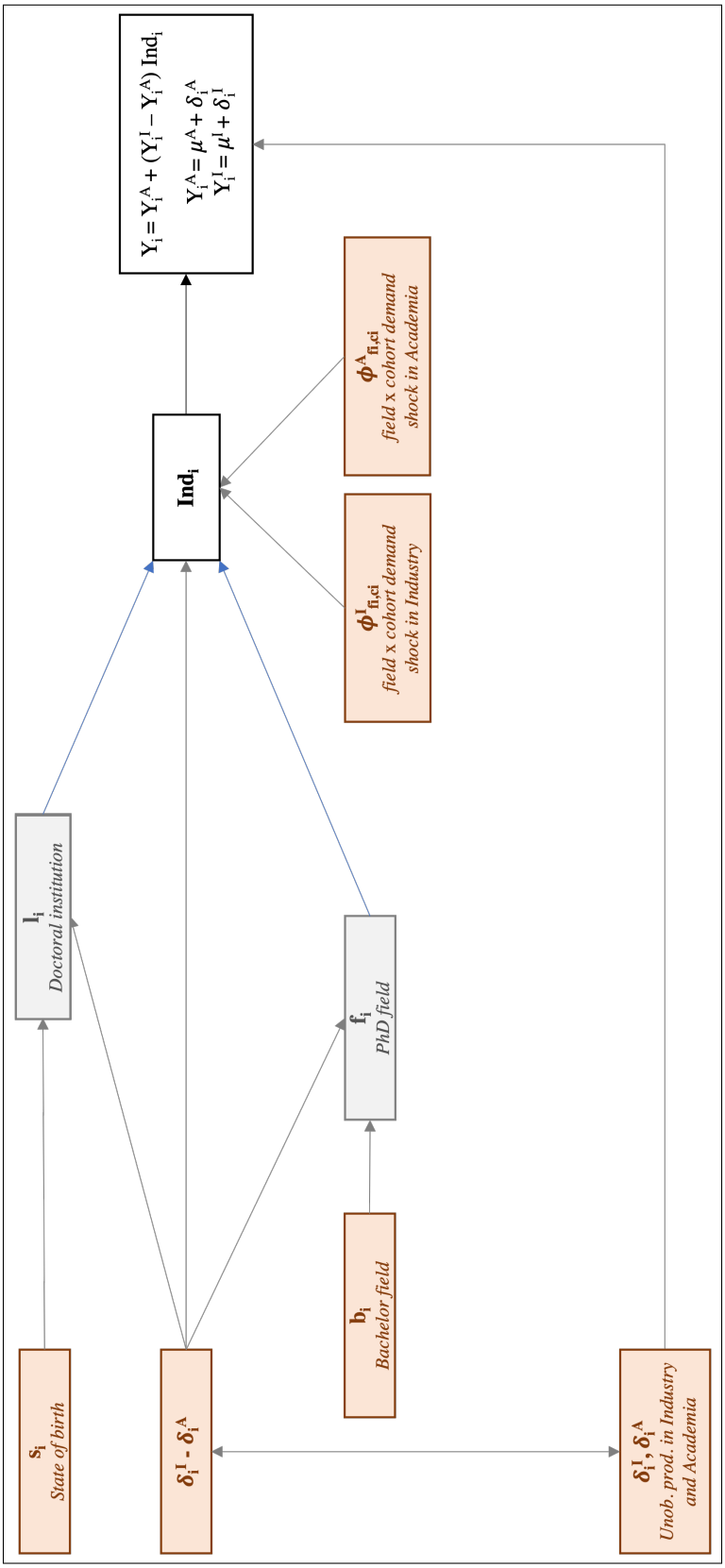


Figure E.20: Model dynamics

Appendix F Bachelor major selection

Assume that there are 2 bachelor majors: a and b. Assume individuals have perfect foresight so that they know which sector they want to join after a PhD (equivalently, individuals know about the value of their δ_i^I, δ_i^A). The decision process consists of 2 steps: (i) individuals choose between bachelor major a or b (ii) individuals choose between Industry and Academia after their PhD. Note that PhD major in this model is deterministic and equals to bachelor major. Note also that by construction I condition on individuals who pursue a PhD. None of these two features change the conclusion of the model. The decision tree is presented in Figure F.21.

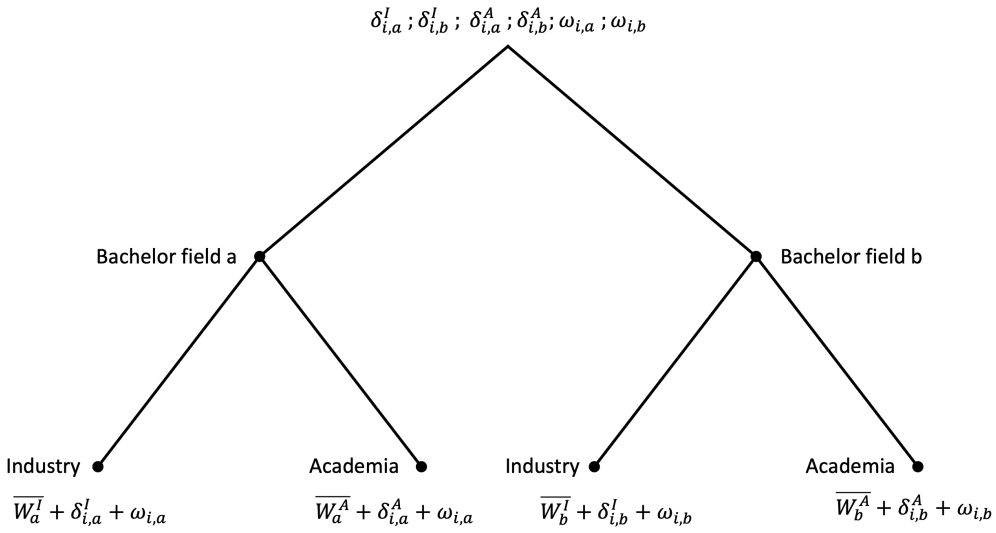


Figure F.21: Individuals' decision process

1. Sector choice after PhD graduation: I solve for the two-step decision process starting with the choice of going to Industry vs Academia (conditional on bachelor major):

$$\mathbf{1}\{j(i) = I | b_i = a\} = \begin{cases} 1 & \text{if } \overline{W_a^I} - \overline{W_a^A} + \delta^I_{i,a} - \delta^A_{i,a} > 0 \\ 0 & \text{if } \overline{W_a^I} - \overline{W_a^A} + \delta^I_{i,a} - \delta^A_{i,a} \leq 0 \end{cases} \tag{29}$$

$$\mathbf{1}\{j(i) = I | b_i = b\} = \begin{cases} 1 & \text{if } \overline{W_b^I} - \overline{W_b^A} + \delta^I_{i,b} - \delta^A_{i,b} > 0 \\ 0 & \text{if } \overline{W_b^I} - \overline{W_b^A} + \delta^I_{i,b} - \delta^A_{i,b} \leq 0 \end{cases} \tag{30}$$

2. Bachelor major choice: Once individuals have made their choice of sector conditional on bachelor major, they choose which bachelor major to join between a or b. This choice is a function of the previous best responses we solved for in each major. For example, consider individuals who would join the private sector in both cases. The payoff of choosing bachelor major a is then $\overline{W_a^I} + \delta^I_{i,a} + \omega_{i,a}$ and the payoff of choosing bachelor major b is $\overline{W_b^I} + \delta^I_{i,b} + \omega_{i,b}$. These individuals choose bachelor major a iff:

$$\overline{W_a^I} + \delta^I_{i,a} + \omega_{i,a} > \overline{W_b^I} + \delta^I_{i,b} + \omega_{i,b} \iff (\overline{W_a^I} - \overline{W_b^I}) + (\delta^I_{i,a} - \delta^I_{i,b}) + (\omega_{i,a} - \omega_{i,b}) > 0$$

For the exogeneity assumption to hold, the bachelor major choice equations shouldn't be correlated with Equations 29 and 30 involving the differences $\delta^I_{i,a} - \delta^A_{i,a}$ and $\delta^I_{i,b} - \delta^A_{i,b}$. Using the previous example, this means that (note that I omit the mean earnings for clarity below since any covariance involving them drops

in the equations):

$$\begin{cases} Cov(\delta^I_{i,a} - \delta^A_{i,a}, \delta^I_{i,a} + \omega_{i,a} - \delta^I_{i,b} - \omega_{i,b}) & = 0 \\ Cov(\delta^I_{i,b} - \delta^A_{i,b}, \delta^I_{i,a} + \omega_{i,a} - \delta^I_{i,b} - \omega_{i,b}) & = 0 \end{cases} \tag{31}$$

Using the same idea, we can write the conditions for the other cases (individuals who go to Industry if their bachelor major is a and Academia if their bachelor major is b ; individuals who go to Academia if their bachelor major is a and Industry if their bachelor major is b ; individuals who always go to Academia regardless of their bachelor major):

$$\begin{cases} Cov(\delta^I_{i,a} - \delta^A_{i,a}, \delta^I_{i,a} + \omega_{i,a} - \delta^A_{i,b} - \omega_{i,b}) & = 0 \\ Cov(\delta^I_{i,b} - \delta^A_{i,b}, \delta^I_{i,a} + \omega_{i,a} - \delta^A_{i,b} - \omega_{i,b}) & = 0 \end{cases} \tag{32}$$

$$\begin{cases} Cov(\delta^I_{i,a} - \delta^A_{i,a}, \delta^A_{i,a} + \omega_{i,a} - \delta^I_{i,b} - \omega_{i,b}) & = 0 \\ Cov(\delta^I_{i,b} - \delta^A_{i,b}, \delta^A_{i,a} + \omega_{i,a} - \delta^I_{i,b} - \omega_{i,b}) & = 0 \end{cases} \tag{33}$$

$$\begin{cases} Cov(\delta^I_{i,a} - \delta^A_{i,a}, \delta^A_{i,a} + \omega_{i,a} - \delta^A_{i,b} - \omega_{i,b}) & = 0 \\ Cov(\delta^I_{i,b} - \delta^A_{i,b}, \delta^A_{i,a} + \omega_{i,a} - \delta^A_{i,b} - \omega_{i,b}) & = 0 \end{cases} \tag{34}$$

For each of the 4 cases, we can develop the covariances conditions:

$$\begin{cases} (1)\ Var(\delta^I_{i,a}) - Cov(\delta^I_{i,a}, \delta^I_{i,b}) - Cov(\delta^A_{i,a}, \delta^I_{i,a}) + Cov(\delta^A_{i,a}, \delta^I_{i,b}) + Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) = 0 \\ (2)\ Cov(\delta^I_{i,b}, \delta^I_{i,a}) - Var(\delta^I_{i,b}) - Cov(\delta^A_{i,b}, \delta^I_{i,a}) + Cov(\delta^A_{i,b}, \delta^I_{i,b}) + Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b}) = 0 \end{cases}$$

$$\begin{cases} (3)\ Var(\delta^I_{i,a}) - Cov(\delta^I_{i,a}, \delta^A_{i,b}) - Cov(\delta^A_{i,a}, \delta^I_{i,a}) + Cov(\delta^A_{i,a}, \delta^A_{i,b}) + Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) = 0 \\ (4)\ Cov(\delta^I_{i,b}, \delta^I_{i,a}) - Cov(\delta^I_{i,b}, \delta^A_{i,b}) - Cov(\delta^A_{i,b}, \delta^I_{i,a}) + Var(\delta^A_{i,b}) + Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b}) = 0 \end{cases}$$

$$\begin{cases} (5)\ Cov(\delta^I_{i,a}, \delta^A_{i,a}) - Cov(\delta^I_{i,a}, \delta^I_{i,b}) - Var(\delta^A_{i,a}) + Cov(\delta^A_{i,a}, \delta^I_{i,b}) + Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) = 0 \\ (6)\ Cov(\delta^I_{i,b}, \delta^A_{i,a}) - Var(\delta^I_{i,b}) - Cov(\delta^A_{i,b}, \delta^A_{i,a}) + Cov(\delta^A_{i,b}, \delta^I_{i,b}) + Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b}) = 0 \end{cases}$$

$$\begin{cases} (7)\ Cov(\delta^I_{i,a}, \delta^A_{i,a}) - Cov(\delta^I_{i,a}, \delta^A_{i,b}) - Var(\delta^A_{i,a}) + Cov(\delta^A_{i,a}, \delta^A_{i,b}) + Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) = 0 \\ (8)\ Cov(\delta^I_{i,b}, \delta^A_{i,a}) - Cov(\delta^I_{i,b}, \delta^A_{i,b}) - Cov(\delta^A_{i,b}, \delta^A_{i,a}) + Var(\delta^A_{i,b}) + Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b}) = 0 \end{cases}$$

From (1) and (2) we get (1'):

$$\begin{aligned} (1')\ &Var(\delta^I_{i,a}) - Cov(\delta^A_{i,a}, \delta^I_{i,a}) + Cov(\delta^A_{i,a}, \delta^I_{i,b}) + Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) = \\ &Var(\delta^I_{i,b}) + Cov(\delta^A_{i,b}, \delta^I_{i,a}) - Cov(\delta^A_{i,b}, \delta^I_{i,b}) - Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b}) \end{aligned}$$

From (3) and (4) we get (2'):

$$\begin{aligned} (2')\ &Var(\delta^I_{i,a}) - Cov(\delta^A_{i,a}, \delta^I_{i,a}) + Cov(\delta^A_{i,a}, \delta^A_{i,b}) + Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) = \\ &Cov(\delta^I_{i,b}, \delta^I_{i,a}) - Cov(\delta^I_{i,b}, \delta^A_{i,b}) + Var(\delta^A_{i,b}) + Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b}) \end{aligned}$$

From (5) and (6) we get (3'):

$$(3')\ Cov(\delta^I_{i,a},\delta^A_{i,a}) - Cov(\delta^I_{i,a},\delta^I_{i,b}) - Var(\delta^A_{i,a}) + Cov(\delta^I_{i,a}-\delta^A_{i,a},\omega_{i,a}-\omega_{i,b}) = \\ -Var(\delta^I_{i,b}) - Cov(\delta^A_{i,b},\delta^A_{i,a}) + Cov(\delta^A_{i,b},\delta^I_{i,b}) + Cov(\delta^I_{i,b}-\delta^A_{i,b},\omega_{i,a}-\omega_{i,b})$$

From (7) and (8) we get (4'):

$$(4')\ Cov(\delta^I_{i,a},\delta^A_{i,a}) - Cov(\delta^I_{i,a},\delta^A_{i,b}) - Var(\delta^A_{i,a}) + Cov(\delta^I_{i,a}-\delta^A_{i,a},\omega_{i,a}-\omega_{i,b}) = \\ -Cov(\delta^I_{i,b},\delta^A_{i,a}) + Cov(\delta^I_{i,b},\delta^A_{i,b}) - Var(\delta^A_{i,b}) - Cov(\delta^I_{i,b}-\delta^A_{i,b},\omega_{i,a}-\omega_{i,b})$$

From (1') and (2') we get (A):

$$(A)\ Cov(\delta^A_{i,a},\delta^I_{i,b}) - Var(\delta^I_{i,b}) - Cov(\delta^A_{i,b},\delta^I_{i,a}) + 2Cov(\delta^I_{i,b}-\delta^A_{i,b},\omega_{i,a}-\omega_{i,b}) = \\ Cov(\delta^A_{i,a},\delta^A_{i,b}) - Cov(\delta^I_{i,b},\delta^I_{i,a}) - Var(\delta^A_{i,b})$$

From (1') and (3') we get (B):

$$(B)\ Var(\delta^I_{i,a}) + Cov(\delta^A_{i,a},\delta^I_{i,b}) - Cov(\delta^A_{i,b},\delta^I_{i,a}) + 2Cov(\delta^I_{i,a}-\delta^A_{i,a},\omega_{i,a}-\omega_{i,b}) \\ = Cov(\delta^I_{i,a},\delta^I_{i,b}) + Var(\delta^A_{i,a}) - Cov(\delta^A_{i,b},\delta^A_{i,a})$$

From (1') and (4') we get (C):

$$(C)\ 2Cov(\delta^A_{i,b},\delta^I_{i,a}) + Var(\delta^A_{i,a}) - Var(\delta^A_{i,b}) - 2Cov(\delta^I_{i,a}-\delta^A_{i,a},\omega_{i,a}-\omega_{i,b}) - \\ 2Cov(\delta^I_{i,b}-\delta^A_{i,b},\omega_{i,a}-\omega_{i,b}) = 2Cov(\delta^A_{i,a},\delta^I_{i,b}) + Var(\delta^I_{i,a}) - Var(\delta^I_{i,b})$$

From (2') and (3') we get (D):

$$(D)\ Var(\delta^I_{i,a}) + 2Cov(\delta^A_{i,a},\delta^A_{i,b}) - Var(\delta^A_{i,b}) + 2Cov(\delta^I_{i,a}-\delta^A_{i,a},\omega_{i,a}-\omega_{i,b}) - \\ 2Cov(\delta^I_{i,b}-\delta^A_{i,b},\omega_{i,a}-\omega_{i,b}) = 2Cov(\delta^I_{i,a},\delta^I_{i,b}) + Var(\delta^A_{i,a}) - Var(\delta^I_{i,b})$$

From (D) we get:

$$Cov(\delta^I_{i,a},\delta^I_{i,b}) - Cov(\delta^A_{i,a},\delta^A_{i,b}) = \\ \frac{1}{2}(Var(\delta^I_{i,a}) - Var(\delta^A_{i,b}) - Var(\delta^A_{i,a}) + Var(\delta^I_{i,b})) + Cov(\delta^I_{i,a}-\delta^A_{i,a},\omega_{i,a}-\omega_{i,b}) - Cov(\delta^I_{i,b}-\delta^A_{i,b},\omega_{i,a}-\omega_{i,b})$$

From (A) we get:

$$Cov(\delta^I_{i,a},\delta^I_{i,b}) - Cov(\delta^A_{i,a},\delta^A_{i,b}) = \\ Cov(\delta^A_{i,b},\delta^I_{i,a}) + Var(\delta^I_{i,b}) - Cov(\delta^A_{i,a},\delta^I_{i,b}) - Var(\delta^A_{i,b}) - 2Cov(\delta^I_{i,b}-\delta^A_{i,b},\omega_{i,a}-\omega_{i,b})$$

From (B) we get:

$$Cov(\delta^I_{i,a},\delta^I_{i,b}) - Cov(\delta^A_{i,b},\delta^A_{i,a}) = \\ Var(\delta^I_{i,a}) + Cov(\delta^A_{i,a},\delta^I_{i,b}) - Cov(\delta^A_{i,b},\delta^I_{i,a}) - Var(\delta^A_{i,a}) + 2Cov(\delta^I_{i,a}-\delta^A_{i,a},\omega_{i,a}-\omega_{i,b})$$

which together imply:

$$Cov(\delta^I_{i,a}, \delta^A_{i,b}) - Cov(\delta^A_{i,a}, \delta^I_{i,b}) =$$
$$\frac{1}{2}(Var(\delta^I_{i,a}) + Var(\delta^A_{i,b}) - Var(\delta^A_{i,a}) - Var(\delta^I_{i,b})) + Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) + Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b})$$

From (2'):

$$Cov(\delta^A_{i,a}, \delta^I_{i,a}) - Cov(\delta^A_{i,b}, \delta^I_{i,b}) = Var(\delta^I_{i,a}) + Cov(\delta^A_{i,a}, \delta^A_{i,b}) - Cov(\delta^I_{i,b}, \delta^I_{i,a}) - Var(\delta^A_{i,b})$$
$$+Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) - Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b})$$

which implies:

$$Cov(\delta^A_{i,a}, \delta^I_{i,a}) - Cov(\delta^A_{i,b}, \delta^I_{i,b}) = \frac{Var(\delta^I_{i,a}) - Var(\delta^A_{i,b}) + Var(\delta^A_{i,a}) - Var(\delta^I_{i,b})}{2}$$

Our final equations are then:

$$(*) \quad Cov(\delta^I_{i,a}, \delta^I_{i,b}) - Cov(\delta^A_{i,a}, \delta^A_{i,b}) = \frac{Var(\delta^I_{i,a}) - Var(\delta^A_{i,b}) - Var(\delta^A_{i,a}) + Var(\delta^I_{i,b})}{2} +$$
$$Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) - Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b})$$

$$(**) \quad Cov(\delta^I_{i,a}, \delta^A_{i,b}) - Cov(\delta^A_{i,a}, \delta^I_{i,b}) = \frac{Var(\delta^I_{i,a}) + Var(\delta^A_{i,b}) - Var(\delta^A_{i,a}) - Var(\delta^I_{i,b})}{2}$$
$$+Cov(\delta^I_{i,a} - \delta^A_{i,a}, \omega_{i,a} - \omega_{i,b}) + Cov(\delta^I_{i,b} - \delta^A_{i,b}, \omega_{i,a} - \omega_{i,b})$$

$$(***) \quad Cov(\delta^A_{i,a}, \delta^I_{i,a}) - Cov(\delta^A_{i,b}, \delta^I_{i,b}) = \frac{Var(\delta^I_{i,a}) - Var(\delta^A_{i,b}) + Var(\delta^A_{i,a}) - Var(\delta^I_{i,b})}{2}$$

Assuming for simplicity that $(\delta^I_{i,a}, \delta^A_{i,a}, \delta^I_{i,b}, \delta^A_{i,a})$ are drawn from a random distribution with the same variance and that $(\omega_{i,a},\ \omega_{i,b})$ are random parameters (in the sense of uncorrelated with the differences $\delta^I - \delta^A$ for each bachelor field, these equations simplify into:

$$Cov(\omega_{i,a} - \omega_{i,b}, \delta^I_{i,a} - \delta^A_{i,a}) = 0 \tag{35}$$
$$Cov(\omega_{i,a} - \omega_{i,b}, \delta^I_{i,b} - \delta^A_{i,b}) = 0 \tag{36}$$

$$Cov(\delta^A_{i,a}, \delta^I_{i,b}) = Cov(\delta^I_{i,a}, \delta^A_{i,b}) \tag{37}$$
$$Cov(\delta^A_{i,a}, \delta^A_{i,b}) = Cov(\delta^I_{i,a}, \delta^I_{i,b}) \tag{38}$$
$$Cov(\delta^I_{i,b}, \delta^A_{i,b}) = Cov(\delta^A_{i,a}, \delta^I_{i,a}) \tag{39}$$

Appendix G Marginal Treatment Effects

Denote treatment as D_i, with $D_i = 0$ meaning that individual i goes to Academia and $D_i = 1$ meaning that i goes to Industry. In what follows, I ignore the subscript i for clarity. The associated potential outcomes in the untreated (Academia) and treated (Industry) states are denoted respectively by Y_0 and Y_1, and are assumed to be a linear function of observables $\mathbf{X}$ and unobservables (U_0, U_1): $Y_j = \mu_j(\mathbf{X}) + U_j$ for $j = \{0, 1\}$. When the outcome considered is earnings, $U_0 = \delta^A$ and $U_1 = \delta^I$. When the outcome is publications, $U_0 = \theta_p^A$ and $U_1 = \theta_p^I$. The treatment indicator is a function of observables $\mathbf{Z}, \mathbf{X}$ and unobservables V:

$$D = \mathbf{1}\{\mu_D(Z, X) > V\} \tag{40}$$

V represents the unobserved characteristics that make individuals less likely to select into treatment and is usually interpreted as unobserved resistance or distaste for treatment. Given Equation 7, V is a function of $\delta_i^I - \delta_i^A$ and $\varepsilon_i^I - \varepsilon_i^A$. Note that a key feature of this model is that the unobserved gain from treatment $(U_1 - U_0)$ can be correlated with V.[33] The observed outcome Y is then equal to:

$$Y = (1 - D)Y_0 + DY_1 \tag{41}$$

The model can then be identified either through strong parametric restrictions on U_0, U_1 and V, or by using an instrumental variable Z (which is how I will proceed) which requires weaker assumptions. It is common in the literature to work with the quantiles of V rather than its values, in order to obtain a uniform random variable between 0 and 1. I therefore transform the selection equation as follows:

$$D = \mathbf{1}\{\mu_D(Z, X) > V\} \iff D = \mathbf{1}\{F_V(\mu_D(Z, X)) > F_V(V)\} \iff D = \mathbf{1}\{P(Z, X) > U_D\}$$

with F_V the cumulative distribution function of V. Two key variables are $P(Z, X)$, the propensity score and U_D, a uniformly distributed random variable between 0 and 1. Remember that V is the unobserved disutility for going into the private sector, so U_D gives us the quantiles of consumer types in terms of their unobserved disutility for treatment. Importantly for what follows, individuals with lower values of U_D are more likely to join the private sector for unobservable reasons while individuals with higher values of U_D are less likely to enter the private sector (more likely to enter Academia) for unobservable reasons. In this setup, the *marginal treatment effect* for individuals with observables $X = x$ and disutility for treatment $U_D = u$ is:

$$\text{MTE}(X = x, U_D = u) = \mathbb{E}[Y_1 - Y_0 | X = x, U_D = u] \tag{42}$$

which makes it clear that treatment effect heterogeneity may result from both observed and unobserved characteristics. For instance, for individuals with X that make them more likely to enter the private sector, I can test whether they have smaller or higher earning gains/publication loss than others. Similarly, considering individuals with lower U_D that make them more likely to enter the private sector, I can test whether they have smaller or higher earning gains/publication loss than others. A common way to present the results is to plot the MTE as a function of U_D for average values of X. If the slope of the curve is flat, then $\mathbb{E}[Y_1 - Y_0 | X = x, U_D = u]$ is constant so that there is no heterogeneity in treatment effect across individuals with different propensities for joining the private sector vs Academia (or equivalently for individuals with different distaste for joining the private sector vs Academia). If the slope is upward or downward sloping, there is heterogeneity in treatment effect across individuals with different propensities for joining the private sector vs Academia.

The assumptions needed for the calculation of the MTE are the same as for the IV framework, with in particular a valid exclusion restriction which can be written as $(U_0, U_1, V) \perp\!\!\!\perp Z | X$ where $\perp\!\!\!\perp$ denotes conditional independence. In practice, provided the reader found the instrumental variable previously discussed convincing enough, this means I can use it to estimate MTE. Following the literature, I further assume additive separability between the observed and unobserved components. This allows me to write the MTE as:

$$\text{MTE}(X = x, U_D = u) = x(\beta_1 - \beta_0) + \mathbb{E}[U_1 - U_0 | U_D = u] \tag{43}$$

[33] This is obvious for earnings, but it could also be true for publications

It also implies that treatment affect heterogeneity coming from observed characteristics affects the intercept of the MTE curve (plotted as a function of U_D) but not its slope (Cornelissen et al., 2016). While this MTE framework is more restrictive than the 2SLS one, it allows me to bring more nuance into treatment heterogeneity and the pattern of selection.

Appendix H Calculating the sum of expected earnings

I detail here how I estimate the sum of the expected (discounted) earnings that individual i can expect to earn if she starts her career in sector j. Under the full model that allows for transitions across sectors during the career, this sum is equal to:

$$\sum_{t=0}^{T} \rho^t \ \mathbf{E}\left[W_i^{j_t} \mid j_0\right] = \sum_{t=0}^{T} \rho^t \ \mathbf{E}\left[\overline{W_t^{j_t}} + \delta_i^{j_t} \mid j_0\right] \tag{44}$$

with $j_0(i)$ the sector joined by i at the beginning of her career and j_t the sector she actually works in at time t. Under the simplified model which assumes no transition across sector during the career, this sum simplifies to:

$$\sum_{t=0}^{T} \rho^t \ \mathbf{E}\left[W_{it}^{j}\right] = \sum_{t=0}^{T} \rho^t \ \mathbf{E}\left[\overline{W_t^{j}} + \delta_i^{j}\right] = \sum_{t=0}^{T} \rho^t \ \mathbf{E}\left[\overline{W_t^{j}}\right] + \sum_{t=0}^{T} \rho^t [\delta_i^{j}] \tag{45}$$

My procedure is applicable for both cases but to ease the notations, I refer to the mathematical case of no transition. My procedure is as follows:

- Using all observations in my sample, I estimate a flexible regression of (log) earnings on an indicator for *starting* one's career in Industry, PhD major fixed effects, PhD cohort of graduation fixed effects, years of experience fixed effects and the interactions of these variables. This allows me to get $\mathbf{E}\left[\overline{W_t^{j}}\right]$ for each individual i who started her career in sector j and each year of experience t. I therefore have $T = 40$ observations for each individual as I predict earnings for years of experience 1 to 40. Figure H.22 shows the expected sector-mean earnings by year of experience
- In order to create individual-level variation, I then use the earnings observations I have for each individual (let's assume for exposition that I observe earnings in year k) and I calculate the gap between the real observed earnings at time k W_{it}^{k} and $\mathbf{E}\left[\overline{W_t^{k}}\right]$. Call this gap g. For each predicted earnings observation $\mathbf{E}\left[\overline{W_t^{j}}\right]$, I then use g to shift the predicted curve up (if $g > 0$) or down (if $g<0$)

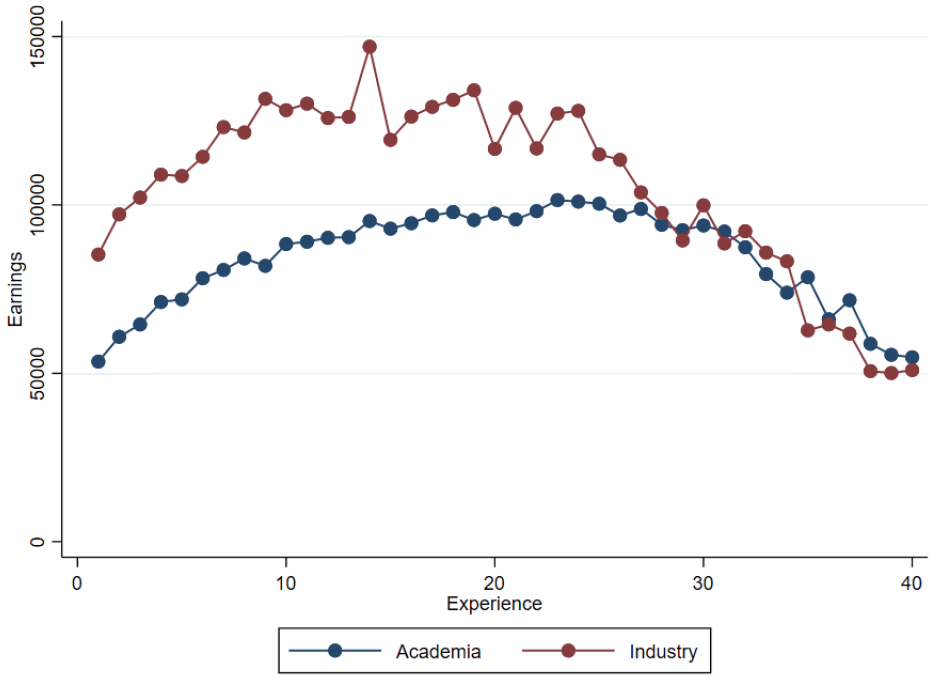


Figure H.22: Predicted earnings by years of experience and sector joined at graduation