The returns to specialization: evidence from education-occupation match in the US, 1993 to 2017*

by

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ABSTRACT

How do college majors translate into occupations over time? Are college graduates with a certain major going to wider or narrower sets of occupations? What are the implications of the returns to certain major-occupation mapping? We investigate these questions using detailed data on majors and occupations from the National Survey of College Graduates from 1993 to 2017. We find that, over the past quarter-century, the college major-occupation mapping is remarkably stable with cyclical fluctuations around the recession years. This cyclicality is most pronounced among the majors with the highest occupational variety. In addition, college-graduate men tend to have majors that map to a concentrated set of jobs relative to college-graduate women. Furthermore, the wider a major's occupation variety is, the lower the wage is for both men and women with that major. That is, there is a positive return to specialization. This wage effect also works partly through employment where men and women with majors with greater occupational variety are less likely to be employed full time. We also document some structural changes after the Great Recession that new graduates in degree fields that are remote to finance jobs tend to stay in their specialized field, while veterans in those fields branch out to other occupations.

Keywords: college major, occupation, returns to specialization

JEL: I23, I26, J24

I. Introduction

Labor economists have long been interested in how college students choose their majors and the wage returns to different majors thereafter (Berger, 1988; Arcidiacono, 2004; Wiswall and Zafar, 2015; Altonji, Blom, and Meghir, 2012; Altonji, Arcidiacono, and Maurel, 2016). However, a major itself does not generate returns to investment in human capital but the job that the major maps into does. This major-occupation mapping should be at the center of the analysis of returns to education but has not drawn much attention with exceptions in Robst (2007a) and Ransom and Phipps (2017).

How do college majors translate into occupations over time? Are college graduates with a certain major going to wider or narrower sets of occupations? What are the implications of the returns to major-occupation mapping? In this paper, we investigate these questions using detailed data on majors and occupations from the National Survey of College Graduates (NSCG) from 1993 to 2017. We measure the major-occupation mapping using the occupational variety measure as used in Ransom and Phipps (2017). This measure is the inverse of a Herfindahl-Hirschman Index that captures the variety of occupations held by individuals whose undergraduate degree was in a specific field. We find that, over the past quarter-century, the college major-occupation mapping is remarkably stable with cyclical fluctuations around the recession years. This cyclicality is mostly pronounced among the majors with highest occupational variety. In addition, college-graduate men tend to have majors that map to a concentrated set of jobs relative to college-graduate women. Furthermore, the wider a major's occupation variety is, the lower the wage is for both men and women with that major. That is, there is a positive return to specialization. This wage effect also works partly through employment where men and women with majors with greater occupational variety are less likely to be employed full time. We also document some structural changes after the Great Recession that new graduates in degree fields that are remote to finance jobs tend to stay in their specialized field, while veterans in those fields branch out to other occupations.

Our paper contributes to the understanding of education-occupation match that has not been thoroughly studied in the literature. Two notable papers on this topic are Ransom and Phipps (2017) and Robst (2007a). Ransom and Phipps (2017) use the NSCG data in years 1993, 2003, and 2010 to study the occupational distribution of individuals with a bachelor's degree. They construct two measures of the major-occupation mapping: a distinctiveness measure and a variety measure. They find that the occupational variety has increased from 1993 to 2003 but decreased from 2003 to 2010. We extend their study by incorporating the most recent waves from the NSCG to observe the patterns from a full recovery from the Great Recession. In addition, we examine the returns to occupation variety, which has not been explored in the existing literature.

Robst (2007a) uses the 1993 NSCG data to examine education and job match. The main finding is that if a person works in the field that is outside of their degree field, there would be a wage penalty. Nordin et al (2010) extend Robst's (2007) analysis by applying the same specification on the Swedish population and find similar results. While Robst's focus is also education and job match, we are interested in how the transferability of a degree (to different occupations) affects wage.

Our paper also speaks to a vast literature on the choice of college majors and the returns to fields of study (see, for example, Altonji et al., 2012; Hamermesh and Donald, 2008; Lindley and McIntosh, 2015; Kelly et al., 2010; Webber, 2014). Although our main focus is on how wages are correlated with major-level characteristics, i.e., a major's occupational variety, we need to consider how individuals' choices of majors affect wages. Individuals select a college major based on a variety of factors including expected earnings (Berger, 1988; Arcidiacono, 2004; Montmarquette et al., 2002; Wiswall and Zafar, 2015) or the relative pay of occupations related to those majors (Long et al., 2014), patterns of labor force participation (Polachek, 1978), uncertainty (Altonji, 1993), non-price preferences (Easterlin, 1995), the likelihood of graduation (Montmarquette et al., 2002), and the knowledge content of occupations and the market pay off to that knowledge content (Freeman and Hirsch, 2008). Altonji et al. (2016) develop a dynamic model of educational decision-making and discuss empirical challenges surrounding causal identification of the effect of educational choices on earnings. Our paper differs from the existing literature by introducing a specific aspect of a certain major rather than lumping everything into an indicator variable. Nevertheless, all the empirical issues pertinent to estimating the effects of major choices on earnings apply to our context.

Another related line of literature is on schooling-job match (see Cohn and Kahn, 1995; Duncan and Hoffman, 1981; Sicherman, 1991; Groot and van den Brink, 2000; Hartog, 2000; Hartog and Oosterbook, 1988; Hersch, 1991; Robst, 1995a;b; 2007b). This literature mainly focuses on the concept of overeducation, undereducation and the inefficiencies associated with both. Workers who possess more schooling than their job requires are deemed overeducated, while those with less schooling than required are undereducated. The main finding is that overeducation affects wages with the returns to surplus schooling being lower than the returns to required schooling. This result holds regardless of how researchers determine required schooling. This earlier line of literature mainly focuses on the level of education. Sloane (2003) finds that workers may be mismatched if the level of schooling is appropriate but the type of schooling is not. Our study complements this line of literature by focusing on the type of education-job match rather than the level of match.

Finally, our paper contributes to the human capital literature. Human capital accumulated in school is usually considered general. But is it really general or is the extent of its generality determinate of its value? Our study contributes to this literature by showing that the more specific the human capital is towards a certain occupation, the higher the returns are. That is, while some of the skills acquired in college are general, others are specific to the field and desired occupation and there is a positive return to that specificity. As such, overeducation and undereducation can also be reframed as to whether a worker has learned enough (or excessively) in school towards a certain job.

The outline of the paper is as follows. Section II introduces data and measures. We present our main findings in section III and section IV concludes.

II. Data and measures

The data for this paper comes from the National Survey of College Graduates (NSCG). The survey is conducted by the U.S. Census Bureau on behalf of the National Science Foundation (NSF) to track the progress of education initiatives and study outcomes of those in higher education. We use the surveys for the years 1993, 2003, 2010, 2013, 2015, and 2017.

For the 1993 and 2003 waves the sample comes from the U.S. Census of the corresponding decade and those responding to the long form that reported possessing at least a bachelor's degree and were less than 72 years old in April of the beginning of the decade. The remaining waves come from the American Community Survey (ACS) plus some data collected solely by the NSF surveys. The ACS is a randomized address-based survey in which an entire household is interviewed by phone, mail, email, or in-person methods. Again, those with at least bachelor's degrees were taken from the ACS survey and those under 76 years of age.

Following the work of Ransom and Phipps (2017), we measure how majors are mapped to jobs using the occupational variety (OV), which is the inverse of the Herfindahl-Hirschman Index (HHI) of each (highest earned) field of degree to variety of jobs. The OV of major *m* in year *t* is calculated as the following:

$$OV_{mt} = (\sum_{j=1}^{J_{mt}} s_j^2)^{-1},$$

where *m* is individual's major, *t* is year (survey year or graduation year), J_{mt} the total number of jobs that major *m* maps into in year *t*, and s_j is the share of those with major *m* in year *t* who work in job *j*.

The HHI is constructed within each gender for each major by taking the sum of the square of the share of graduates of each degree field in each job. This measure is then inverted to create the OV. A high OV means a major develops non-specialized skills and places its graduates in a wide variety of jobs uniformly while a low OV means a major develops specialized skills such that either its graduates go to a narrow set of specialized jobs or its graduates can still land in a variety of jobs but the majority of the individuals with this major concentrate in a few jobs. We calculate the major-level OV based on the field of the highest degree earned of the 105 majors in the NSCG.

Table 1 lists the majors with the highest and lowest OVs. We can see that majors with the highest occupational variety are Biology, General Psychology, Sociology, and History; majors with the lowest occupational variety are Physical Therapy, Mechanical Engineering, Aerospace Engineering, and Geology. Figure 1 graphs the occupational distribution of the Law degree (OV: 0.019) and the Biology degree (OV: 0.177). We can see that only 20% of the Biology students become Biological Scientists and another

10% become Biological Technicians. They take on other occupations outside their field fairly evenly and become Secondary Teachers and Managers. On the other hand, 83% of the Law students become Lawyers and Judges, which gives the Law degree a very low OV.

In order to track the changes in OV over time, we need to calculate the OV by time. However, this calculation is sensitive to the choice of how we define "year". We thus generate two OV measures, one based on graduation year and the other survey year. By graduation year each HHI is calculated by the year that individuals receive their (highest) degree then calculating the share of each field of degree in each job by gender. By survey year each HHI is calculated by the year that individuals are surveyed. These two ways of calculating the OV captures different trends in the labor market and these distinctions will be discussed in greater details in the following section. The primary difference is that the graduation year captures changes in skill developments of the same graduation cohort and long run equilibrium outcomes in the major-job match. The survey year captures a snapshot of the labor market across different graduation cohorts at a certain point in time.

The main empirical challenge to address in the estimation of the relationship between major-level OV and earning is selection into majors. Since the OV is essentially a major-level measure, any selection into major that can bias the estimates of the effect of major on earning will cause potential bias in our estimates of the major-level OV on earning. Even if we can randomly assign major, the major-level OV is determined in equilibrium by supply and demand of skills.

Although we cannot fully identify the causal effect of OV on earning, we can study the major-job mapping when the mapping is somewhat affected by exogenous demand shocks during a recession. The idea is that the Great Recession in 2008 primarily affected those in the finance industry and so the impact of these demand shocks should be different to majors that map into jobs that have different degrees of separation from finance jobs in terms of skill development.

In order to measure how far a job is from finance in terms of skill demand, we use the angle of separation of these skills between a given occupation and finance generated. The NSCG asks respondents to indicate whether they use a list of skills on one's job at least 10% of the time. We use this list of skills to construct the distance measure. The skills used are Accounting, Finance, or Contracts; Applied Research – towards a scientific end; Basic Research – towards another incentive; Computer Programming, Systems, or Application Development; Development; Design; Human Resources; Management; Other; Production, operations, or Maintenance; Quality Management; Sales, Professional Services; and Teaching. The Angel of Separation between job *j* and the finance occupation is calculated based on the following equation:

$$\theta_{j,fin} = \cos^{-1} \frac{\sum_i a_{i,j} a_{i,fin}}{\sqrt{\sum_i a_{i,j}^2 \sum_i a_{i,fin}^2}},$$

where $a_{i,j}$ represents the percentage of individuals working in job *j* that use skill *i* at least 10% of the time in the year of 2003 (the best measure we have prior to the great recession which would have influenced heavily skill usage). $a_{i,fin}$ represents the percentage of individuals working in Finance that use skill *i* at least 10% of the time in the year of 2003. The idea is that we can represent the skills that Finance and job *j* use as vectors and then use the angel of separation between those two vectors to represent the distance between Finance and job *j*.

In Table 2, we list the 10 closest as well as the 10 furthest jobs to finance based on their Angel of Separation from Finance based on the aforementioned skills. For example, Economists, Actuaries, Managers, and Insurance services are all very close to finance in terms of the skill requirements, while all teachers, primarily postsecondary, share the least skills with finance.

We restrict our analysis sample to those who are currently employed full-time. The summary statistics are reported in Table 3 for six waves of the NSCG survey from 1993 to 2017 by gender. Across the survey years, there are more men working full-time than women in absolute terms. The average age of full-time workers with at least college degrees is between 39 and 43, with men slightly older than women after the 2010s. These full-time workers have, on average, 12 to 17 years of labor market experience where full-time male workers have longer work experience than female workers. Full-time women are also on average more likely to have Hispanic origin than men, more likely to be African American, less likely to be white, less likely to have children under 6, and less likely to be married. In terms of pre-labor market human capital, full-time male workers are more likely to have a bachelor's degree and PhDs than full-time female workers, especially after the 2010s. They are, however, less likely to have master degrees than women. In terms of the labor market outcomes, full-time male workers have higher annual salary than full-time female workers across years. Men also tend to have degrees that map to a concentrated set of jobs than women. This can be seen in Figure 2 where we overlay the densities of OV for men and women. We can see that the distribution of OV for both genders are skewed to the left but the female sample has a fatter tail.

Figure 3a plots the OV against graduation years by the OV quartiles within each year. We can see that the occupational variety is remarkably stable with slight downward trends for the lower two quartiles, meaning majors that used to match to a concentrated set of jobs specialize even more. For the upper two quartiles, before the recession, there are slight upward trends in occupational variety, meaning majors that used to match to a wide set of jobs generalize even more. This finding is consistent to Beaudry et al.'s (2016) finding that since the demand for cognitive skills has been decreasing since about 2000, highly skilled workers are taking jobs that are formerly held by less educated workers. The polarization in major-job mapping also matches the overall trend of polarization in the labor market as documented in Acemoglu and Autor (2011). More interestingly, the pre-recession increase in OV in the upper two quartiles is completely reversed in the years following the recession. That is, we see a trend of specialization following the recession years across different quartiles of the OV distribution. We observe similar trends in OV in the male (Figure 3b) and female (Figure 3c) samples.

To benchmark our results to the findings in Ransom and Phipps (2017), we also examine the changes in OV by survey year. We can see from Figures 4a, 4b,and 4c, that there is also an upward trend in the upper two quartiles before the recession and downward trend afterwards, which is consistent with what we find using the graduation years.

III. Results

A. Labor market returns to major-level occupational variety

The major-level occupational variety is the equilibrium results of multiple supply and demand factors. On the supply side, students choose to enter into different majors based on their preference, ability, expected returns, etc. On the demand side, whether individual graduates with certain majors are needed by the market determines how the majors are mapped into different jobs. This equilibrium mapping thus has implications to labor market returns. On the one hand, a larger OV can indicate employability in a wider set of jobs. On the other hand, a large OV can indicate insufficient demand in a major's best matched occupations. Therefore, it is ultimately an empirical question about the returns to occupation variety. In Figure 5, we plot log salary against occupational variety. We can see that there is a clear negative correlation between the two.

To formally investigate the labor market returns to occupational variety, we consider the following equation:

$$\mathrm{y_i} = \beta_0 + \beta_1 OV_i + \beta_2 X_i + \beta_3 IM_i + \epsilon_i, \quad (1)$$

where y_i is the log salary of worker i. OV_i is the occupational variety measure of worker i's most recent college major. X_i is a set of covariates including education, age, race, and ethnicity. IM_i is the inverse Mills ratio which corrects for selection into full-time employment.[1] This correction is important because full-time workers may have very different major-job match relative to part-time workers. We also control for year, major, occupation fixed effects. We estimate equation (1) separately for male and female full-time workers, and the results are reported in Table 4.

At a first glance, we can see that there is a persistent negative relationship between salary and OV with different specifications for both the male (Panel A) and female (Panel B) samples. From column (1) in Panel A, a one unit increase in the OV measure will lead to a 161% decrease in men's annual salary. That is, everything else being equal, a man major in Biology, which is the major with the highest OV at 0.177, will earn 26 percentage points less than a man major in Medicine, which is the major with the lowest OV at 0.018. When we control for major fixed effect in column (2), this effect drops to 80%. Controlling for occupation fixed effect in column (3) captures roughly the same variations as controlling for major fixed effect. When we control for parents' education in column (4), the estimate decreases to 112% but is still highly

[1] To construct the inverse Mills ratio, we estimate a Probit participation function with all the controls in equation (1) as well as controls for family size, total income of other family members, presence of children under age 6, and a dummy variable for living alone.

significant. We observe similar magnitude and significance levels in the female sample regarding the effect of OV on salary.

When we separate our sample by quartiles of degree popularity (measured as the total number of graduates with a certain degree) in Table 5, we see the relationship between OV and salary is similar to those find in the full sample. To be specific, there is a persistent negative relationship between log salary and OV across different quartiles of degree popularity in both the male and the female samples. Note that the estimates in the male sample for the third quartile is positive. However, this estimate is not significantly different from zero.

When we calculate the OV based on survey year in Tables 6 and 7, we observe a similar pattern of a negative relationship between OV and salary among men and women although some of the coefficients are not precisely estimated. The difference might be due to the fact that the survey year calculation lumps different graduation cohorts together and therefore are more heterogeneous.

To sum up, we observe a persistent negative relationship between occupational variety and salary among the college graduates. This negative relationship suggests positive labor market returns to specialization. By specialization, we simply mean that graduates from a degree major tend to concentrate in jobs that are closely related to their college major. This returns to specialization might just reflect higher demand for certain skills in the labor market. If graduates from a degree major can be fully absorbed into a few jobs that are closely related to the major, they tend to have a higher salary. This finding is consistent with Robst (2007a)'s finding that if one's major is better matched with her job, she earns more.

B. Labor supply and major-level occupational variety

The previous subsection established a negative return to major-level occupational variety at the intensive margin. In this subsection, we examine how occupational variety is related to labor market outcomes at the extensive margin. In Table 8, we estimate a linear probability model by replacing the outcome variable in equation (1) to an indicator variable that equals to 1 if an individual is employed full time versus not. We can see that higher OV is correlated with a lower probability of full-time employment both in the male and the female sample. We observe similar patterns in Table 9 when we calculate the OV based on survey year. That is, if an individual majors in a field with a high OV, she is not only less likely to be employed full time but also earn lower salary conditional on full-time employment.

C. Major-level occupational variety and the great recession

As the OV reflects partially the market demand for certain skills, we further explore how does the OV respond to exogenous demand shocks during a recession. Since the financial sectors are hit hardest during the recession, we explore the heterogeneity in distance from finance of different occupations. As discussed in the previous section, we use the angel of separation of a vector of skills between a given occupation and finance to measure the distance to finance. The idea is that if a certain occupation requires skills that are similar to finance jobs, it is likely to be affected more severely by the recession.

Applying this distance to finance measure, in Table 10, we regress the OV of worker *i*'s major on the distance from finance of worker *i*'s occupation, and interact the distance measure with an indicator of post-recession years. This difference-in-difference setup allows us to examine how OV varies with distance to finance and how does this relationship changes with a demand shock. We find that the further apart an individual's occupation is from finance, the lower her major's OV is. For example, Postsecondary Teacher is a job that is very different from finance. Our estimate suggests that those in teaching jobs have majors that map into a concentrated set of jobs. This relationship holds for both the calculations by survey year and those by graduation year. When we look at the impact of the recession on this relationship, we observe opposite patterns using OVs based on the graduation year versus the survey year. For OV calculated by graduation year, those individuals who have a job further away from finance go to an even more concentrated set of jobs after the recession. This is likely if the recession has a widespread impact on finance and related occupations such that those jobs stop demanding new graduates post-recession with more specialized skills. For OV calculated by survey year, those individuals who have a job further away from finance go to a relatively wider set of jobs after the recession. That is, even though fresh graduates in a degree field may not land in jobs outside of their specialized degree fields, veterans with certain degrees are now branching out to other jobs after the recession. This is likely if veterans' skills are obsolete and thus are crowded out in specialized positions due to the more highly specialized wave of young graduates. Thus, for OV calculated based on survey year, we see a decline in specialization after the recession. In addition to this, those with skill sets similar to finance likely specialized even more to enhance job security. For example Economists could have pushed requirements within their field to need econometric skills or some other specific knowledge of the field such as behavioral economics knowledge. With such, we would also observe specialization in the occupations closely related to finance.

IV. Conclusion

In this paper, we document multiple stylized facts that have not been documented in the literature using the National Survey of College Graduates from 1993 to 2017. We find that, over the past quarter-century, the college major-occupation mapping is remarkably stable with cyclical fluctuations around the recession years. This cyclicality is mostly pronounced among the majors with highest occupational variety. In addition, college-graduate men tend to have majors that map to a concentrated set of jobs relative to college-graduate women. Furthermore, the wider a major's occupation variety is, the lower the wage is for both men and women with that major. That is, there is a positive return to specialization. This wage effect also works partly through employment where men and women with majors with greater occupational variety are less likely to be employed full time. We also document some structural changes after the Great Recession that new graduates in degree fields that are remote to finance jobs tend to stay in their specialized field, while veterans in those fields branch out to other occupations.

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Fig. 1 Occupational Distribution of Law Degree versus Biology Degree

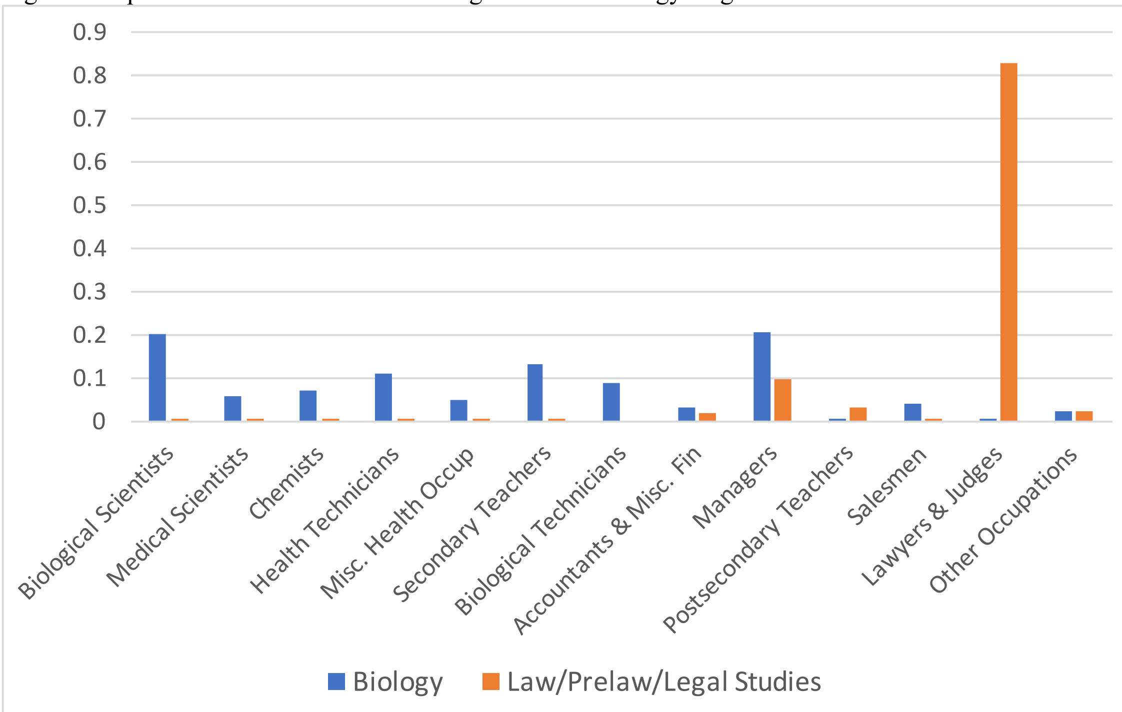


Fig. 2 Distribution of Occupational Variety by Gender, NSCG 1993 to 2017, full-time workers

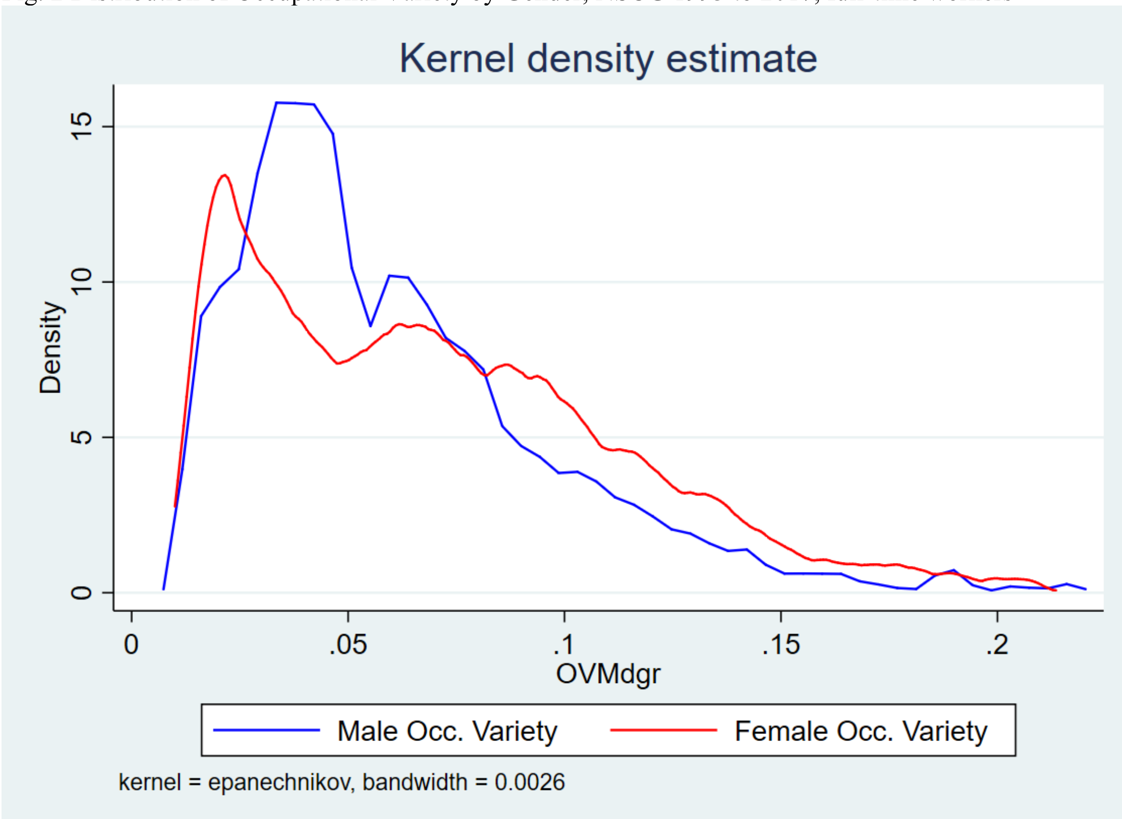
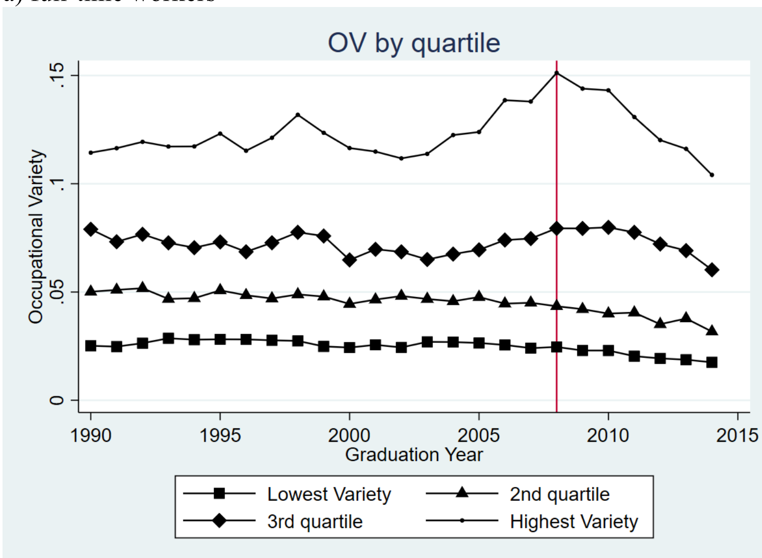
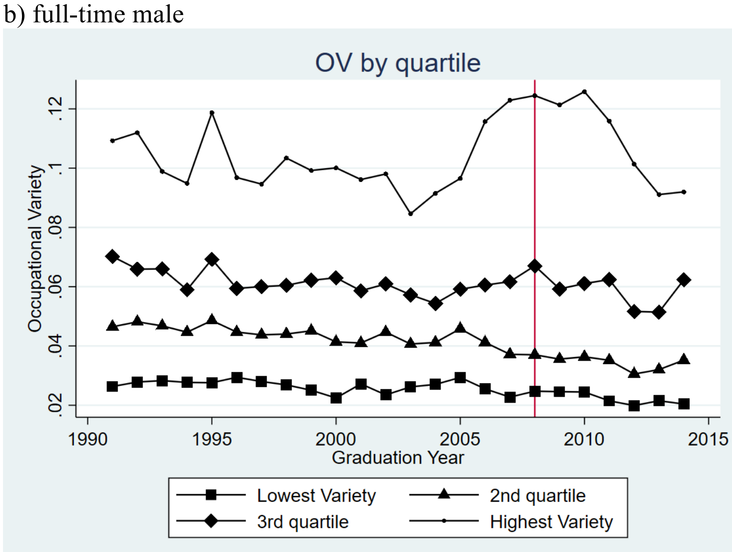


Fig 3. Occupational Variety by Quartile over Graduation Year, NSCG 1993 to 2017

a) full-time workers



b) full-time male



c) full-time female

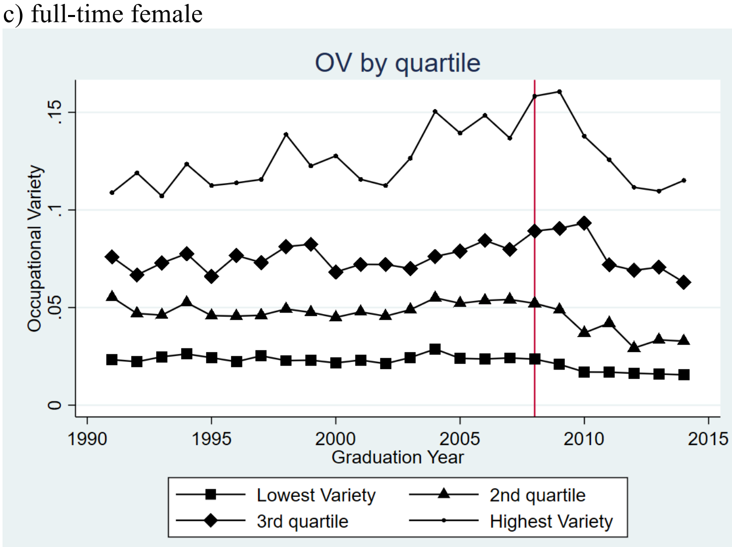
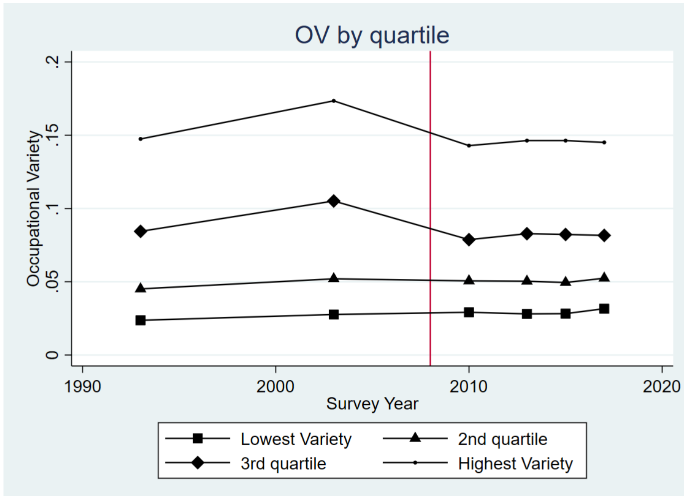
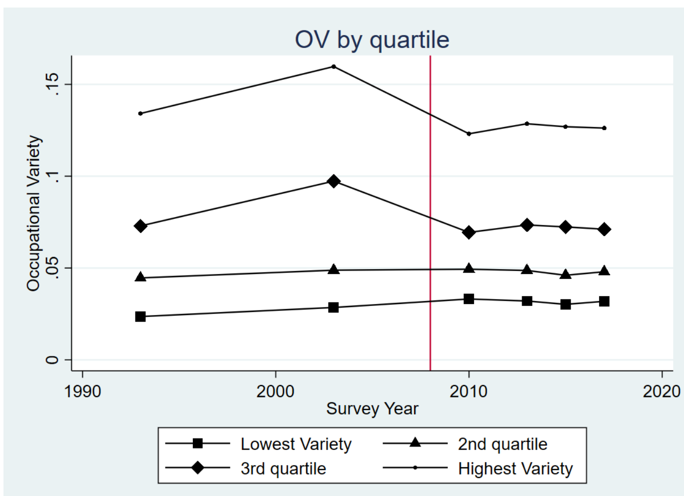


Fig 4. Occupational Variety by Quartile over Survey Year, NSCG 1993 to 2017

a) full-time workers



b) full-time male



c) full-time female

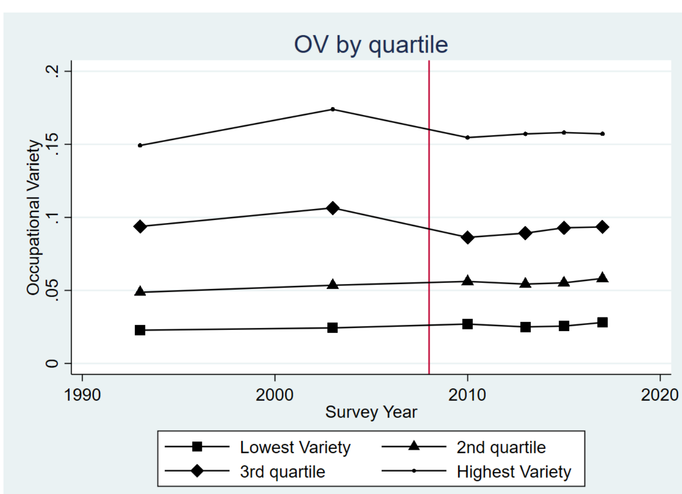


Fig. 5 Salary and Occupational Variety, NSCG, 1993 to 2017, full-time workers

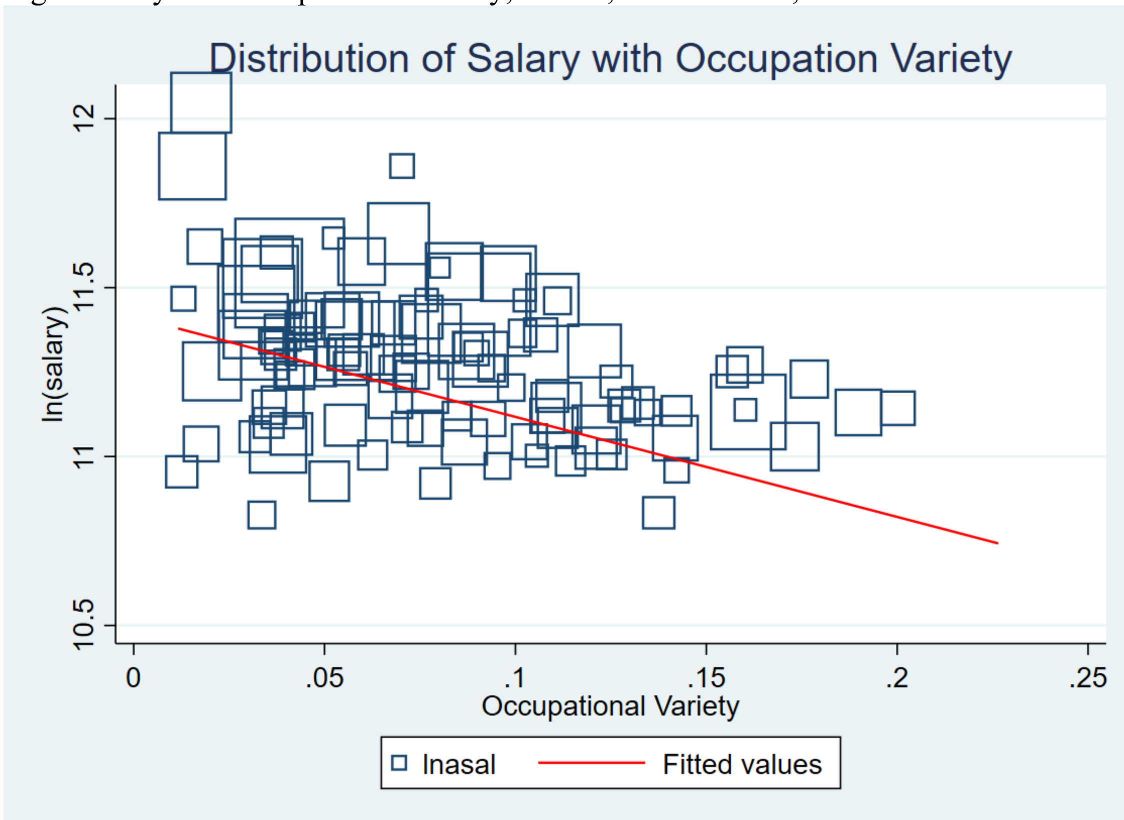


Table 1. Occupational Variety of Majors

Major	OV
Top 10	
Biology, General	0.177
General Psychology	0.158
Sociology	0.144
History	0.139
Liberal Arts/General Studies	0.136
Environmental Science	0.128
Education, General	0.127
Other Biological Sciences	0.126
Communications, General	0.123
Music	0.122
Bottom 10	
Geology	0.034
Aerospace Engineering	0.033
Mechanical Engineering	0.032
Physical Therapy	0.03
Social Work	0.0292
Civil Engineering	0.026
Pharmacy	0.024
Law/Prelaw/Legal Studies	0.0194
Medicine	0.018
Nursing	0.018

Table 2. Occupations' Distance to Finance

Job code	Job title
Closest Jobs: Top 10	
230240	Forestry and conservation scientists
412320	Economists
570900	Environmental engineers
651710	Actuaries
721530	Managers
762000	Insurance, securities, real estate and business services
780310	Accounting clerks and bookkeepers
780320	Secretaries, receptionists, typists
780330	Administrative (record clerks etc)
785000	Other Occupations
Furthest Jobs: Top 10	
182860	Postsecondary Teachers: Mathematics and Statistics
482780	Postsecondary Teachers: Economics
482900	Postsecondary Teachers: Political Science
482930	Postsecondary Teachers: Sociology
482980	Postsecondary Teachers: OTHER Social Sciences
632530	Teachers: Secondary - computer, math or sciences
732520	Teachers: Elementary
742810	Postsecondary Teachers: English
742820	Postsecondary Teachers: Foreign Language
742830	Postsecondary Teachers: History

Table 3. Summary Statistics, NSCG 1993 to 2017, full-time workers

Survey Year	1993		2003		2010		2013		2015		2017	
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
N. of obs.	26,668	38,196	19,865	29,764	13,742	21,998	21,611	30,859	19,007	27,485	14,841	23,807
Demographic Variables												
Age	39	39	43	43	41	43	39	41	40	41	42	43
	(8.06)	(7.57)	(9.49)	(8.99)	(11.03)	(10.60)	(11.61)	(11.62)	(11.41)	(11.66)	(11.41)	(11.62)
Exp	12	12	15	15	14	16	12	15	13	15	15	17
	(6.80)	(6.61)	(9.09)	(8.83)	(10.25)	(10.34)	(10.23)	(10.83)	(10.14)	(10.78)	(10.37)	(10.84)
Hispanic	0.08	0.07	0.09	0.07	0.12	0.10	0.12	0.10	0.13	0.10	0.11	0.09
	(0.28)	(0.26)	(0.29)	(0.26)	(0.32)	(0.30)	(0.33)	(0.30)	(0.33)	(0.30)	(0.32)	(0.29)
Afr. Amer.	0.15	0.08	0.12	0.07	0.15	0.08	0.13	0.07	0.13	0.07	0.11	0.07
	(0.36)	(0.27)	(0.33)	(0.25)	(0.36)	(0.28)	(0.34)	(0.26)	(0.34)	(0.25)	(0.31)	(0.25)
Asian	0.10	0.09	0.12	0.14	0.18	0.19	0.18	0.19	0.18	0.19	0.21	0.21
	(0.30)	(0.29)	(0.33)	(0.34)	(0.39)	(0.40)	(0.38)	(0.39)	(0.39)	(0.40)	(0.40)	(0.41)
White	0.66	0.75	0.76	0.79	0.68	0.73	0.70	0.74	0.70	0.75	0.70	0.74
	(0.47)	(0.43)	(0.43)	(0.40)	(0.47)	(0.45)	(0.46)	(0.44)	(0.46)	(0.44)	(0.46)	(0.44)
Child<6			0.17	0.26	0.17	0.22	0.17	0.21	0.19	0.22	0.20	0.22
			(0.38)	(0.44)	(0.37)	(0.41)	(0.38)	(0.41)	(0.39)	(0.41)	(0.40)	(0.42)
Married	0.61	0.74	0.64	0.79	0.60	0.76	0.56	0.70	0.59	0.71	0.64	0.75
	(0.49)	(0.44)	(0.48)	(0.41)	(0.49)	(0.43)	(0.50)	(0.46)	(0.49)	(0.45)	(0.48)	(0.43)
Education												
BAs	0.66	0.64	0.57	0.58	0.54	0.57	0.51	0.55	0.49	0.54	0.51	0.55
	(0.48)	(0.48)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
MAs	0.26	0.21	0.30	0.25	0.32	0.29	0.37	0.32	0.39	0.34	0.37	0.33
	(0.44)	(0.41)	(0.46)	(0.43)	(0.47)	(0.45)	(0.48)	(0.47)	(0.49)	(0.47)	(0.48)	(0.47)
Prof	0.05	0.10	0.07	0.09	0.08	0.08	0.06	0.05	0.05	0.05	0.06	0.05
	(0.22)	(0.30)	(0.26)	(0.29)	(0.27)	(0.27)	(0.23)	(0.22)	(0.22)	(0.21)	(0.23)	(0.22)
PhD	0.03	0.05	0.06	0.08	0.06	0.07	0.07	0.08	0.06	0.07	0.07	0.07
	(0.17)	(0.22)	(0.24)	(0.27)	(0.24)	(0.25)	(0.25)	(0.27)	(0.24)	(0.26)	(0.25)	(0.26)
Labor Market Variables												
Salary	64,432	84,403	74,669	104,327	77,734	103,417	72,075	96,209	77,460	103,153	85,468	112,257

	(59417.89)	(68013.88)	(52414.44)	(80061.76)	(56962.99)	(79267.11)	(65709.79)	(95282.80)	(70105.19)	(101925.51)	(69271.60)	(99027.83)
OV (Grad Yr)	0.08	0.07	0.08	0.07	0.08	0.07	0.08	0.07	0.08	0.07	0.08	0.06
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
OV (Surv Yr)	0.08	0.07	0.09	0.09	0.08	0.07	0.08	0.07	0.08	0.07	0.08	0.07
	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Dist. to Fin	0.72	0.68	0.74	0.72	0.71	0.72	0.72	0.73	0.71	0.73	0.70	0.72
	(0.30)	(0.26)	(0.29)	(0.26)	(0.26)	(0.25)	(0.26)	(0.25)	(0.26)	(0.25)	(0.26)	(0.25)

Table 4. Log Salary and Occupation Variety in Graduation Year, NCSG 1993-2017, full-time workers

	(1)	(2)	(3)	(4)
Panel A. Men				
Occup Variety	-1.615***	-0.795***	-0.900***	-1.116***
	(0.1052)	(0.1847)	(0.0882)	(0.1299)
Observations	171635	170981	171635	111523
Panel B. Women				
Occup Variety	-1.485***	-0.855***	-0.521***	-1.751***
	(0.3012)	(0.3044)	(0.1735)	(0.2949)
Observations	115469	115089	115469	75094
Inverse Mills Ratio	X	X	X	X
Age, Race, and Ethnicity	X	X	X	X
Education	X	X	X	X
Year Fixed Effect	X	X	X	X
Major Fixed Effect		X		
Occup Fixed Effect			X	
Parents' education				X

Note: Standard errors are clustered at survey year. Each regression includes indicators for race (Black, Asian, White) and ethnicity (Hispanic), indicators for education (Masters, PhDs, Professional Degrees), and year dummies. Column (2) includes 105 major dummies. Column (3) includes 115 occupation dummies. Column (4) include dummies for father's and mother's education.

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

Table 5. Log Salary and Occupation Variety in Graduation Year by Degree Popularity Quartile, NCSG 1993-2017, full-time workers

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
Panel A. Men				
Occup Variety	-1.039***	-0.860***	0.0595	-1.138**
	(0.2020)	(0.1908)	(0.3048)	(0.5217)
Observations	26963	29188	31963	23409
Panel B. Women				
Occup Variety	-1.919***	-1.984***	-2.000***	-1.617***
	(0.4104)	(0.2035)	(0.2855)	(0.4334)
Observations	19815	19577	19469	16233
Inverse Mills Ratio	X	X	X	X
Age, Race, and Ethnicity	X	X	X	X
Education	X	X	X	X
Year Fixed Effect	X	X	X	X
Parents' education	X	X	X	X

Note: Standard errors are clustered at survey year. Each column is a regression over a different quartile of degree popularity. Each regression includes indicators for race (Black, Asian, White) and ethnicity (Hispanic), indicators for education (Masters, PhDs, Professional Degrees), year dummies, and dummies for father's and mother's education.

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

Table 6. Log Salary and Occupation Variety in Survey Year, NCSG 1993-2017, full-time workers

	(1)	(2)	(3)	(4)
Panel A. Men				
Occup Variety	-1.357***	-0.142	-0.558***	-1.064**
	(0.1451)	(0.5056)	(0.0475)	(0.1843)
Observations	258661	257199	258661	157160
Panel B. Women				
Occup Variety	-0.678	-0.377**	-0.228	-1.025
	(0.4028)	(0.1137)	(0.1540)	(0.4461)
Observations	166924	166277	166924	107762
Inverse Mills Ratio	X	X	X	X
Age, Race, and Ethnicity	X	X	X	X
Education	X	X	X	X
Year Fixed Effect	X	X	X	X
Major Fixed Effect		X		
Occup Fixed Effect			X	
Parents' education				X

Note: Standard errors are clustered at survey year. Each regression includes indicators for race (Black, Asian, White) and ethnicity (Hispanic), indicators for education (Masters, PhDs, Professional Degrees), and year dummies. Column (2) includes 105 major dummies. Column (3) includes 115 occupation dummies. Column (4) include dummies for father's and mother's education.

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

Table 7. Log Salary and Occupation Variety in Survey Year by Degree Popularity Quartile, NCSG 1993-2017, full-time workers

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
Panel A. Men				
Occup Variety	-0.0592	-1.037***	0.00962	-2.172***
	(0.2288)	(0.1631)	(0.2215)	(0.3224)
Observations	39718	39456	43430	34556
Panel B. Women				
Occup Variety	-2.008***	-0.305	-1.502**	-0.750
	(0.2407)	(0.4016)	(0.4184)	(0.5048)
Observations	27377	27181	27379	25825
Inverse Mills Ratio	X	X	X	X
Age, Race, and Ethnicity	X	X	X	X
Education	X	X	X	X
Year Fixed Effect	X	X	X	X
Parents' education	X	X	X	X

Note: Standard errors are clustered at survey year. Each column is a regression over a different quartile of degree popularity. Each regression includes indicators for race (Black, Asian, White) and ethnicity (Hispanic), indicators for education (Masters, PhDs, Professional Degrees), year dummies, and dummies for father's and mother's education.

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

Table 8. Employment and Occupation Variety in Graduation Year, NCSG 1993-2017, full-time workers

	(1)	(2)	(3)	(4)
Panel A. Men				
Occup Variety	-1.314***	-0.440	-0.733***	-1.377***
	(0.2823)	(0.4634)	(0.2456)	(0.3763)
Observations	194258	193418	194114	127015
Panel B. Women				
Occup Variety	-1.369***	-0.485	-0.702***	-1.199***
	(0.1847)	(0.3681)	(0.1962)	(0.2417)
Observations	154116	153518	153889	100963
Age, Race, and Ethnicity	X	X	X	X
Education	X	X	X	X
Year Fixed Effect	X	X	X	X
Major Fixed Effect		X		
Occup Fixed Effect			X	
Parents' education				X

Note: Standard errors are clustered at survey year. Each column is a regression over a different quartile of degree popularity. Each regression includes indicators for race (Black, Asian, White) and ethnicity (Hispanic), indicators for education (Masters, PhDs, Professional Degrees), year dummies, and dummies for father's and mother's education.

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

Table 9. Employment and Occupation Variety in Survey Year, NCSG 1993-2017, full-time workers

	(1)	(2)	(3)	(4)
Panel A. Men				
Occup Variety	-0.723**	0.502**	-0.503***	-0.943**
	(0.3108)	(0.2159)	(0.1525)	(0.4504)
Observations	294160	292355	293880	180012
Panel B. Women				
Occup Variety	-1.360***	-0.526	-0.775***	-1.210***
	(0.2016)	(0.3956)	(0.1720)	(0.1971)
Observations	220348	219298	220032	143125
Age, Race, and Ethnicity	X	X	X	X
Education	X	X	X	X
Year Fixed Effect	X	X	X	X
Major Fixed Effect		X		
Occup Fixed Effect			X	
Parents' education				X

Note: Standard errors are clustered at survey year. Each column is a regression over a different quartile of degree popularity. Each regression includes indicators for race (Black, Asian, White) and ethnicity (Hispanic), indicators for education (Masters, PhDs, Professional Degrees), year dummies, and dummies for father's and mother's education.

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

Table 10. Occupation variety and distance from finance occupation, NCSG 1993-2017, full-time workers

Dependent variable: OV	(1) Grad year	(2) Survey year
Separation from Finance	-0.0211***	-0.0426***
	(0.0019)	(0.0011)
Separation X Post2008	-0.0182***	0.0164***
	(0.0043)	(0.0012)
Post2008	0.00294	-0.0366***
	(0.0029)	(0.0009)
Inverse Mills Ratio	X	X
Age, Race, Edu, and Ethnicity	X	X
Year Fixed Effect	X	X
Parents' education	X	X
Observations	179578	256526

Note: Standard errors are clustered at survey year. Separation from finance is measured as the angle of separation from finance occupation of a certain degree holder. Each regression includes indicators for race (Black, Asian, White) and ethnicity (Hispanic), indicators for education (Masters, PhDs, Professional Degrees), and year dummies.

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