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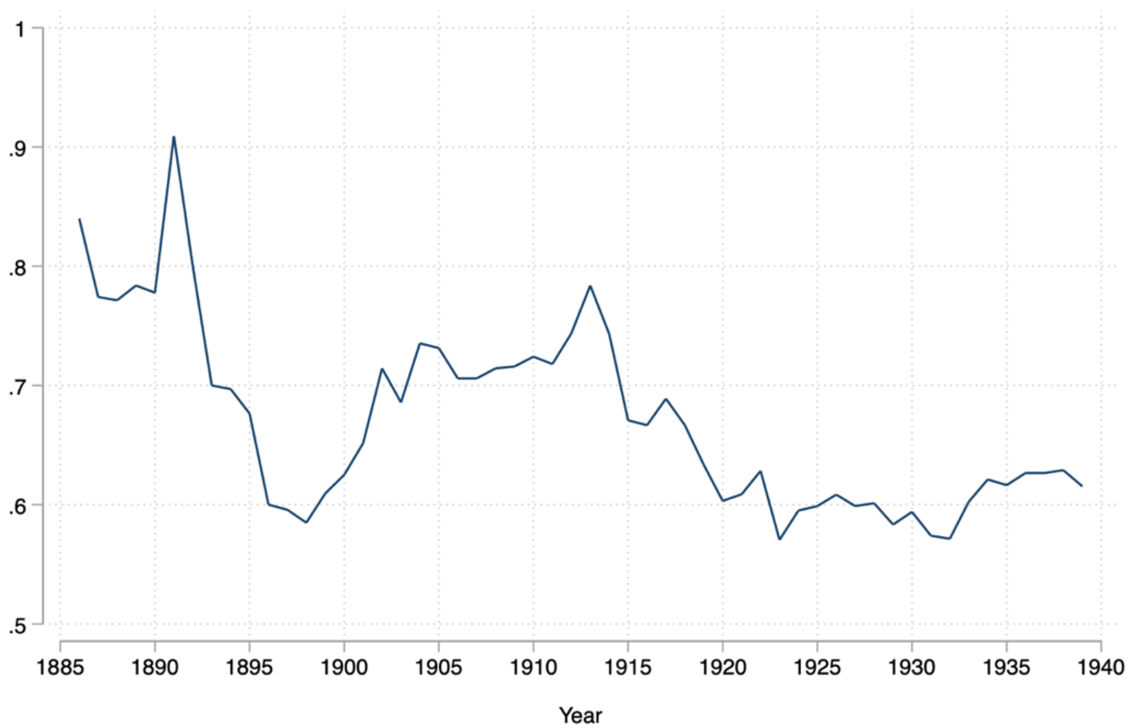
On-Line Appendix to:

The Evolution of Talent Allocation into Academia: Institution-Building and Graduates' Choices During Japan's Industrialization

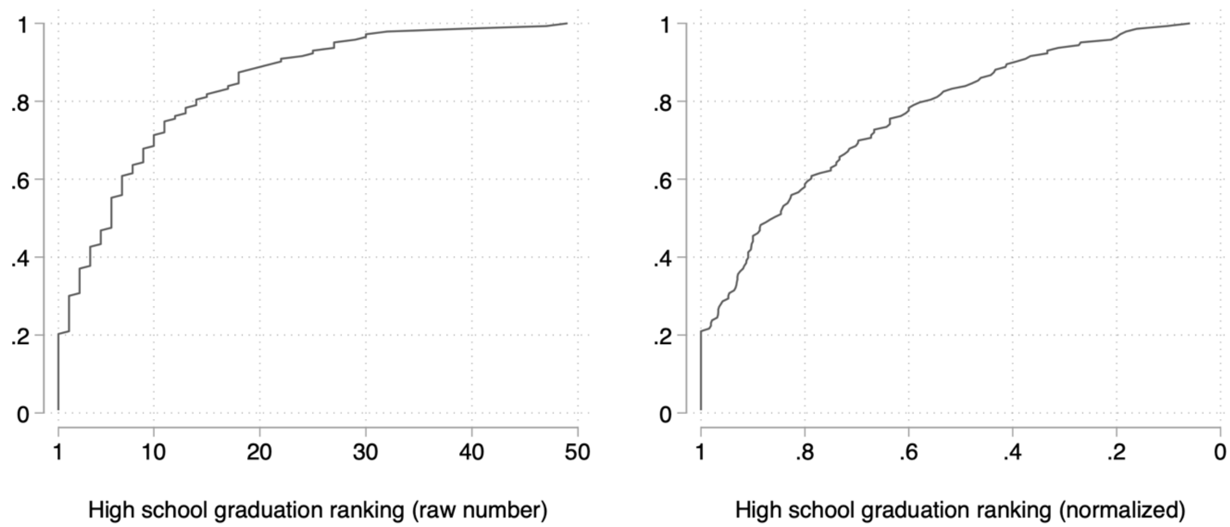
A. Figures and Tables Cited in the Main Text

Figure A1. Share of Core Faculty Among Engineering Faculty in Tokyo Imperial University



Note: The figure presents the number of full and assistant professors at the engineering department in Tokyo Imperial University in each year, divided by the total number of faculty members in that year. Our calculations based on *Tokyo Teikoku Daigaku Ichiran*, 1886-1939.

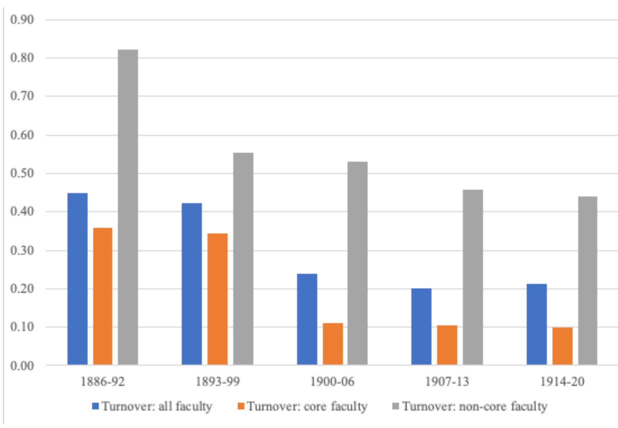
Figure A2. Empirical Cumulative Distribution of High-School Graduation Ranking Among Core Engineering Faculty in Tokyo Imperial University



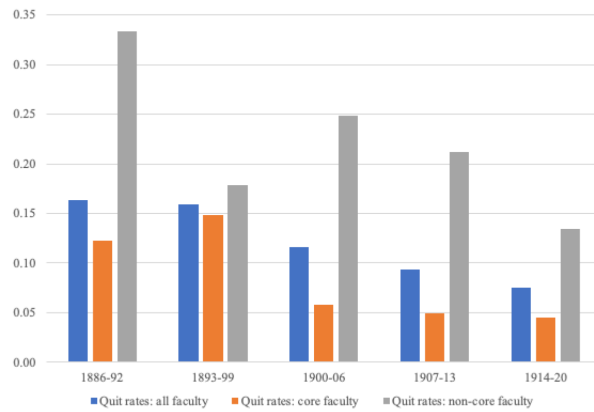
Note: The figures present the empirical cumulative distribution of high school graduation ranking among core engineering faculty members of Tokyo Imperial University. The left panel uses the raw numbers of the high school graduation ranking as the horizontal axis. The right panel uses the normalized high school graduation ranking as the horizontal axis. The normalized high school graduation rankings ($Norm\_Rank_i$) are calculated as follows: $Norm\_Rank_i = (N_i - R_i)/(N_i - 1)$, where R_i is the raw number of the high school graduation ranking of graduate i and N_i is the number of graduates in the school that graduate i belonged to.

Figure A3. Turnover and Quit Rates Among Engineering Faculty

Panel A. Turnover Rates

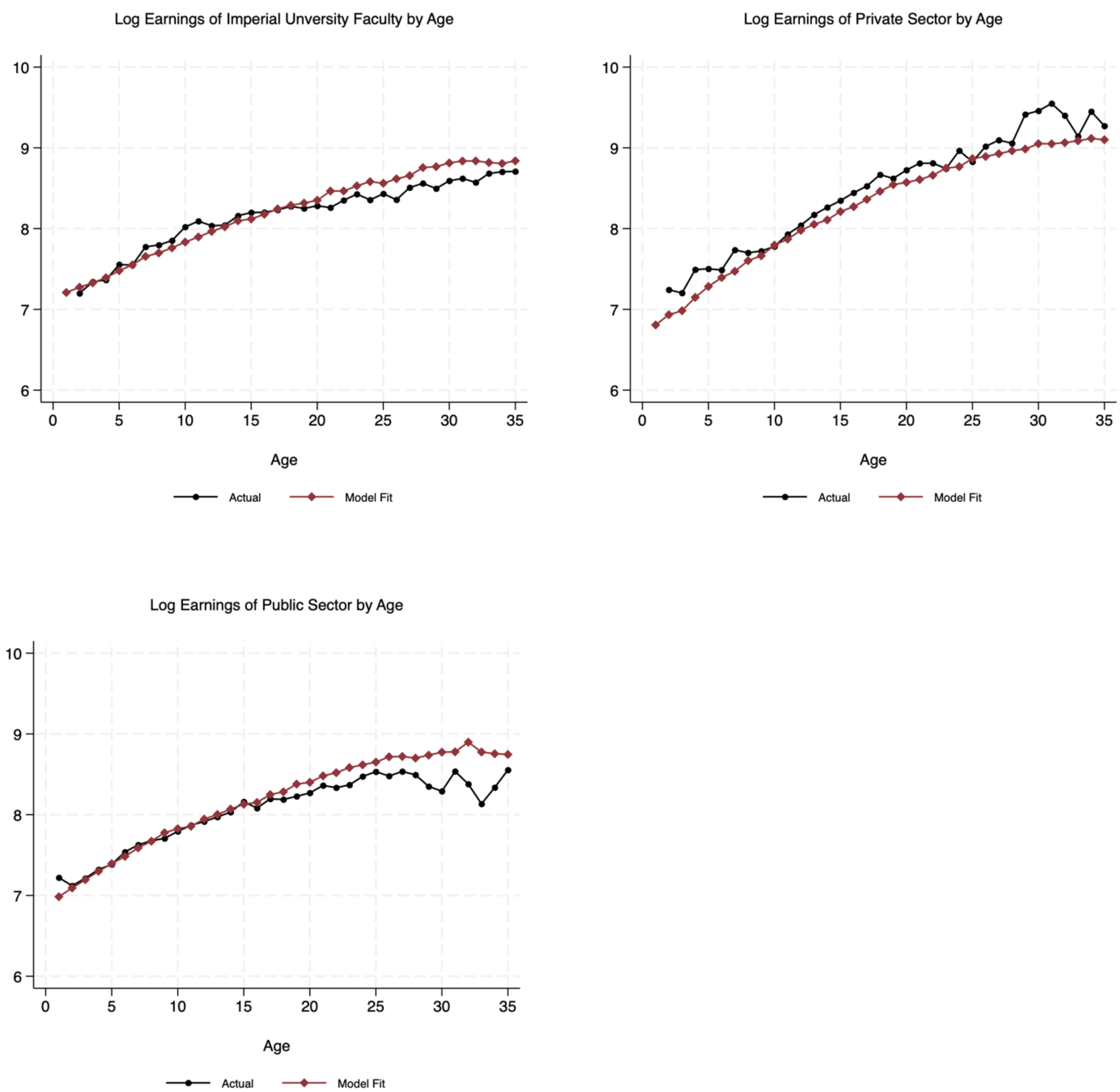


Panel B. Quit Rates



Note: Turnover rate = (# hires + # quits)/ (total # of faculty) in a given year. Quit rate = # quits / total # of faculty in a given year. The bars represent averages over five seven-year periods. Our calculations based on *Tokyo Teikoku Daigaku Ichiran*, 1886-1939.

Figure A4. Age-Earning Profiles: Model Fit and Counterfactuals [Not Up to Date]



Note: The figures depict actual and simulated (with estimated parameters) earnings profiles of engineering faculty (academia), those in the private sector, and those in the public sector by age (years after graduation). In each figure, the black line with circles represents the actual earnings profiles in the data, while the red line with diamonds represents the simulated earnings profiles with estimated parameters.

Table A1. Tokyo Imperial University Salary Scales

Panel A (yen per annum)

	Year					
Grade (full professors)	1893	1897	1907	1910	1919	1920
1	1200	1600	2000	2500	3000	4500
2	1000	1400	1800	2200	2700	4100
3	1000	1200	1600	2000	2500	3800
4	900	1100	1400	1700	2200	3400
5	800	1000	1200	1500	2000	3100
6		900	1000	1300	1700	2700
7		800	900	1200	1500	2400
8			800	1100	1200	2000
9				1000	1100	1800
10					1000	1600
11						1400
12						1200

	Year					
Grade (asst. professors)	1893	1897	1907	1910	1919	1920
1	600	800	1000	1200	2000	3100
2	500	700	900	1100	1700	2800
3	400	600	800	1000	1500	2600
4	300	500	700	850	1200	2400
5		400	600	750	1100	2200
6		300	500	600	850	2000
7			400	500	750	1800
8			300	400	600	1600
9					500	1400
10						1300
11						1200
12						1100

Source: *Tokyo Daigaku Hyakunenshi* (1977, Vol. 8).

Table A1. Tokyo Imperial University Salary Scales (Continued)

Panel B (yen per annum, deflated by the consumer price index, 1897 = 1)

	Year					
Grade (full professors)	1893	1897	1907	1910	1919	1920
1	1664	1600	1363.5	1831.6	919.4	1318.8
2	1386	1400	1227.1	1611.8	827.5	1201.5
3	1386	1200	1090.8	1465.3	766.2	1113.6
4	1248	1100	954.4	1245.5	674.2	996.4
5	1109	1000	818.1	1099.0	612.9	908.5
6		900	681.7	952.4	521.0	791.3
7		800	613.6	879.2	459.7	703.3
8			545.4	805.9	367.8	586.1
9				732.6	337.1	527.5
10					306.5	468.9
11						410.3
12						351.7

	Year					
Grade (asst. professors)	1893	1897	1907	1910	1919	1920
1	832	800	681.7	879.2	612.9	908.5
2	693	700	613.6	805.9	521.0	820.6
3	555	600	545.4	732.6	459.7	761.9
4	416	500	477.2	622.7	367.8	703.3
5		400	409.0	549.5	337.1	644.7
6		300	340.9	439.6	260.5	586.1
7			272.7	366.3	229.8	527.5
8			204.5	293.1	183.9	468.9
9					153.2	410.3
10						381.0
11						351.7
12						322.4

Source: *Tokyo Daigaku Hyakunenshi* (1977, Vol. 8). Consumer price deflator from Ohkawa K. et al. (1967), *Choki Keizai Tokei* ((Estimates of Long-Term Economic Statistics of Japan Since 1868), Vol. 8, *Bukka* (Prices), Toyo Keizai Shimposha, Tokyo, p. 135.

Table A2. Share of Engineering Faculty among All and Top Graduates by Graduation Years

	Share of engineering faculty among engineering graduates	Of which: Top graduates
All cohorts until 1918: Tokyo Imperial University	0.071	0.322
All cohorts until 1918: all Imperial Universities	0.101	0.407
Graduated before 1900: Tokyo Imperial University	0.113	0.292
Graduated before 1900: all Imperial Universities	0.138	0.381
Graduated after 1900: Tokyo Imperial University	0.059	0.338
Graduated after 1900: all Imperial Universities	0.091	0.422

Note: Our calculations. The reported numbers are the shares of respective graduates who were employed as engineering faculty in corresponding Imperial Universities at least once during their careers.

Table A3. Structural Estimation Parameters (1)

Earning Parameters

	Specification				
	(1)	(2)	(3)	(4)	(5)
Academia:					
Intercept	7.301 [0.040]	7.356 [0.041]	7.405 [0.041]	7.325 [0.040]	7.345 [0.043]
Year after graduation	0.080 [0.003]	0.081 [0.003]	0.080 [0.003]	0.081 [0.003]	0.081 [0.003]
Year after graduation² (×100)	-0.096 [0.007]	-0.090 [0.007]	-0.086 [0.007]	-0.094 [0.008]	-0.089 [0.008]
Year trend (×100)	-0.577 [0.091]	-0.829 [0.102]	-0.965 [0.094]	-0.726 [0.088]	-0.835 [0.110]
Error variance	0.347 [0.005]	0.345 [0.005]	0.344 [0.004]	0.346 [0.005]	0.345 [0.005]
Private:					
Intercept	5.531 [0.053]	5.411 [0.069]	5.475 [0.056]	5.436 [0.053]	5.425 [0.065]
Year after graduation	0.102 [0.003]	0.079 [0.004]	0.071 [0.004]	0.103 [0.003]	0.086 [0.004]
Year after graduation² (×100)	-0.142 [0.007]	-0.080 [0.011]	-0.062 [0.009]	-0.145 [0.008]	-0.104 [0.011]
Year trend (×100)	3.687 [0.096]	4.254 [0.143]	4.263 [0.118]	3.830 [0.102]	4.186 [0.139]
Error variance	0.580 [0.006]	0.579 [0.007]	0.579 [0.007]	0.578 [0.007]	0.588 [0.007]
Public/Military:					
Intercept	6.932 [0.029]	6.967 [0.036]	6.990 [0.032]	6.928 [0.031]	6.914 [0.039]
Year after graduation	0.109 [0.002]	0.112 [0.003]	0.112 [0.003]	0.108 [0.002]	0.108 [0.003]
Year after graduation² (×100)	-0.189 [0.006]	-0.193 [0.008]	-0.193 [0.007]	-0.187 [0.006]	-0.188 [0.008]
Year trend (×100)	-0.126 [0.073]	-0.281 [0.084]	-0.340 [0.076]	-0.095 [0.069]	-0.074 [0.093]
Error variance	0.344 [0.005]	0.342 [0.006]	0.341 [0.005]	0.343 [0.004]	0.343 [0.005]

Note: The table shows the estimates on the earning parameters in the structural estimation. Each specification includes different set of individual characteristics as explanatory variables in non-pecuniary preferences. Specification (1) only includes the cohort trend in the set of individual-specific characteristics; specification (2) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate was also an honor student; specification (3) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate was also a top student after the second year; specification (4) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate graduated in 1894 or thereafter; and specification (5) includes all those individual-specific characteristics. The reported estimates are multiplied by 100 if necessary. The standard errors in parentheses are calculated by the parametric bootstrap procedure described in Appendix D.3.

Table A4. Structural Estimation Parameters (2)

Switching Cost Parameters

	Specification				
	(1)	(2)	(3)	(4)	(5)
Academia:					
Intercept	-0.672 [0.122]	-0.653 [0.166]	-0.652 [0.141]	-0.777 [0.120]	-0.710 [0.145]
Year after graduation	0.028 [0.010]	0.026 [0.010]	0.026 [0.012]	0.025 [0.010]	0.028 [0.010]
Year after graduation^2 (×100)	-0.098 [0.028]	-0.095 [0.031]	-0.094 [0.032]	-0.095 [0.027]	-0.098 [0.029]
Private:					
Intercept	-0.625 [0.131]	-0.623 [0.187]	-0.642 [0.160]	-0.748 [0.142]	-0.670 [0.180]
Year after graduation	-0.007 [0.009]	-0.003 [0.012]	-0.006 [0.011]	-0.005 [0.010]	-0.005 [0.012]
Year after graduation^2 (×100)	-0.007 [0.024]	-0.020 [0.031]	-0.008 [0.028]	-0.015 [0.027]	-0.013 [0.029]
Public/Military:					
Intercept	-1.613 [0.225]	-1.632 [0.280]	-1.567 [0.240]	-1.712 [0.242]	-1.708 [0.190]
Year after graduation	0.054 [0.016]	0.054 [0.019]	0.056 [0.019]	0.048 [0.019]	0.059 [0.019]
Year after graduation^2 (×100)	-0.090 [0.038]	-0.095 [0.045]	-0.104 [0.048]	-0.077 [0.047]	-0.107 [0.046]

Note: The table shows the estimates on the switching cost parameters in the structural estimation. Each specification includes different set of individual characteristics as explanatory variables in non-pecuniary preferences. Specification (1) only includes the cohort trend in the set of individual-specific characteristics; specification (2) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate was also an honor student; specification (3) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate was also a top student after the second year; specification (4) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate graduated in 1894 or thereafter; and specification (5) includes all those individual-specific characteristics. The reported estimates are multiplied by 100 if necessary. The standard errors in parentheses are calculated by the parametric bootstrap procedure described in Appendix D.3.

Table A5. Structural Estimation Parameters (3)

Preference Shock and Type Distribution Parameters

	Specification				
	(1)	(2)	(3)	(4)	(5)
Preference variance	0.094 [0.010]	0.094 [0.014]	0.095 [0.012]	0.082 [0.009]	0.090 [0.010]
Type distribution					
Type 1	0.240 [0.025]	0.319 [0.031]	0.332 [0.033]	0.301 [0.030]	0.234 [0.032]
Type 2	0.071 [0.013]	0.068 [0.016]	0.068 [0.014]	0.074 [0.016]	0.074 [0.017]
Type 3	0.322 [0.028]	0.283 [0.032]	0.284 [0.031]	0.284 [0.030]	0.270 [0.032]
Type 4	0.367 [0.026]	0.330 [0.030]	0.316 [0.035]	0.341 [0.031]	0.422 [0.036]

Preference Heterogeneity Parameters

	Specification				
	(1)	(2)	(3)	(4)	(5)
Academia:					
Type 1 (×100)	-0.135 [0.201]	-0.820 [0.227]	-0.791 [0.220]	-0.882 [0.157]	-1.278 [0.212]
Type 2 (×100)	1.664 [0.358]	1.940 [0.637]	1.682 [0.611]	1.420 [0.326]	1.543 [0.356]
Type 3 (×100)	0.570 [0.176]	0.326 [0.284]	0.393 [0.249]	0.520 [0.167]	0.316 [0.238]
Type 4 (×100)	-0.734 [0.195]	0.112 [0.236]	0.120 [0.211]	0.038 [0.162]	0.233 [0.176]
Public/Military:					
Type 1 (×100)	-0.824 [0.171]	-0.492 [0.179]	-0.454 [0.152]	-0.558 [0.160]	-0.927 [0.184]
Type 2 (×100)	1.920 [0.303]	1.985 [0.552]	1.865 [0.529]	1.757 [0.305]	1.768 [0.319]
Type 3 (×100)	0.439 [0.166]	0.378 [0.221]	0.415 [0.221]	0.431 [0.180]	0.342 [0.209]
Type 4 (×100)	-0.218 [0.178]	-0.258 [0.195]	-0.295 [0.185]	-0.247 [0.149]	-0.017 [0.152]

Note: The table shows the estimates on the preference shock, type distribution, and preference heterogeneity parameters in the structural estimation. Each specification includes different set of individual characteristics as explanatory variables in non-pecuniary preferences. Specification (1) only includes the cohort trend in the set of individual-specific characteristics; specification (2) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate was also an honor student; specification (3) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate was also a top student after the second year; specification (4) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate graduated in 1894 or thereafter; and specification (5) includes all those individual-specific characteristics. The reported estimates are multiplied by 100 if necessary. The standard errors in parentheses are calculated by the parametric bootstrap procedure described in Appendix D.3.

Table A6. Structural Estimation Parameters (4)

Earning Heterogeneity Parameters

	Specification				
	(1)	(2)	(3)	(4)	(5)
Academia:					
Type 1	-0.251 [0.020]	0.178 [0.020]	0.169 [0.020]	0.184 [0.019]	0.195 [0.020]
Type 2	0.504 [0.025]	0.538 [0.027]	0.539 [0.032]	0.533 [0.029]	0.546 [0.026]
Type 3	-0.085 [0.017]	-0.261 [0.022]	-0.255 [0.021]	-0.268 [0.022]	-0.253 [0.020]
Type 4	0.141 [0.015]	-0.060 [0.017]	-0.064 [0.018]	-0.055 [0.017]	-0.043 [0.018]
Private:					
Type 1	-0.533 [0.036]	-0.126 [0.039]	-0.131 [0.037]	-0.172 [0.037]	-0.468 [0.040]
Type 2	1.178 [0.060]	1.304 [0.072]	1.298 [0.060]	1.204 [0.051]	1.225 [0.063]
Type 3	0.421 [0.034]	0.456 [0.039]	0.453 [0.033]	0.455 [0.036]	0.438 [0.039]
Type 4	-0.248 [0.033]	-0.538 [0.040]	-0.549 [0.035]	-0.488 [0.039]	-0.237 [0.039]
Public/Military:					
Type 1	0.185 [0.015]	0.149 [0.018]	0.143 [0.017]	0.161 [0.016]	0.163 [0.019]
Type 2	0.474 [0.022]	0.535 [0.027]	0.535 [0.026]	0.472 [0.026]	0.495 [0.025]
Type 3	-0.180 [0.017]	-0.204 [0.021]	-0.208 [0.017]	-0.193 [0.018]	-0.182 [0.021]
Type 4	-0.056 [0.015]	-0.079 [0.016]	-0.078 [0.017]	-0.084 [0.015]	-0.061 [0.014]

Note: The table shows the estimates on the earning heterogeneity parameters in the structural estimation. Each specification includes different set of individual characteristics as explanatory variables in non-pecuniary preferences. Specification (1) only includes the cohort trend in the set of individual-specific characteristics; specification (2) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate was also an honor student; specification (3) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate was also a top student after the second year; specification (4) includes the cohort trend and the dummy equal to one and zero otherwise if the top graduate graduated in 1894 or thereafter; and specification (5) includes all those individual-specific characteristics. The reported estimates are multiplied by 100 if necessary. The standard errors in parentheses are calculated by the parametric bootstrap procedure described in Appendix D.3.

B. Data and the Sample

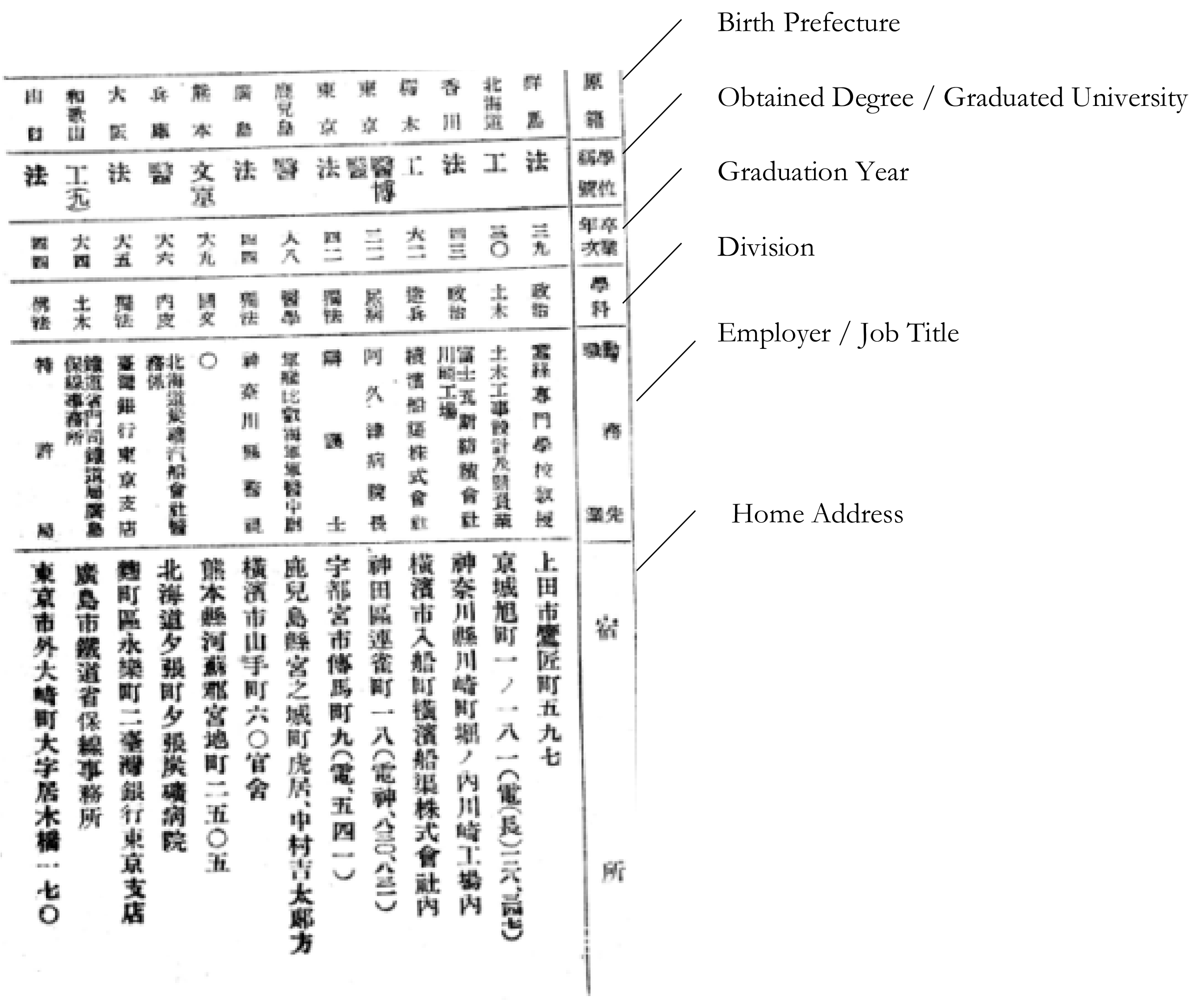
B.1. Annual Alumni Surveys of Imperial Universities' Graduates ("*Gakushikai Kaiin Shimeiroku*")

As mentioned in the main text, our first data source is the database covering all bachelor's degree recipients in Science and Engineering from Japan's Imperial Universities starting from the first graduation cohorts in the late 1870s and until the 1920 graduation cohorts, developed in collaboration with Shotaro Yamaguchi and funded by the National Science Foundation grant #2022440 (Yamaguchi, Braguinsky, and Nakajima, 2021). The Alumni Association of Imperial Universities, *Gakushikai*, annually publishes alumni lists containing information about addresses and workplaces for each graduate belonging to the association. Digital images of those surveys for every year from 1890 to 1940 (with two missing years, 1893 and 1894) were provided to us by *Gakushikai*. We obtained information for all the identified graduates who were found in these lists. Even though membership in the association was voluntary, more than 90% of all graduates joined it, and for all of them we have information about their addresses and workplaces. Figure B1 below shows how the information for each graduate appears in this list. Among those information, employer/job title and home address were annually updated while the other information was unchanged across the periods.

While some parts of the afore-mentioned alumni surveys were used in past studies by Japanese historians (Uchida, 1979; Uemura, 2017a,b; Sawai, 2020), the database above is the first one to use *all* the data available on science and engineering graduates from those surveys (comprising about 90% of all graduates). One of the most challenging part in creating the full longitudinal database from the alumni surveys was to keep track of name changes that were common in Japan at that time, mostly due to frequent cases of adult adoption.[1] The writing of characters in the names also varies from year to year, which presented another challenge. The list of all different names and name writing variations was created and shared with the current authors by Shotaro Yamaguchi. Furthermore, as we worked on cleaning and verifying the data, there were multiple instances where survey information was updated with a lag and more exact information was available from published biographies and other historical sources. In such cases, we updated the employer/address information from the surveys by the corrected information we found in other sources, making sure to keep the original survey data and recording the sources on which we based our updates. For Imperial University engineering faculty whose data are used in the current paper we also cross-checked the information from the alumni surveys with Imperial University Calendars and also with Japan's *Who is Who* used to obtain eanrings data. These two data sources are described below.

[1] It was common in the Edo and Meiji era that people occasionally had multiple names and changed their own names. Although the government enforced laws prohibiting multiple names and renaming in 1873, it relaxed the regulations due to a strong backlash (Yamanushi, 1962). As a result, we observe many cases of changes in both family and given names for the same individuals. For most cases, however, both old and new names were listed for the same individual in separate sections of *Shimeiroku* which were used to identify such cases. Sources used to track name changes include also *Imperial University Calendars*, High-school Registries (*High-school Calendars*), Japan Doctors Index (*Dainihon Hakushiroku*) and other sources

Figure B1. A sample page from the annual alumni surveys of Imperial Universities' graduates



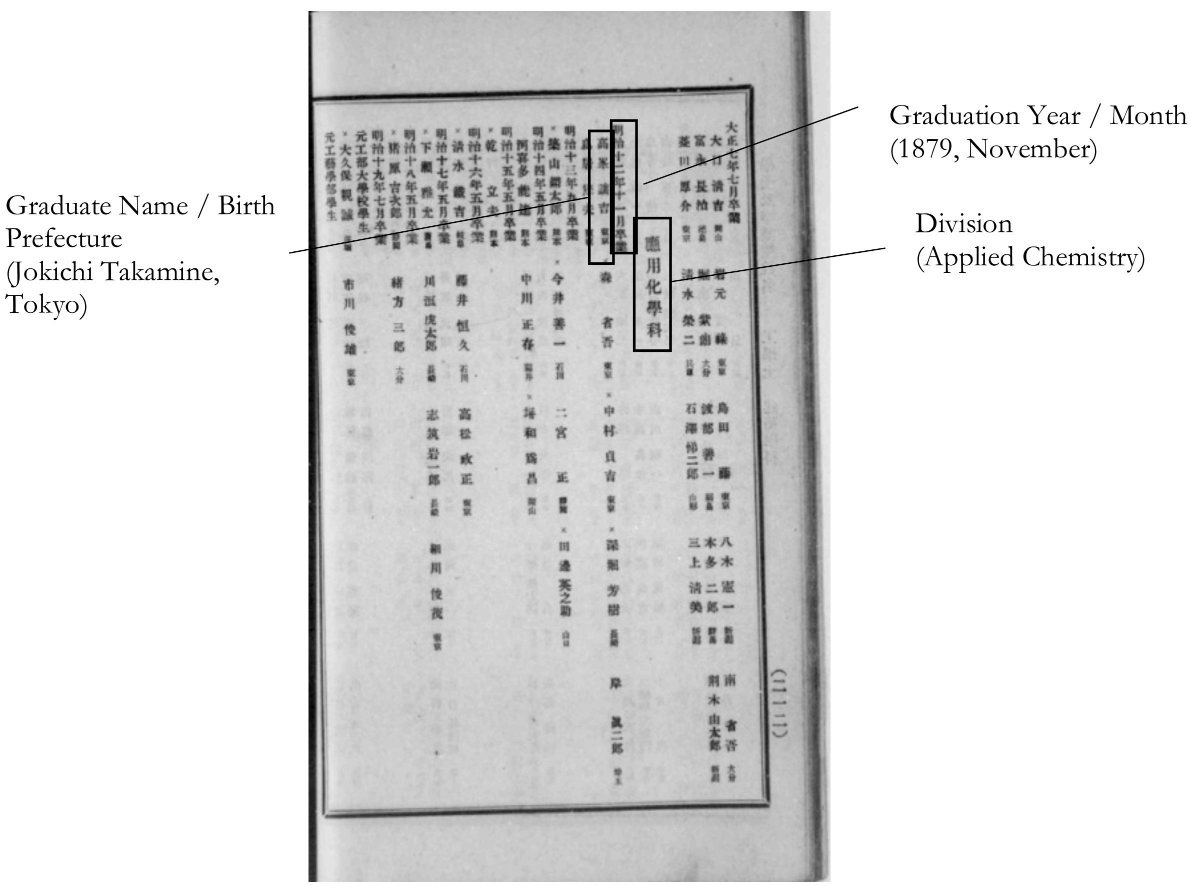
Source: Annual Alumni Surveys of Imperial Universities' Graduates ("*Gakushikai Kaiin Shimeiroku*") Taisho 9 (1920). The graduate names are not displayed.

B.2. Annual Calendars of Imperial Universities (*Ichiran*)

Each Imperial University in Japan published annual Calendars (such as *Tokyo Teikoku Daigaku Ichiran*, also called *Tokyo Teikoku Daigaku Yoran* in some years) which are available in open access through the National Diet Library Digital Collections (https://dl.ndl.go.jp/en/). Those calendars have the section listing all graduates' names in all prior cohorts. The list of graduates starts with the first graduation cohorts from their predecessors: the 1877 cohort from University of Tokyo for science and the 1879 cohort from *Kobu Daigakko* for engineering. Importantly, in Tokyo Imperial University Calendars, in particular, up until 1918 the students were listed in the order (*Sekiji*, in Japanese) of the average of their test scores in each year, while the graduates were listed in the order of average test scores over all three years of university education, with the score of their graduation diploma added as the fourth component. As shown in Figure B2, the graduate names are listed for each science or engineering division and each graduation cohort. The order of the graduates is based on their graduation rank for Tokyo Imperial University graduates until the 1918 cohorts, and Japanese alphabetical orders for other graduates. For example, Figure B2 shows that Jokichi Takamine (who discovered adrenaline) graduated the applied chemistry division of Tokyo Imperial University at the top of the class of six people in 1879.

We digitized the data on all the graduates in Science and Engineering from the first graduation cohorts in the late 1870s and until the 1920 graduation cohorts listed in those calendars. These data were then matched with Annual Alumni Surveys of Imperial Universities' Graduates (described in the previous section) to follow the graduates' employers and addresses updated in those surveys on an annual basis. We also digitized the data on all the engineering faculty listed in the Imperial University Calendars until 1939 and used these data to assign jobs (professors and assistant professors as core faculty v. lecturers) and to double-check the data in alumni surveys.

Figure B2. A sample page of graduates lists in Tokyo Imperial University *Ichiran*



Source: Annual Catalog of Tokyo Imperial University (*Ichiran*) Taisho 7 (1918).

B.3. Matching with Patent Publication Records

The collaborating team in Japan, comprised of Hiroyasu Inoue, Kentaro Nakajima, Tetsuji Okazaki, and Yukiko Umeno Saito has constructed a historical database of patent specification records. The original records of every patent specification (from the first patent based on the Patent Law) are preserved by the Japan Patent Office and their image data are available in the Patent Information Platform (J-PlatPat) operated by the Industrial Property Information and Training Institute (INPIT, https://www.j-platpat.inpit.go.jp/). The collaborating team digitized bibliographic information recorded in all patent specifications for patents granted between 1885 and 1940 (around 126,000 patents), which include patent numbers and titles, technology classes, inventors' and assignees' names and addresses.[2]

The digitized patent records above were shared by the Inoue et al. collaborative team with Yamaguchi and Braguinsky, who then undertook the task of name-based matching of patent inventors and University graduates. As mentioned above, different combinations of different forms and old forms of characters in which names were written were considered and name changes of university graduates were tracked by extensively investigating various sources, including Calendars of Imperial Universities, public high schools, Japanese Personnel Inquiry Records (*Jinji Koushinroku*), Imperial University Graduates Directory (*Teikoku Daigaku Shusshin Meikan*) and online searches. To avoid false matches of same-name but different individuals, we manually checked the consistency of employer and address information between the graduates' records and the patent records for all individual matches and dropped those where we were not sure that it was one and the same person (the fraction of cases dropped through this manual check was about 10 percent of the total number of initial matches).[3] In the end, we have 7,719 patents matched to 1,451 unique inventors who were also Imperial University graduates in Engineering or Science after this manual data cleaning process.

B.4. Top Graduates' Earnings Data Based on *Who is Who in Japan* (*Nihon Shinshiroku*)

Examining how top graduates made their occupational choices and the role played by pecuniary versus non-pecuniary preferences requires individual-level earnings data. Such data are not available from the alumni surveys, nor are they systematically available for the universe of all Imperial University graduates in science and engineering from any other source we are aware of. It turned out, however, that *Who is Who in Japan* (*Nihon Shinhiroku*) contains information on income taxes paid by the individuals included in its listings, starting from the volume published in 1902.[4]

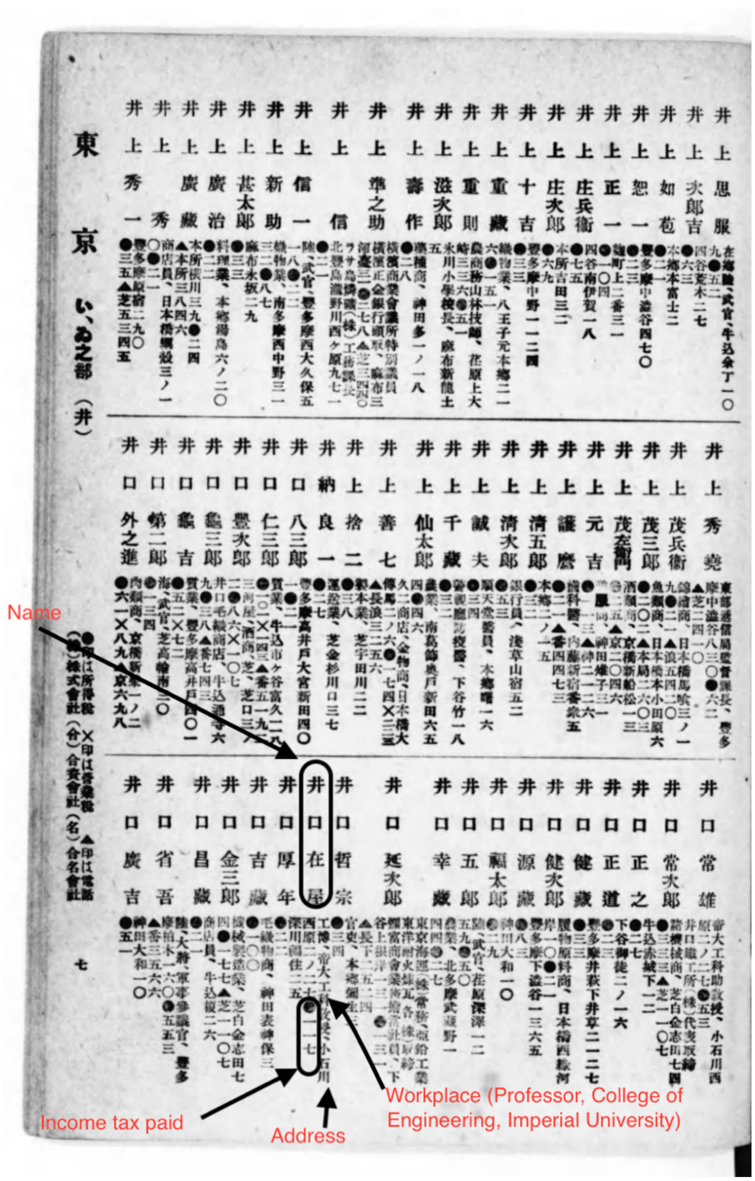
[2] The detailed process of digitizing Japanese historical patent records is described in Inoue et al. (2020) (in Japanese). As Inoue et al. (2020) mention, the Japan Patent Office in Tokyo was destroyed by the Great Kanto Earthquake in 1923, and all the documents until that time were lost. The patent information available today for the years before 1923 was organized by re-collecting documents that were scattered outside Tokyo, such as at the regional branch offices. Therefore, for a considerable number of patents before 1911, bibliographic information is incomplete.

[3] In determining if the patent record belonged to a given graduate or not we chose to err on the side of caution an rejected a match if we could not definitively ascertain that we had a positive match.

[4] We are grateful to Junichi Yamasaki for pointing out this source of data to us.

Who is Who in Japan was first published in 1889 by a private company called *Kojunsha* with the aim of creating a list of prominent people across various professions, based on information about income taxation and some additional criteria (*Nihon Shinshiroku,* Vol. *2,* p. 4). For more than a decade, it included only names, workplaces and addresses, but from the 1902 edition, it started publishing also income (and business) tax data. The coverage areas, which in 1889 included only Tokyo and vicinity were also expanded over time (more on this below). Figure B3 shows the 1919 entry for Inokuty Aria, Professor at the College of Engineering in the Imperial University and a top graduate in our sample.

Figure B3. A sample page from *Who is Who in Japan* (*Nihon Shinshiroku*)



Source: *Nihon Shinshiroku*, Taisho 8 (1919), p. 7, url: https://dl.ndl.go.jp/pid/1704493/1/85

Using names, addresses, and workplaces in *Who is Who in Japan* we hand-matched top graduates from the College of Engineering who comprise our sample for structural estimation of occupational choice and hand-coded the data on income taxes they paid. The matching process was rather smooth as top graduates from our main panel database turned out to be quite likely to make it to the list in *Who is Who in Japan* (although subject to some caveats discussed in the sample selection issue subsection below), so we were able 260 out of 301 individuals in at least one year, giving us 3,293 non-missing income tax observations in years 1902-1933.

We also needed to convert income tax data into actual earnings. The income tax code changed multiple times during our sample (including emergency wartime tax imposed during the Russo-Japanese war and the transition to the system of excess progressive rates from the system of simple progressive rates in 1913). Those changes are documented in annual reports by Japan's Tax Bureau (*Shuzeikyoku Tokei Nemposho*). We use the tax schedules reported in those reports for each year from 1902-1933 to back-calculate the earnings that gave rise to income taxes reported in *Who is Who in Japan* (details are available upon request).

The median annual real income (nominal income deflated by the consumer price index) among top graduates used for structural estimation in our paper is 3,784 yen, with the average of 6,307 yen and standard deviation of 13,809 yen. Clearly, the incomes exhibit a lot of variances, which can also be seen in the 90-10 percentile differential, which is 8,573 yen—10,327 yen at the 90th percentile vs. 1,754 yen at the 10th percentile. Not surprisingly, both median and especially average incomes are much higher in the private sector than in academia and the public/military sectors and the variance is also much higher in the private sector (Table B1).

Table B1. Real Income Distribution by Occupations (Raw Data, Yen per Year)

Occupation	Mean	Median	St. Dev.	90th pct	10th pct	# obs.
Imperial University	4,511	3,630	3,675	7,705	1,904	972
Private Sector	10,034	4,957	21,593	20,114	1,788	1,164
Public/Military Sector	3,798	3,399	2,177	6,370	1,616	1,034

Note: Our calculations based on the data from *Who is Who in Japan* and Japan's Tax Bureau annual reports described in Appendix B.4.

Sample Selection Issues

Several issues/limitations with respect to the data from *Who is Who in Japan* need to be mentioned. To begin with, the income tax data only start from 1902 (and we are missing also years of 1904 and 1906, as mentioned in the main text). This means that for cohorts that graduated prior to 1901, we do not have their income tax (and income) data until 1902, although we do have their occupational choice data. We use information about the occupational choice in 1901 as a starting point for those who graduated prior to 1902 in the structural estimations that start from 1902.

Overall, as mentioned, we could match 260 out of 301 top graduates in our sample to *Who is Who in Japan* in at least one year between 1902-1933 (86 percent match rate). But in about 40 percent of all potential year-observations on those individuals, the income tax data are missing. This happens for various reasons, including cases where individuals would be missing from some editions for no apparent reason, or their addresses and workplaces would be listed but no income tax data would be reported.[5] There are two features of the *Who is Who in Japan* editions, however, which lead to some systematic missing income tax data which we discuss here.

First, the data collected by *Who is Who in Japan* did not cover the whole country and the areas changed over time. More specifically, the coverage included taxpayers residing in six major cities and areas surrounding them: Tokyo, Yokohama, Osaka, Kyoto, Kobe, and Nagoya, throughout our estimation period. The city of Fukuoka and the surrounding area (home to Kyushu Imperial University founded in 1911) was first added in 1919 and remained in coverage until the end of our estimation period in 1933. Other areas, however, would be included in some but not in other years. For instance, the area around the large naval facility in Yokosuka was included in the 1902-1903 editions but not in subsequent years, while the areas around naval facilities in Sasebo and Kure were included only in 1919-1922. Smaller cities such as Hachioji, Nagasaki, Hiroshima, Sendai, Kanazawa, cities in the northern-most island of Hokkaido, as well as Japanese colonies of Taiwan, Korea, Sakhalin, and the Chinese province of Kwantung were also included in coverage in some of *Who is Who in Japan* editions, (temporarily) enlarging the set of individuals for whom we could observe their income tax data.

Since we have workplaces and addresses data for all the graduates in the main panel database, we can calculate the share of observations on top graduates who resided in the areas not covered by *Who is Who in Japan* in any given year and whose income data are missing for that reason. These shares, overall and by sector of employment are presented in Table B2, while Figure B4 shows how this overall share changed over time. We can see that on average about 16 percent of observations on top graduates are on residents outside the areas covered by *Who is Who in Japan* across all years between 1902-1933 (20-25 percent in 1902-1918, dropping to 10-15 percent thereafter). Since the major Imperial Universities in Tokyo and Kyoto were always included, and Fukuoka hosting Kyushu Imperial University got included in 1919, this left only Tohoku Imperial University in Sendai outside of coverage for most of the time. Thus, the share of observations outside the covered areas is the lowest in the Imperial University sector (less than 10 percent). The shares of observations outside the covered areas in the private and public/military sectors are higher, but still well below 20 percent.

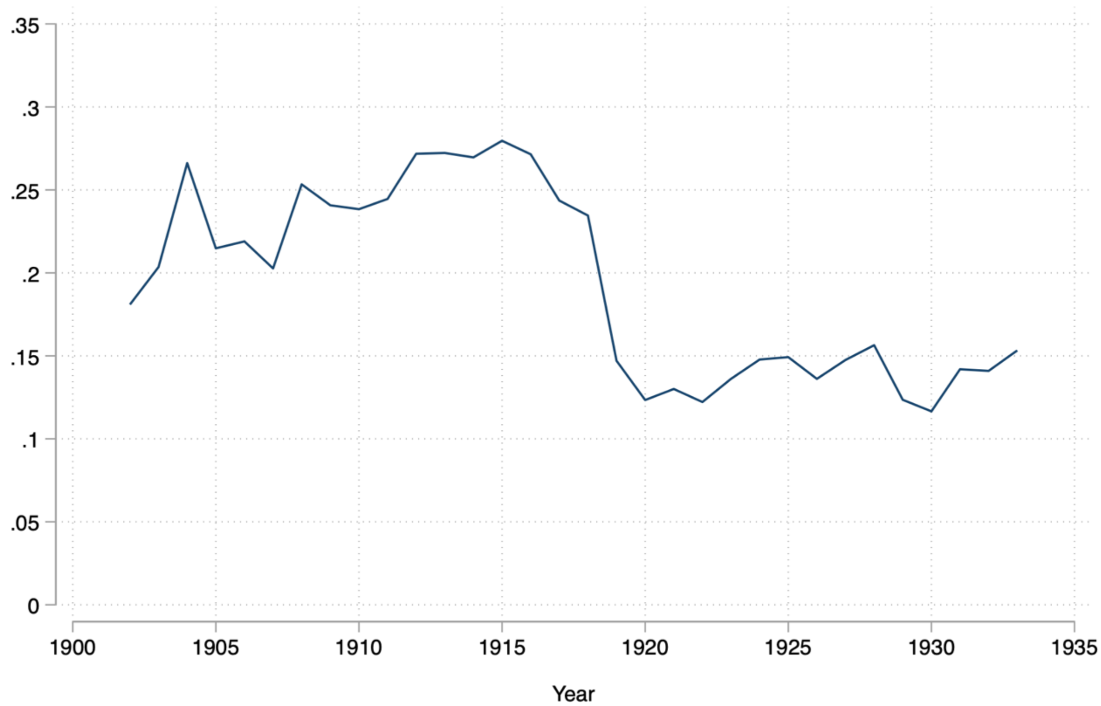
Table B2. Share of Observations in the Areas Not Covered by *Who is Who in Japan*

Total (%)	Imperial University (%)	Private Sector (%)	Public/Military Sector (%)
15.65	9.76	18.56	16.77
[0.43]	[0.69]	[0.73]	[0.76]

Note: The table shows the share of observations, in total and by working sector, on top graduates who resided in the areas not covered by *Who is Who in Japan* in any given year and whose income data are missing for that reason. The standard errors are in parentheses.

[5] Some editions of *Who is Who in Japan* explicitly mention that they could not calculate the income tax paid by some individuals due to incomes from multiple sources (and corresponding multiple tax entries) which proved impossible to aggregate. We have verified that such omissions affect very high earners in the private sector, so if anything, this would bias our estimates against finding high non-pecuniary preferences for academic jobs, offsetting potential opposite biases discussed immediately below.

Figure B4. Share of Observations in the Areas Not Covered by *Who is Who in Japan* by Year

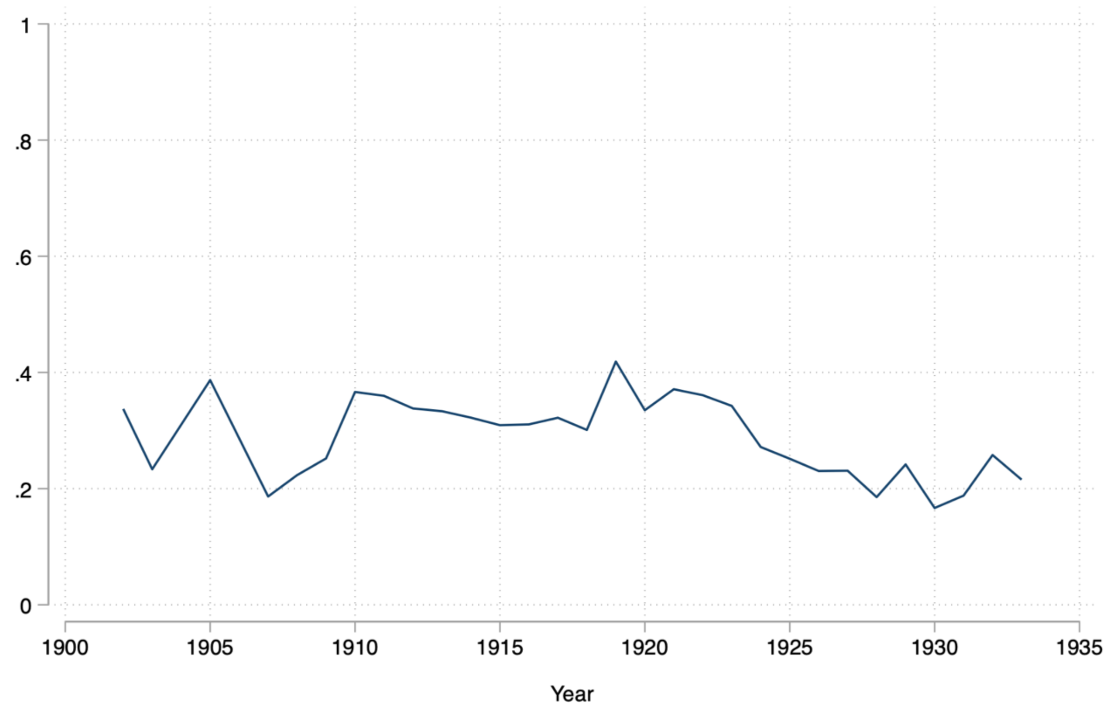


Note: The figure shows the overall share of observations, by year, on top graduates who resided in the areas not covered by *Who is Who in Japan* in any given year and whose income data are missing for that reason. Our calculations are based on the data from *Who is Who in Japan* and *Tokyo Teikoku Daigaku Ichiran.*

Second, *Who is Who in Japan* only included individuals above a certain income tax threshold. When it started publishing income tax data in 1902, the threshold below which individuals were not included was set at the tax amount of five yen, corresponding to 500 yen of personal income. This corresponds to salary grade 4 for assistant professors (see Table A1 above), so that the lowest-ranked assistant professors would not be included (all full professors, even at the lowest salary grade would still be covered). The income tax threshold below which individuals were not included was increased multiple times in subsequent editions, but overall, the share of top graduates in our data who resided in covered areas but whose income tax data are missing remained largely stable over time at around 30 percent (Figure B5).[6]

[6] The slight decline in this share in the 1920s-early 1930s is explained by the fact that no new cohorts were added past 1918 while individuals become more likely to have incomes above the threshold as they age. We discuss this in the context of the relationship between missing year-income observations and age immediately below.

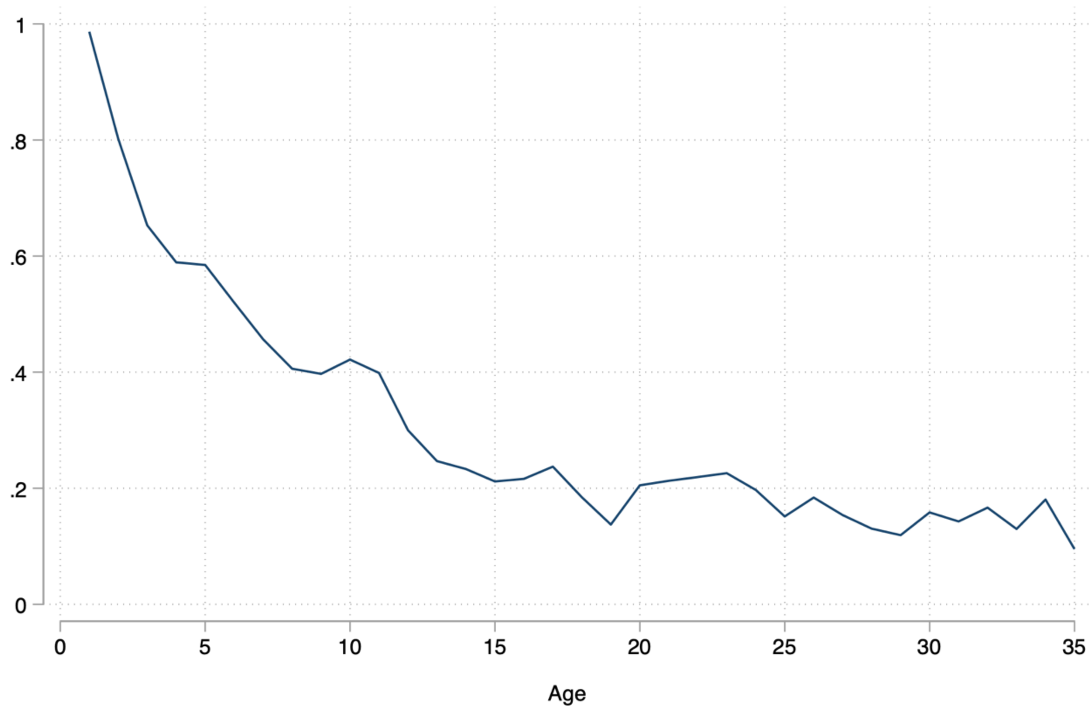
Figure B5. Share of Missing Observations in the Areas Covered by *Who is Who in Japan* by Year



Note: The figure shows the overall share of missing earnings observations, by year, on top graduates who resided in the areas covered by *Who is Who in Japan* in any given year but whose income data are missing. Our calculations are based on the data from *Who is Who in Japan* and *Tokyo Teikoku Daigaku Ichiran.*

As mentioned, individuals could be missing from *Who is Who in Japan* despite residency in areas included in coverage for various reasons, not just because their income tax was below the threshold. However, inasmuch as income data are missing due to income tax below the threshold, this does create a potential sample selection issue since we may be missing information on very low earners. Since our structural estimation of occupational choice relies on comparing earnings across different sectors of employment, it would not necessarily present a problem if the observations were missing in similar ways for academia as well as non-academia. Table B3 shows, however, that we tend to be missing relatively more year-income observations among the individuals residing in areas covered by *Who is Who in Japan* in the private and public/military sector (30-33 percent) compared to academia (22 percent). In turn, this seems to be due to two factors.

Figure B6. Share of Missing Observations in the Areas Covered by *Who is Who in Japan* by Age



Note: The figure shows the overall share of missing earnings observations, by year after graduation, on top graduates who resided in the areas covered by *Who is Who in Japan* in any given year but whose income data are missing. Our calculations are based on the data from *Who is Who in Japan* and *Tokyo Teikoku Daigaku Ichiran.*

Table B3. Share of Missing Observations in the Areas Covered by *Who is Who in Japan*

Total (%)	Imperial University (%)	Private Sector (%)	Public/Military Sector (%)
29.34	22.12	30.67	33.68
[0.68]	[1.18]	[1.13]	[1.20]

Note: The table shows the share of observations, in total and by working sector, on top graduates who resided in the areas covered by *Who is Who in Japan* in any given year but whose income data are missing. The standard errors are in parentheses.

First, as can be seen from Table B1, earnings in the private sector exhibit much higher variance. Thus, there could be relatively more observations where top graduates employed in the private sector would not meet the inclusion criteria in *Who is Who in Japan* for that particular year. As Table B3 shows, we have about 10 percentage points more observations on individuals who reside in covered areas but for whom we have missing income data in the private sector than in Imperial Universities. If most of those are indeed low-income individuals, we may be potentially overestimating average earnings in the private sector, although it is impossible to say by how much.

Second, as earnings increase with age (experience), our top graduates are less likely to clear the threshold for being included in *Who is Who in Japan* while they are still young. Figure B6 shows the relationship between age (years after graduation) and the empirical probability of having non-missing income-year observations in our data. We do not have observations on income tax data for almost anyone in the first couple of years, but then the share of missing income observations quickly declines and stabilizes at around 20 percent after about 13 years. Hence, and in contrast to most extant studies which examine early career choices, our estimations of occupational choice rely mostly on data points pertaining to mid- later-career observations, with earnings at younger age extrapolated from the fitted parameters of the model.

Figure B7 breaks down the age distribution of missing year-income observations by three occupational sectors. While we miss relatively more top graduates employed in the public/military and especially the private sector up until post-graduation year seven, beyond that the patterns are similar, so that all sectors are more or less equally affected by missing incomes at younger ages.

Figure B7.
Share of Missing Observations in the Areas Covered by *Who is Who in Japan* by Age and Sector

Note: The figure shows the shares of missing earnings observations, by year after graduation and by each sector, on top graduates who resided in the areas covered by *Who is Who in Japan* in any given year but whose income data are missing. The black solid line, red long-dashed line, and blue short-dashed line represent academia, the private sector, and the public sector, respectively. Our calculations are based on the data from *Who is Who in Japan* and *Tokyo Teikoku Daigaku Ichiran.*

C. Illustrative Cases

This appendix describes some case evidence that support our argument in the main text.

C.1. Difficulty in Retaining Top Talent: Ichisuke Fujioka

The case of Ichisuke Fujioka who graduated at the top of his cohort from the Electrical Engineering division of what at the time was Imperial College of Engineering in 1881 is cited in the main text as an example of the difficulty the University had in retaining top talent early on. Fujioka worked as faculty at the Imperial College of Engineering after his graduation and was then appointed as an Assistant Professor at the Department of Engineering at Tokyo Imperial University when it was established in 1886. His status was that of Category Five Senior Civil Servant (Segawa, 1933) which at the time paid annual salary between 700-900 yen (*Tokyo Teikoku Daigaku Goju-nenshi*, Vol. I, p. 954). He resigned in less than a year, however, to become the chief engineer at Tokyo Electric Light Company, one of the first private electric utility companies in Japan. His biographers do not tell us how much the utility company paid him, but we have the data on the salaries of two chief engineers at cotton spinning firms in the same year. Tsunezo Saito, who graduated a year later than Fujioka and not at the top of his class but as number four out of six graduates, was paid 75 yen per month (900 yen annualized) as the chief engineer of Mie Spinners (Mie Spinners Company Report #2, available upon request), while Kyozo Kikuchi, who graduated two years later than Fujioka as number two in the class of three, was paid 100 yen per month (1,200 yen annualized) as the chief engineer of Hirano Spinners (Hirano Spinners Company Report #1, available upon request). Given Fujioka's higher status and the fact that the utility which hired him was much larger than either of the above two cotton spinning firms, we can assume that he was offered a significantly higher salary than he had been receiving as engineering faculty. But even at 1,200 yen, the salary offered by the utility company would have been 50% higher than the salary offered by the University.

C.2. University Career of an Industry Innovator: Kyoji Suehiro

In Table C1 we utilize the biographical knowledge about specific events mapped into the career timeline of Kyoji Suehiro to illustrate how invention translated into higher earnings for engineering faculty in some detail. Suehiro was the top graduate from the Naval Architecture division of the Engineering Department in 1900 and joined the engineering faculty in 1902 after a one-year stint with Mitsubishi Shipbuilding Co. His income in 1902-1905 corresponds to the salary schedule for an assistant professor in those years, inclusive of service allowance (see Table A1 and the discussion in the main text). Most of the increase observed in 1907-09 (prior to the sabbatical) can also be accounted for by the general salary increase and more incentives for teaching introduced by the University in 1907. After returning from the sabbatical in 1912, Suehiro was promoted to full professor and his salary almost doubled, commensurate with the difference between assistant and full professor salary scales (*ibid.*). All in all, through the first 12 years of his academic career, Suehiro had been earning salaries that any productive faculty member would expect in his place.

Table C1. Kyoji Suehiro's Timeline and Earnings

Year	Patents	Job title	Doctoral degree	Sabbatical abroad	Income tax paid (yen)	Calculated income (yen)
1902	0	Asst. Prof.	0	0	10	833
1903	0	Asst. Prof.	0	0	10	833
1904	0	Asst. Prof.	0	0	No data	
1905	0	Asst. Prof.	0	0	23	968
1906	0	Asst. Prof.	0	0	No data	
1907	0	Asst. Prof.	0	0	53	1,767
1908	0	Asst. Prof.	0	0	55	1,833
1909	0	Asst. Prof.	1	1	55	1,833
1910	0	Asst. Prof.	1	1	na (sabbatical)	
1911	0	Professor	1	0	na (sabbatical)	
1912	1	Professor	1	0	99	2,912
1913	0	Professor	1	0	101	2, 912
1914	0	Professor	1	0	102	2,933
1915	2	Professor	1	0	89	2,644
1916	1	Professor	1	0	89	2,644
1917	0	Professor	1	0	78	2,400
1918	1	Professor	1	0	86	2,291
1919	0	Professor	1	0	291	5,306
1920	0	Professor	1	0	291	6,846
1921	0	Lecturer	1	0	32	2,025
1922	1	Professor	1	0	230	5,908
1923	0	Professor	1	0	1,393	18,428
1924	0	Professor	1	0	1.132	16,055
1925	0	Professor	1	0	497	9,450
1926	1	Professor	1	0	440	8,738
1927	3	Professor	1	0	799	12,716
1928	0	Professor	1	0	758	12,284
1929	0	Professor	1	0	876	13,526
1930	3	Professor	1	0	898	13,758

Notes: His research that led to the 1912 patent (also patented globally) was awarded the 1922 Imperial Academy Prize (most prestigious academic prize in Japan). Helped found Mitsubishi Shipbuilding Research Institute in 1918 and was its director in 1919-20. Stayed as Mitsubishi Shipbuilding consultant. All patents from 1926 assigned to Mitsubishi Shipbuilding. Became the first director of the Tokyo Imperial University Earthquake Institute in Nov. 1925 and stayed in this position until he passed away in April 1932.

During his sabbatical, Suehiro started conducting research in rotary-transmission dynamometer which eventually won him the Imperial Academy Prize (the most prestigious academic prize in Japan), and he also applied for the patent related to this technology in Japan, Great Britain, and the United States in 1912 (the patent was granted in Japan in the same year and in 1913 and 1914 in Great Britain and the U.S., respectively). We can see some increase in his income, which may be due to a bonus from the university, in 1914, although the increase is modest. Several years later (in 1919-1920), however, his earnings increase by much more than implied by the University salary increase in Table A1. Those were the years when according to his biography, he re-established research-based collaboration with Mitsubishi Shipbuilding. In particular, in late 1918, Mitsubishi Shipbuilding accepted Suehiro's proposal to establish the Mitsubishi Shipbuilding Research Institute and he became the first head of that institute. Even though he did not stay in this position for long, Suehiro remained a consultant for Mitsubishi Shipbuilding and all his subsequent patents were assigned to it. He was also appointed the director of the Earthquake Institute established by Tokyo Imperial University in November 1925 and served in this position until he passed away in 1932. As can be seen from Table C1, all this appears to have contributed to earnings way above the standard salary of an engineering faculty professor throughout the 1920s. All in all, we see extra income based on complementary assets and university-industry collaboration, accruing to a star faculty, in addition to non-pecuniary attractiveness of an engineering faculty job.

C.3. Building Complementary Assets: Mastatoshi Okochi

Masatoshi Okochi (1878-1952) who spearheaded one of the most important complementary assets for the engineering faculty, *Riken* mentioned in the main text, graduated at the top of his cohort from the ordnance division in 1903 and was immediately hired as a lecturer in the engineering department upon graduation, becoming assistant professor the next year and promoted to full professor in 1911 immediately following a two-year sabbatical in France. A prolific inventor, Okochi had 73 domestic and 14 global patents over his illustrious career. In 1921 he was appointed as the director of *Riken*, the Institute of Physical and Chemical Research (currently a National Research and Development Agency, but a private institution at the time). In this capacity he reorganized *Riken* into a system of independent laboratories each led by a Chief Scientist recruited from among the prominent professors at the Imperial University and given autonomy to manage research topics, personnel and budget. This was followed by an explosion in innovative activity by University faculty affiliated with *Riken*. As mentioned in the main text, 32 Imperial University faculty members from our panel data joined *Riken* labs since its inception and continued after Okochi became the director. Regression estimations controlling for year and individual fixed effects (not shown) indicate that after they joined *Riken*, the number of patents they applied for in any given year jumped four times (from 0.07 to 0.27 patent applications per year). Splitting the years spent in *Riken* into those before and after Okochi's reforms shows that most of the increase happened following Okochi's ascendance to presidency—the number of patent applications per year doubled from prior to 1917 to the 1917-1921 period and it more than doubled once again in the 1922-25 period. Moreover, many of those patents were co-inventions with students whom the professors could now hire as research assistants at *Riken* (details are available upon request). Indeed, *Riken* was so successful in generating industry technologies that it generated a whole industrial group of companies (Riken Industrial Group). Alongside with other institutes affiliated with the University, *Riken* provided a vehicle through which university engineering and science faculty could develop industrial technologies, patent them and reap rewards, all while working their academic jobs at the same time.

D. Structural Estimation Details

Here we summarize in more detail the structural estimation we employ in Section VII. In the first section, we provide the full description of the structural model. In the second and third sections, we discuss the estimation procedure and how to obtain the standard errors, respectively. In the fourth section, we describe the details on our simulation analyses. Finally, we describe the intuitive arguments on the identification of the parameters.

D.1. The Model

Time is discrete. Each graduate i has a finite decision horizon $a \in \{0, \dots, A\}$. At each age a, graduates choose among three occupation choices: working in academia (Imperial Universities' faculty) ($j = 1$), working in industry (the private sector) ($j = 2$), or working for the government or military ($j = 3$). Individuals get utility from both earnings $w_{ij}(a)$ and non-pecuniary utility (age-invariant utility $\beta_j X_i + \omega_{ij}$, where X_i are observable individual characteristics and ω_{ij} is an unobserved component, and age-variant utility $\rho\varepsilon_{ij}(a)$) if they choose occupation j. Their utility from earnings can be described by the CRRA utility function. They also have to incur a job switching cost $c_j(a)$ each time they move to occupation j from another occupation. Denote their occupation choice at age a by an indicator $d_{ij}(a)$ (equal to 1 if occupation j is chosen and 0 otherwise). Thus, the instantaneous utility for an individual at age a consisting of non-random flow of utility, $u_{ij}(a)$, and additively separable utility shocks, $\rho\varepsilon_{ij}(a)$, is written as:

$$U_{ij}(a) = \underbrace{\frac{[w_{ij}(a)]^{1-\gamma}}{1-\gamma} - c_j(a)[1 - d_{ij}(a-1)] + \beta_j X_i + \omega_{ij}}_{u_{ij}(a)} + \rho\varepsilon_{ij}(a),$$

for each occupation j, where we assume that $\varepsilon_{ij}(a)$ is independent and identically distributed across individuals and over time and follows the Type I extreme value distribution $G(\varepsilon)$, while ρ is a scaling parameter. Since utility is additive invariant, we normalize the non-pecuniary utility in industry to 0, so $\beta_j X_i + \omega_{ij}$ represents the value relative to the private sector. The (logged) wage process for individual i in sector j is given by:

$$\ln w_{ij}(a) = b_{j1} + b_{j2}a + b_{j3}a^2 + b_{j4}t + \nu_{ij} + \sigma_j\varsigma_{ij}(a),$$

where ν_{ij} is an individual-specific earning potential in sector j (with the mean of 0) and $\{\varsigma_{ij}(a)\}_{j=1}^{3}$ are ex post idiosyncratic earning shocks that depend on age a and follow joint standard normal distribution $N(0, I)$ independentl. We assume that individuals cannot observe these idiosyncratic shocks at the time occupation choices are made in each period. We also assume that the job switching cost function takes the following log-linear form and is quadratic in terms of individual age:

$$\ln c_j(a) = c_{j1} + c_{j2}a + c_{j3}a^2.$$

This allows for individuals of different ages to face different frictions (e.g., the cost of changing a job can be higher for older individuals).

At each age a, graduates maximize the expected present value of remaining lifetime utility. Defining the individual state space by $s_i(a) = \{a,\ \{d_{ij}(a-1),\ \omega_{ij},\ \nu_{ij}\}_{j=1}^{3}\}$, we can write the value function as the conditional expectation of the flows of current and future utility, which also satisfies:

$$V_i\big(s_i(a)\big) = \max_{d_{ij}(a)} \quad E\left[u_{ij}(a) + \rho\varepsilon_{ij}(a) + \delta \int V_i\big(s_i(a+1)\big)dG(\varepsilon)\middle|\, s_i(a)\right],$$

where δ is a discount factor and the integral refers to integration over $\varepsilon_{ij}(a)$. The expectation operator is taken over the distributions of current $\varsigma_{ij}(a)$ and future $\varsigma_{ij}(a)$ conditional on the individual state space $s_i(a)$. Following the tradition of dynamic discrete choice models, we can have a closed form of conditional choice probability. Define $v_i\big(s_i(a)\big) = \int V_i\big(s_i(a)\big)dG(\varepsilon)$ to be the integrated value function. Then, one can also define the choice-specific value function:

$$v_{ij}\big(s_i(a)\big) = E\big[u_{ij}(a) + \delta v_i\big(s_i(a+1)\big)\big|s_i(a), d_{ij}(a) = 1\big],$$

as the value of $v_i\big(s_i(a)\big)$ conditional on choosing occupation j net of the utility shock. Using these notations, we can rewrite the individual optimization problem as:

$$v_i\big(s_i(a)\big) = \max_{d_{ij}(a)} \quad v_{ij}\big(s_i(a)\big) + \rho\varepsilon_{ij}(a),$$

The distributional assumption of $\varepsilon_{ij}(a)$ implies that the conditional occupation choice probability at age a can be written as the following logit form (Rust, 1987):

$$P\big[d_{ij}(a) = 1\big|s_i(a)\big] = \frac{\exp\big[v_{ij}\big(s_i(a)\big)/\rho\big]}{\sum_k \exp\big[v_{ik}\big(s_i(a)\big)/\rho\big]}.$$

Therefore, given individual state variables (age and previous period occupation choice), unobserved non-pecuniary gains and earning potential, and parameter values, we can derive the joint distribution of earnings and occupation choice from the model.

D.2. EM Algorithm

This section describes the EM algorithm we use in our estimation. Denote the set of parameters that is invariant across types by θ, the set of unobserved heterogeneity by U, and the proportion of the q-th type in the population by π_q. Then, the algorithm is given as follows.

1. Start with the initial guess of $\theta^{(1)}$, $U_q^{(1)}$, and $\pi_q^{(1)}$.

2. E-step: Given $\theta^{(n)}$, $U_q^{(n)}$, and $\pi_q^{(n)}$ for each iteration $n = 1, 2, \dots$, generate the posterior probability of being type q by:

$$\pi_{iq}^{(n)} = \frac{\left\{\prod_{a=1}^{A} P\left[d_{ij}(a) = 1 \middle| s_i(a), \theta^{(n)}, U_q^{(n)}\right] f\left[w_{ij}(a) \middle| s_i(a), \theta^{(n)}, U_q^{(n)}\right]\right\}\pi_q^{(n)}}{\sum_k \left\{\prod_{a=1}^{A} P\left[d_{ij}(a) = 1 \middle| s_i(a), \theta^{(n)}, U_k^{(n)}\right] f\left[w_{ij}(a) \middle| s_i(a), \theta^{(n)}, U_k^{(n)}\right]\right\}\pi_k^{(n)}}.$$

3. M-step: For $\pi_{iq}^{(n)}$ fixed, obtain new parameter estimates $\theta^{(n+1)}$, $U^{(n+1)}$, and $\pi_q^{(n+1)}$ by maximizing the finite mixture of the likelihood:

$$L(\theta^{(n+1)}) = \prod_{i=1}^{N} \sum_{q=1}^{Q} \pi_{iq} \left\{ \prod_{a=1}^{A} P\left[d_{ij}(a) = 1 \middle| s_i(a), \theta^{(n+1)}, U_q^{(n+1)}\right] f\left[w_{ij}(a) \middle| s_i(a), \theta^{(n+1)}, U_q^{(n+1)}\right] \right\},$$

4. Iterate on steps 2-3 until convergence in $\theta^{(n+1)}$, $U_q^{(n+1)}$, and $\pi_q^{(n+1)}$.

We need the initial guess of the model parameters to operationalize this procedure. We follow Traiberman (2019) and first set the initial guess of $\theta^{(1)}$ to the estimates from the single-type version of the model. For the unobserved heterogeneity parameters, we set the initial values to a small perturbation around the results for a single-type version of the model, and for the distribution of unobserved types, we start from the equal proportion (25% for each type).

D.3. Parametric Bootstrap Standard Errors

This section describes the details on our parametric bootstrap procedure used to obtain standard errors in the structural estimation. For finite mixture models, the asymptotic variance is likely to be a poor approximation (McLachlan and Peel, 2004; Arcidiacono et al., 2024). We rely on a parametric bootstrap procedure instead of non-parametric one since the latter is unstable when applied to the EM algorithm (Beffy at al., 2012). We create 100 bootstrap replications, and we take the following steps in each replication.

1. Sample with replacement N individuals from the data used in the main estimation.
2. Draw the unobserved type q from the estimated population distribution of types, $\hat{\pi}$, for each sampled individual and assign the fixed type to each one.
3. Given the individual characteristics, including their graduation cohort, academic status (honor student or top in third year), and unobserved type, calculate the value functions and simulate their earnings and occupation choices until period $T = 35$, the longest panel length in the sample. Repeat this forward simulation on the cross-section of N sampled individuals (see also AX4).
4. For each bootstrapped sample generated from this forward simulation, estimate the structural parameters as in the main estimation. For these estimations, we use the parameters estimated in the main sample as the initial values.

Repeat steps 1-4 100 times. Once we have obtained the parameter estimates for all bootstrap replications, we estimate the standard errors of the parameters as the standard deviations of the estimates across bootstrap replications.

D.4. Model Fit and Counterfactual Simulations

This section details the steps we take for the model fit and counterfactual simulations. These steps are similar to the steps we take in the parametric bootstrap procedure. More specifically, we take the following steps to produce simulated data consistent with the estimated parameters and counterfactual parameters.

1. Draw the unobserved type q from the estimated population distribution of types, $\hat{\pi}$, for each sampled individual and assign the fixed type to each one.
2. Given the individual characteristics, including their graduation cohort, academic status (honor student or top in third year), and unobserved type, calculate the value function for each individual using either the estimated parameters (when assessing the model fit) or the counterfactual parameters (when assessing the counterfactual scenarios).
3. Simulate their earnings and occupation choices until period $T = 35$, the longest panel length in the sample, using the derived value functions in step 2. Repeat this forward simulation on the cross-section of N individuals in our sample 10 times.

This process yields a panel data of simulated earnings and occupation choices that structurally resembles the data we use in estimation or that would be consistent with counterfactual scenarios.

D.5. Intuition behind Identification

Although it is difficult to make a straightforward argument for identification in a complex dynamic structural model without the analytical solution, it is also important for us to understand the intuition on how the parameters in the model can be identified using the variations in our data. The parameters in the model can be categorized into three groups; (1) those in the wage function, (2) those in the switching cost function, and (3) those related to non-pecuniary preferences.

The parameters in the wage functions are identified in the similar way to Mincer regression in Table 2, but with one modification. While Mincer regression does not take the self-selection issue into account, the structural model version reflects the fact that individuals tend to choose a sector with higher expected earnings. However, since we make assumption that the earning shocks are realized ex post after individuals choose occupation, the biases in the coefficient estimates caused by self-selection based on the unobserved earning shocks are not the issues in this estimation.

Second, and most importantly, the identification between the switching costs and non-pecuniary preferences are key in our structural estimation. Both factors influence the variations in individual occupation choices that cannot be explained by the variations in earnings. For example, if some individual chooses to work in academia consistently despite its lower earnings compared to other sectors, it is likely that either (s)he has higher non-pecuniary preference for academia or moving to other sectors is costly due to high switching costs. Even though these two factors are unobservable and it is generally difficult to distinguish one from the other, some variations in individual occupation choices are informative for the identification of these parameters. First, to separate persistence in occupation choices due to non-pecuniary preference as opposed to persistence due to switching costs, we can see whether individuals tend to "return" to their original sectors after moving to other sectors. For example, if persistence in the academic sector is mostly due to higher non-pecuniary preference for academia rather than the existence of switching costs, then we would expect that even if individuals move to other sectors for a short period, once they get a positive shock in the academic sector (or a negative shock wherever they are), they will tend to come back to the academic sector. On the other hand, if persistence in the academic sector is mostly due to switching costs (i.e., individuals somehow choose to work in the academic sector at some point and then are stuck in the same sector due to high switching costs), then once they switch, the move tends to be permanent since the "return" to academia incurs additional higher mobility costs and rational forward-looking agents do not move to other sectors just for a short period if coming back to academia in the future is desirable for them. Second, while our assumption imposes that switching costs are a function of individual age, non-pecuniary preferences are not systematically related to individual age (although they are still age-variant due to independent utility shock $\varepsilon_{ij}(a)$). While the switching costs can be expected to be increasing in individual age (e.g., opportunity costs of learning), individual preferences for specific sectors are relatively stable, so the assumption that only switching costs depend on individual age is not unreasonable. With this specific assumption, the age-dependence of individual occupation choices is also informative for the identification of coefficients in the switching cost function.

Finally, for the identification of the scaling parameter, ρ, the transition rates to other sectors help to pin down the parameter value. More specifically, as we have higher value of ρ, the mobility between sectors becomes less responsive to earning differentials. Therefore, the dependence of individual mobility on sector-specific earnings is key to the identification of the scaling parameter (it is identified together with the levels of the switching costs and non-pecuniary preferences).

E. Career paths before joining academia

Using long-term career data on engineering graduates who become engineering faculty, we can examine various paths the led them to join the Imperial University faculty. Table E1 presents the distribution of previous employment sectors for all engineering faculty at Tokyo Imperial University and separately for core and non-core faculty, with the breakdown of each category into those hired in 1896-1907 versus in 1908-1920.[7]

Table E1. Sectors of Employment Just Before Joining Engineering Faculty

Panel A. All Faculty

	Sector of Previous Job Prior to Joining Faculty						
Variables	Private	Public	Military	Research	Direct	Unknown	Total
All hires	21 (12.14)	38 (21.97)	19 (10.98)	29 (16.76)	52 (30.06)	14 (8.09)	173 (100.00)
Hired in 1896-1907	10 (11.49)	17 (19.54)	7 (8.05)	13 (14.94)	32 (36.78)	8 (9.20)	87 (100.00)
Hired in 1908-1920	11 (12.79)	21 (24.42)	12 (13.95)	16 (18.60)	20 (23.26)	6 (6.98)	86 (100.00)

Panel B. Core Faculty

	Sector of Previous Job Prior to Joining Faculty						
Variables	Private	Public	Military	Research	Direct	Unknown	Total
All hires	10 (9.71)	17 (16.50)	3 (2.91)	19 (18.45)	45 (43.69)	9 (8.74)	103 (100.00)
Hired in 1896-1907	5 (8.47)	9 (15.25)	1 (1.69)	10 (16.95)	27 (45.76)	7 (11.86)	59 (100.00)
Hired in 1908-1920	5 (11.36)	8 (18.18)	2 (4.55)	9 (20.45)	18 (40.91)	2 (4.55)	44 (100.00)

Panel C. Non-core Faculty

	Sector of Previous Job Prior to Joining Faculty						
Variables	Private	Public	Military	Research	Direct	Unknown	Total
All hires	11 (15.71)	21 (30.00)	16 (22.86)	10 (14.29)	7 (10.00)	5 (7.14)	70 (100.00)
Hired in 1896-1907	5 (17.86)	8 (28.57)	6 (21.43)	3 (10.71)	5 (17.86)	1 (3.57)	28 (100.00)
Hired in 1908-1920	6 (14.29)	13 (30.95)	10 (23.81)	7 (16.67)	2 (4.76)	4 (9.52)	42 (100.00)

Note: Panel A represents the number and share (in parentheses) of newly hired engineering faculty by sectors of their immediate previous employment. Panel B and C show the same statistics for core and non-core faculty separately. Here, faculty are categorized as core faculty if they became core faculty at some point in our sample periods. "Direct" refers to faculty who were hired within the first two years after graduation and did not have job records in other sectors prior to becoming faculty.

For the purpose of this estimation, we limited the sample to graduates who became engineering faculty at some point and coded the sector of employment where the graduate worked right before joining engineering faculty

[7] The job histories for those hired in 1895 and earlier are sparse because our graduates panel starts in 1890 and many job observations are missing in early years. We therefore exclude them from this analysis. We also exclude faculty hired after 1920 because we do not have the data on job histories of post-1920 graduates who are an increasing fraction of engineering faculty after 1920.

as private, public, military, or academia/research, while allowing gaps of up to five years between the last pre-faculty employment and the year the graduate was employed by the university. (That is, if the graduate worked in the private sector in year $t-1$, where year t is the year he joined the faculty, his last sector of employment would be private, and the same if employment information was missing in year $t-1$ but he worked in the private sector in year $t-2$, and so on.) If there was no employment information for any of the five years prior to joining the engineering faculty, we coded the previous sector of employment as missing. Since some graduates joined the ranks of faculty immediately or soon after graduation, we coded such graduates in a separate category (labeled "Direct" in Table E1) if they became faculty within two years after graduation and there was no employment information in other sectors during the (at most two) years that elapsed between their graduation year and the year they joined the faculty.

[Table E1 around here]

First, looking at all hires, almost 43.7 percent of core faculty were in the "Direct" category, that is, recruited right after or within two years from graduation, but only 10 percent of non-core faculty came from this category. This reflects the hiring policy where top graduates were offered (almost) immediate "tenure-track" positions upon graduation, while part-time lecturers were mostly brought for their practical expertise. Second, looking at changes over time, the fraction of faculty recruited directly from recent graduates goes down from the 1896-1907 period to the 1908-1920 period, most drastically for non-core faculty but also by about 20 percent for core faculty. In contrast, the fraction of faculty hired from other sectors grows, except for the share hired from the private sector which basically remained flat.

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