Online Appendix to

Superstar Firms and College Major Choice

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In this Online Appendix, we report additional analyses of the relation between superstar firms and college major choice. We then provide further evidence for the role of salience in driving student major choice. Finally, we provide additional details on the college-graduate survey that we conducted on the SurveyMonkey platform.

1 Additional Empirical Evidence

1.1 Robustness of the Main Results

We conduct a number of robustness checks for our main results in Table A2. In the first row, we redo our main tests with biological sciences and health majors included. In the paper, Table 2 excludes these majors because students with biology- and health-related degrees often go to graduate schools before entering the job market (so do not start working in year t). Here we show that the results are similar if we include these majors.

In rows 2 and 3, we show that our results remain highly statistically significant with bootstrapped standard errors and block-bootstrapped standard errors. In the next two rows, we examine the robustness of our results in Table 2 to alternative ways of aggregating industry measures to the major level. Row 4 uses the industry with the maximum absolute value and row 5 computes skewness and other variables by first pooling firms across all related industries.

Rows 6 to 8 of Table A2 show that our results based on the $tail_N$ measure in Table 3, Panel A are robust to other choices of N (1, 3, and 5). Next, we show that leaving out the Tech boom years (1990–2002) from our analysis does not change our results materially.

In the final row, we examine the number of graduates with a master's degree (instead of bachelor's) in related fields. The results are similar to those reported in the paper for bachelor's degrees. A one-standard-deviation increase in $Skew$ measured in years t-7 to t-3 is associated with an 18.25% increase in the number of students graduating with a master's degree in related fields in year t. Note that we do not have sufficient data here to examine the impact on wages or new hires separately.

1.2 Skewness Measured over a Different Horizon

In our main results, we measure industry skewness in years t-7 to t-3 (t being the graduation year) to reflect the fact that college students have to decide their majors by the sophomore year. In this section, we conduct a timing test by measuring *LaggedSkew* in years t-2 and t-1, i.e., the two calendar years right before graduation, but after most students have declared their major. The results of the test are shown in Table A3. *LaggedSkew* in these last two years has a much more muted effect on major choice, reflecting the fact that switching majors is much less common than sticking to a declared major. Furthermore, *LaggedSkew* in the last two years of college is unrelated to entry-level wages upon graduation and to the number of new hires.

1.3 Industry Turnover and Future Operating Performance

One concern with our industry skewness measure is that it may reflect unobserved industry performance dynamics. While we cannot rule this out completely, here we check for any footprints of such an association. First we examine industry job turnover, obtained from BLS and defined as total separations minus hires, as a percentage of employment. Panel A of Table A4 shows that job turnover is not related to *LaggedSkew*. The result suggests that students who are attracted by *LaggedSkew* do not face different job separation risks.

Next, we examine the relation between our skewness measure and various proxies for future industry operating performance at the time of graduation (Panel B), five years after graduation (Panel C), and ten years after graduation (Panel D). Columns (1) and (2) analyze *Return_on_Equity* (*RoE*, defined as earnings divided by book equity) and *Return_on_Assets*

(RoA, defined as earnings divided by firm assets) as measures of industry performance. Columns (3) and (4) examine Net_Profit_Margin (NPM, defined as earnings divided by firm sales), and $Sales\_Growth$ (year-on-year changes in firm sales). As we see from the table, $Skew$ does not predict any of these industry performance measures in any specification.

1.4 Specific Salient Events

In this subsection, we zoom in on two specific types of salient events in the equity market: initial public offerings (IPOs) and firm defaults/delistings, both of which can attract substantial media and public attention to the relevant industry. While IPOs are salient positive events, likely drawing students to related majors, defaults and delistings are significant negative events, which are likely to drive students away. We get the data on IPOs and their first day returns from Green and Hwang (2012). Other data on stock returns, firm characteristics, and bond ratings are available from CRSP and Compustat. We identify a default event as one in which the firm's long-term issuer credit rating, for the first time, drops to "D," "SD," "N.M." A firm is delisted when the delisting code ($DLSTCD$) from CRSP is between 400 and 490, 572, or 574.

We conduct regressions similar to equation (1), but now replace return skewness with various measures based on these specific events. The results are reported in Table A5. In Columns (1) and (2), our main independent variable of interest is the first day return of all IPOs; in Columns (3) and (4) it is the total number of firm defaults and delistings divided by the total number of rated firms in the industry. We find consistent evidence throughout Table A5: big first-day IPO returns are positively related to future major enrollment, while firm defaults and delistings are negatively associated with major enrollment.

1.5 Total number of bachelors in science and engineering majors

While Table 2 shows that *LaggedSkew* is positively related to the number of bachelors in related fields, it is possible that salient occurrences of superstar firms lead to an overall increase in the number of students who choose science and engineering majors. In Table A6, we show that this is not the case. Neither the maximum skewness nor the average skewness across our majors predicts the total number of bachelors in science and engineering majors.

2 More Evidence on the Effect of Industry Salience

Our evidence in the main text on the joint dynamics of quantities (the number of graduates/new hires) and prices (the average wage) points to a relatively larger shift in labor supply than in labor demand with the occurrences of superstar firms. In other words, college students are attracted by superstar firms in deciding their majors, not because they rationally anticipate improved job prospects, but because they are drawn to extreme, salient events. In this section, we provide more evidence on the effect of salience on college major choice.

2.1 Structural Breaks in Industry Valuation

While the focus of the paper is on superstar performers within an industry, in this and the next subsection, we provide additional evidence for the supply side of human capital investment by linking time variation in the relative popularity/salience of industries to student major choice. To start, we exploit structural breaks in industry valuation during the NASDAQ bubble in the late 1990s to identify superstar industries. Our logic is similar to that of Charles, Hurst, and Notowidigdo (2018), who argue that sudden, sharp increases in local house prices in the early 2000s are the result of speculative activity and are unlikely to be caused by changes in local economic conditions. In the same way, our underlying assumption is that abrupt, sharp increases in stock valuations during the Tech Bubble were a result of stock market speculation. In other words, we argue that these sharp price appreciations did not merely reflect changes in rational expectations of industry fundamentals that could affect overall labor demand.

We follow the same two-stage estimation procedure as in Charles, Hurst, and Notowidigdo (2018). In the first stage, we estimate industry-specific OLS regressions with a single structural break, and search for the time of the structural break that maximizes the R^2 of the following regression:

$$R_{i,t} = \alpha_i + \tau_i t + \lambda_i (t - t_i^*) \mathbb{1}(t > t_i^*) + \epsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the cumulative return of industry i up to quarter t, t_i^* is the date of the structural break in the industry's valuation, restricted to be between 1990Q1 to 1999Q4 (the NASDAQ index peaked in Q1 of 2000). τ_i is the linear time-trend in price appreciation before the structure break, and λ_i is the size of the structural break—reflecting the change in the growth rate at the structural break. This procedure follows standard approaches in time-series econometrics to identify a single break point (e.g., Bai 1997; Bai and Perron 1998).

In the second stage, we conduct an event-time study by comparing the number of college graduates from related majors around the time of the structural break. More specifically, we estimate the following regression:

$$log(bachelor_{i,t}) = \alpha + \beta Post_{i,t} \times \lambda_i + \gamma \mathbf{X}_{i,t-3} + \mu_i + \tau_t + \epsilon_{i,t}, \tag{2}$$

where $Post_{i,t}$ is a dummy variable that equals one if year t is 3 years after the structural break t_i^* (so the structural break occurs by the sophomore year of the year t graduates); we further control for industry and time fixed effects on the right-hand-side of the equation. The difference-in-difference coefficient β then measures the difference in the number of graduates from related major fields before vs. after the structural break weighted by the size of the break.

Online Appendix Table A7 presents these regression results. Panel A shows the result of the first stage. There is significant variation across industries both in terms of the timing of the structural break and the magnitude of the break, consistent with the finding in Campello and Graham (2013) that some non-tech industries also experienced a boom during the tech bubble. Not surprisingly, Computer Science-related industries experience the largest structural break among all science-engineering majors in our sample. Interestingly, Earth and Ocean Sciences-related industries experience a negative structural break, possibly because investors view them as "boring" relative to tech-related industries in this period.

Panel B reports the change in the number of college graduates from related majors around the structural break. As can be seen from Column (1), the size of the structural break is significantly associated with subsequent changes in major enrollment; more specifically, a one-standard-deviation increase in the magnitude of the structural break is associated with a 7.9% increase in the number of graduates in related major fields. Columns (2)–(5) examine changes in industry fundamentals around the same break points; we do not see similar structural breaks in any of the commonly used proxies for industry performance.[1] In sum, our results based on structural breaks in industry valuation provide further evidence for a plausibly causal impact of extreme events on college major choice.

2.2 *Law & Order* and the Legal Profession

In this subsection, we provide more direct evidence on the role of salience on the supply side of education choice by honing in on just one industry. More specifically, we exploit time variation in the viewership of one of the longest-running TV series in the US, *Law & Order*, to gauge the popularity/salience of the legal profession among prospective students. We then examine its impact on the subsequent number of students applying to and enrolled in law

[1] Using the full sample period, Online Appendix Table A11 confirms that *LaggedSkew* in years t-7 to t-3 does not significantly predict these proxies for industry performance measured in years t, t+5, and t+10.

schools, as well as the future wages earned by entry-level lawyers. Unlike the rest of the paper, where we examine all NSF majors, here we focus on law for a couple of reasons. First, work flow and occupational conditions in the legal profession do not fluctuate significantly on a year-on-year basis, making endogeneity (e.g., TV series viewership reflects changes in lawyer working conditions, which caused prospective students to respond) less of a concern. *Law & Order* viewership fluctuations across seasons are more likely driven by the public appeal of a particular season's story line than by changing job prospects in the legal profession. Second, we have detailed data on law school test (LSAT) takers, applicants, graduates, as well as data on entry-level employment and wages, which allow us to examine the impact of salience in more detail.

Law & Order was shown for 20 seasons on NBC between 1990 and 2010. We obtain the annual viewership data from Broadcasting & Cable (historical issues of the magazine are available from ABI/Inform Global). Law school applicants are required to take The Law School Admission Test (LSAT). Statistics on the numbers of test takers and law school applicants are provided by The Law School Admission Council.[2] The median age of LSAT test takers is 23 (i.e., about one year after they receive their undergraduate degree), and we study the impact of the popularity of *Law & Order* 4 to 8 years before students take LSAT.[3] We also examine the number of law school graduates (those who obtain a JD degree, which typically takes 3 years to complete), available from IPEDS, as well as information on the average salary and number of entry-level lawyers (SOC code = 23-1011, title = "Lawyers") from BLS. Note that our data here are a time-series, so we cannot include time fixed effects. In the application and enrollment analysis, we control for a linear time trend. In the analysis of job opportunities, we adjust lawyers' salary and net new hires by the corresponding figures for other professional occupations.[4] All regressions include lagged average lawyer wages,

[2] We obtain the number of LSAT takers from 1993 to 2017 and the number of applicants and applications from 2000 to 2015.

[3] To prepare for law school admissions, most students choose one of the following five majors: Political Science, History, English, Psychology, and Criminal Justice. In other words, most law school students make up their mind for future careers by the sophomore year.

[4] These are occupations that require a "doctoral or professional degree" and no prior work experience, as stated by the BLS projections. They are mostly jobs for MDs or PhDs.

again to show incremental effects beyond Cobweb models.

As can be seen from Table A8, the lagged viewership of *Law & Order* positively forecasts students' interest and enrollment in law schools, but negatively forecasts future wages of entry-level lawyers. More specifically, a one-standard-deviation increase in the log number of viewers of the TV series in years t-8 to t-4 is followed by a 4.5% increase in the number of students taking the LSAT in year t, a 12.4% rise in the number of unique applicants, and a 5.2% increase in the number of law school graduates from that applicant pool in year t+3.[5] Consistent with a supply-side channel, the rise in the popularity of *Law & Order* in years t-8 to t-4 is associated with a 3.5% drop in the average earnings of entry-level lawyers, but no significant change in the net new hires in year t+3, when students graduate (our tests appropriately lag the period over which skewness is measured in Columns (4)–(6) to reflect this timing convention, arising from the time taken to complete law degrees). Overall, our evidence from this case study of the legal profession provides further support for a supply-side interpretation of our findings.

3 Details about our own survey using SurveyMonkey

In this section, we provide further details on our own survey of College graduates, conducted in July 2018 on SurveyMonkey, and titled "Looking Back at College Major Choice." The survey instrument is available at `https://personal.lse.ac.uk/loud/ChoiLouMuk_SurveyQuestions.pdf`.

In this survey, we asked specific questions regarding the industry of the respondent's first job after college (as opposed to their current job, as in NSCG), their target industry when they chose their major, the year (high school or freshman/sophomore year of college) when

[5]While LSAT is an entrance exam required for admission to most law schools, the number of LSAT test takers is not equal to the number of law school applicants because each applicant can take the test multiple times and LSAT scores are valid for five years. During our sample period, the average number of test takers is 129,105 per year, and the average number of applicants is 80,325 per year.

they made their major choice (allowing us to more precisely measure the relevant timing for our skewness variable), reasons for switching if they changed the industry they worked in after college, as well as their beliefs about job opportunities and preferences for skewness when they were in college.

We screened our respondents on SurveyMonkey using the following criteria: at the time of the survey, the respondent had to be a) a US college graduate with one of the NSF majors that we examine in the paper, b) between 21 and 65 years old, and c) employed full time for at least one full year. In addition, we also screened respondents based on whether they cared/worried about job market outcomes when they chose their majors, leaving out those that chose majors based purely on academic interest.[6] We then matched the survey data to industry return skewness and other control variables used in earlier tests, leaving us with a final sample of 351 respondents with non-missing data.

In our sample, 50.12% of respondents are male and the median age group of survey respondents is 30–44. The median household income is in the \$75,000–\$95,000 range (demographic information on respondents, such as gender, age and income, was provided to us by SurveyMonkey). The median income in our sample is in the same range as that in other comprehensive national statistics of Science and Engineering graduates (e.g., see `https://www.nsf.gov/statistics/2017/nsf17310/static/data/tab9-16.pdf`). Still, given that SurveyMonkey respondents have clearly chosen to join the platform and to answer our survey, we do not claim that they are identical to the general population; instead, we only compare one respondent to another *within* this dataset.

Note that we back out the skewness relevant to major choice from the year in which the respondent made that choice. For example, if the respondent graduated in 2014 and chose her major in the freshman year (i.e., in 2010-11), we examine cross-sectional return skewness

[6] Specifically, we asked, "How important was the availability of jobs or future income prospects in related industries (where people with this major typically worked) in your major choice decision?" and only kept those who answered "Most Important" or "Somewhat Important" (screening out those that chose "Least Important").

in 2010 and 2011.

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Charles, Kerwin Kofi, Erik Hurst and Matthew J. Notowidigdo, 2018, “Housing Booms and Busts, Labor Market Opportunities, and College Attendance,” American Economic Review, forthcoming.

Green, T. Clifton and Byoung-Hyoun Hwang, 2012, “Initial public offerings as lotteries: Skewness preference and first-day returns,” Management Science 58, 432–444.

Table A1
Industries and Majors

This lists the science and engineering majors used in the paper and a map between majors and 3-digit NAICS industry codes (we exclude NAICS codes that start with 92, which correspond to Public Administration and are not covered in economic census).

1	Aeronautical and astronautical engineering
2	Biological sciences*
3	Chemical engineering
4	Civil engineering
5	Computer sciences
6	Earth and ocean sciences
7	Economics
8	Electrical engineering
9	Health*
10	Industrial and manufacturing engineering
11	Materials science
12	Mechanical engineering

*We exclude Biological sciences and Health majors in our aggregate-level analysis, because many biology- and health-related jobs require an advanced degree and students often go to graduate schools before entering the job market. Lacking information on the actual starting year of their careers, our skewness measure constructed from years t-7 to t-3 is less precise. In the individual-level analysis, we include these two majors because there we do have detailed information on respondents' education and career paths.

(The NSF data include these other majors as well: Agricultural sciences, Astronomy, Atmospheric sciences, Chemistry, Engineering technology, Mathematics, Physics, Political science, Psychology, Sociology)

3-digit NAICS	Industry	Major(s)
113	Forestry and Logging	Earth and ocean sciences
115	Support Activities for Agriculture and Forestry	-
211	Oil and Gas Extraction	Chemical engineering
		Earth and ocean sciences
212	Mining (except Oil and Gas)	Chemical engineering
		Earth and ocean sciences
213	Support Activities for Mining	Chemical engineering
		Earth and ocean sciences
236	Construction of Buildings	Civil engineering
237	Heavy and Civil Engineering Construction	Civil engineering
238	Specialty Trade Contractors	-
311	Food Manufacturing	-
312	Beverage and Tobacco Product Manufacturing	-
313	Textile Mills	Chemical engineering
		Industrial and manufacturing engineering
		Materials science
		Mechanical engineering
314	Textile Product Mills	Chemical engineering
		Industrial and manufacturing engineering
		Materials science
		Mechanical engineering
315	Apparel Manufacturing	Chemical engineering
		Industrial and manufacturing engineering
		Materials science
		Mechanical engineering
316	Leather and Allied Product Manufacturing	Chemical engineering
		Industrial and manufacturing engineering
		Materials science
		Mechanical engineering
321	Wood Product Manufacturing	Chemical engineering
		Industrial and manufacturing engineering
		Materials science
		Mechanical engineering

3-digit NAICS	Industry	Major(s)
322	Paper Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
323	Printing and Related Support Activities	-
324	Petroleum and Coal Products Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
325	Chemical Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
326	Plastics and Rubber Products Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
327	Nonmetallic Mineral Product Manufacturing	-
331	Primary Metal Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
332	Fabricated Metal Product Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
333	Machinery Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
334	Computer and Electronic Product Manufacturing	Computer sciences Electrical engineering
335	Electrical Equipment, Appliance, and Component Manufacturing	Computer sciences Electrical engineering
336	Transportation Equipment Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
337	Furniture and Related Product Manufacturing	Chemical engineering Industrial and manufacturing engineering Materials science Mechanical engineering
339	Miscellaneous Manufacturing	-
423	Merchant Wholesalers, Durable Goods	-
424	Merchant Wholesalers, Nondurable Goods	-
425	Wholesale Electronic Markets and Agents and Brokers	-
441	Motor Vehicle and Parts Dealers	-
442	Furniture and Home Furnishings Stores	-
443	Electronics and Appliance Stores	-
444	Building Material and Garden Equipment and Supplies Dealers	-
445	Food and Beverage Stores	-
446	Health and Personal Care Stores	-
447	Gasoline Stations	-
448	Clothing and Clothing Accessories Stores	-
451	Sporting Goods, Hobby, Book, and Music Stores	-
452	General Merchandise Stores	-
453	Miscellaneous Store Retailers	-
454	Nonstore Retailers	Computer sciences Electrical engineering
481	Air Transportation	Aeronautical and astronautical engineering
482	Rail Transportation	-
483	Water Transportation	-
484	Truck Transportation	-
485	Transit and Ground Passenger Transportation	-
486	Pipeline Transportation	-

3-digit NAICS	Industry	Major(s)
488	Support Activities for Transportation	-
491	Postal Service	-
492	Couriers and Messengers	-
493	Warehousing and Storage	-
511	Publishing Industries (except Internet)	Computer sciences Electrical engineering
512	Motion Picture and Sound Recording Industries	Computer sciences Electrical engineering
515	Broadcasting (except Internet)	-
516	Internet Publishing and Broadcasting	Computer sciences Electrical engineering
517	Telecommunications	Computer sciences Electrical engineering
518	Internet Service Providers, Web Search Portals, and Data Processing Service	Computer sciences Electrical engineering
519	Other Information Services	Computer sciences Electrical engineering
521	Monetary Authorities - Central Bank	Economics
522	Credit Intermediation and Related Activities	Economics
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	Economics
524	Insurance Carriers and Related Activities	Economics
525	Funds, Trusts, and Other Financial Vehicles	Economics
531	Real Estate	Economics
532	Rental and Leasing Services	Economics
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	Economics
541	Professional, Scientific, and Technical Services	Computer sciences Electrical engineering
551	Management of Companies and Enterprises	-
561	Administrative and Support Services	-
562	Waste Management and Remediation Services	-
611	Educational Services	-
621	Ambulatory Health Care Services	Biological sciences Health
622	Hospitals	Biological sciences Health
623	Nursing and Residential Care Facilities	Biological sciences Health
624	Social Assistance	Biological sciences Health
711	Performing Arts, Spectator Sports, and Related Industries	-
712	Museums, Historical Sites, and Similar Institutions	-
713	Amusement, Gambling, and Recreation Industries	-
721	Accommodation	-
722	Food Services and Drinking Places	-
811	Repair and Maintenance	-
812	Personal and Laundry Services	-
813	Religious, Grantmaking, Civic, Professional, and Similar Organizations	-
814	Private Households	-

Table A2
Robustness Tests

This table repeats the main tests with various robustness tests and reports the coefficient of Skew or proxies that replace Skew. The dependent variables are Log Number of Bachelors, Log Annual Wage, and Net New Hires. The robustness tests are: including Biological sciences and Health majors; calculating standard errors using bootstrap with 10,000 times and block-bootstrap with 10,000 times; when aggregating industries within a major, pick the industry measures with the highest absolute value or pool all industries in the same major together to calculate skewness and other variables; defining Top_N ($Bottom_N$) as the average return of the top (bottom) 5, 3, or 1 firms in an industry minus the median, divided by the standard deviation of returns, after dropping firms in the lowest 50th size percentile; excluding bachelors who graduate from 1990 to 2002; and using the number of masters instead of bachelors.

Robustness Checks	Log Number of Bachelors	Log Annual Wage	Net New Hires
	(1)	(2)	(3)
Including Biological Sciences and Health Majors	0.1252***	-0.0074**	0.0063
	(0.0293)	(0.0028)	(0.0161)
Bootstrapped Standard Errors	0.1574***	-0.0144***	0.0089
	(0.0325)	(0.0036)	(0.0371)
Block-Bootstrapped Standard Errors	0.1574***	-0.0144***	0.0089
	(0.0308)	(0.0031)	(0.0319)
Pick the Industry with the Highest Absolute Value	0.1682***	-0.0086**	0.0052
	(0.0381)	(0.0035)	(0.0275)
Pool All Industries in the Same Major Together	0.1178***	-0.0160***	0.0236
	(0.0269)	(0.0026)	(0.0279)
Defining Tail Using Top and Bottom 5 Firms	0.2199***	-0.0204***	0.0217
	(0.0432)	(0.0045)	(0.0380)
Defining Tail Using Top and Bottom 3 Firms	0.2151***	-0.0207***	0.0281
	(0.0461)	(0.0051)	(0.0404)
Defining Tail Using Top and Bottom 1 Firm	0.1670***	-0.0194***	0.0407
	(0.0476)	(0.0051)	(0.0419)
Excluding Bachelors Who Graduate Between 1990 and 2002	0.1856***	-0.0080***	-0.0275
	(0.0381)	(0.0024)	(0.0291)
Using Masters Instead of Bachekors	0.1825***		
	(0.0289)		

Table A3

Skewness Measures of Different Horizons

This table reruns regressions of Log Number of Bachelors, Log Annual Wage, and Net New Hires, all in year t. The return measures (skewness, mean, and standard deviation of return) are measured in years t-2 to t-1 or years t-7 to t-3. All other variables are the same as Table 2 in the main text. Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables are standardized with zero mean and unit standard deviation. The sample period is from 1966 to 2017 in Columns (1) and (2) and from 1997 to 2017 in Columns (3) to (6).

	Log Number of Bachelors	Log Number of Bachelors	Log Annual Wage	Log Annual Wage	Net New Hires	Net New Hires
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Skew (t-2 to t-1)	0.0793**	0.0651**	0.0010	0.0007	0.0163	0.0217
	(0.0320)	(0.0254)	(0.0035)	(0.0039)	(0.0440)	(0.0585)
Lagged Skew (t-7 to t-3)		0.1530***		-0.0142***		0.0155
		(0.0305)		(0.0027)		(0.0310)
Lagged Mean Return (t-2 to t-1)	-0.0237	-0.0348	-0.0067	-0.0007	-0.0654	-0.0598
	(0.0358)	(0.0319)	(0.0058)	(0.0051)	(0.0565)	(0.0747)
Lagged Mean Return (t-7 to t-3)		0.0738		0.0058*		0.0192
		(0.0529)		(0.0033)		(0.0476)
Lagged Standard Dev of Return (t-2 to t-1)	0.0181	0.0212	-0.0043	-0.0063	-0.0094	-0.0090
	(0.0460)	(0.0448)	(0.0056)	(0.0042)	(0.0679)	(0.0692)
Lagged Standard Dev of Return (t-7 to t-3)		-0.0455		-0.0056		-0.0415
		(0.0521)		(0.0047)		(0.0677)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	501	501	210	210	200	200
Adj. R-Squared	0.83	0.84	0.96	0.96	0.29	0.28

Table A4

Industry Turnover and Operating Performance Measures

This table reports the results of regressions of Industry Turnover (in year t) and operating performance measures (in year t, t+5, or t+10) on skewness measures (measured in years t-7 to t-3) and other controls. Industry Turnover is the total separations minus total hires (both as % of total employment). RoA is the return on assets, defined as earnings divided by total assets. NPM is the net profit margin, that is, earnings divided by sales. Sales growth is the percentage growth in sales. Skew is the employment-weighted cross-sectional skewness of annual returns in an industry.

Panel A: Industry Turnover	
Lagged Skew	-0.0004
	(0.0010)
Lagged Mean Return and Standard Deviation	Yes
Other Controls	Yes
Year and Industry Fixed Effects	Yes
Industry Fixed Effects	Yes
# Observations	1190
Adj. R-Squared	0.91

Panel B: Operating Performance Measures Upon Graduation				
	RoE	RoA	NPM	Sales Growth
	(1)	(2)	(3)	(4)
Lagged Skew	-0.0028	-0.0025	-0.0279	0.0024
	(0.0038)	(0.0024)	(0.0287)	(0.0052)
Lagged Mean Return and Standard Deviation	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Year and Industry Fixed Effects	Yes	Yes	Yes	Yes
# Observations	1988	1988	1988	1988
Adj. R-Squared	0.22	0.17	0.00	0.19

Panel C: Operating Performance Measures 5 Years After Graduation				
	RoE	RoA	NPM	Sales Growth
	(1)	(2)	(3)	(4)
Lagged Skew	0.0030	0.0004	0.0011	0.0056
	(0.0025)	(0.0014)	(0.0040)	(0.0044)
Lagged Mean Return and Standard Deviation	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Year and Industry Fixed Effects	Yes	Yes	Yes	Yes
# Observations	1592	1592	1592	1592
Adj. R-Squared	0.13	0.11	0.00	0.14

Panel D: Operating Performance Measures 10 Years After Graduation				
	RoE	RoA	NPM	Sales Growth
	(1)	(2)	(3)	(4)
Lagged Skew	-0.0013	0.0030	0.0533	-0.0014
	(0.0065)	(0.0042)	(0.0543)	(0.0077)
Lagged Mean Return and Standard Deviation	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Year and Industry Fixed Effects	Yes	Yes	Yes	Yes
# Observations	1168	1168	1168	1168
Adj. R-Squared	0.12	0.06	0.00	0.14

Table A5

Regressions of Number of Bachelors on Other Measures

This table reports the results of regressions of Log Number of Bachelors on other measures of salient, extreme events (measured in years t-7 to t-3, relative to the graduation year t). Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major. Log IPO First Day Dollar Return is the log total dollar amount of IPO first day return. Default and Delisting Rate is the number of defaults (as defined by S&P issuer ratings) plus delisting events divided by the total number of rated firms in an industry.

Our control variables are all measured at year t-3 and include Log Average Wage, the industry-level 3-year average wage obtained from Compustat (up to 1998) or major-level 3-year average wage from BLS (1999 and onward). Other controls are Log Average Market Cap, Log Average Book-to-Market, and Log Average Firm Age, weighted by employment. All industry measures are aggregated to the major level using the map in Appendix Table A1. Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables are standardized with zero mean and unit standard deviation. The sample period is from 1982 to 2011 in Columns (1) and (2) and 1985 to 2017 in Columns (3) and (4).

	Log Number of Bachelors			
	(1)	(2)	(3)	(4)
Lagged Log IPO First Day Dollar Return	0.1481***	0.1482***		
	(0.0417)	(0.0404)		
Lagged Default and Delisting Rate			-0.0146**	-0.0201**
			(0.0069)	(0.0077)
Lagged Log Average Wage		0.0556***		0.0587***
		(0.0174)		(0.0107)
Lagged Log Average Market Cap	-0.0450	-0.0507	-0.1214***	-0.1266***
	(0.0529)	(0.0464)	(0.0240)	(0.0276)
Lagged Log Average Book-to-Market	-0.0809***	-0.1069***	-0.0172	-0.0300
	(0.0276)	(0.0271)	(0.0290)	(0.0263)
Lagged Log Average Firm Age	-0.1022***	-0.0931***	-0.0638**	-0.0548**
	(0.0357)	(0.0333)	(0.0276)	(0.0254)
Year Fixed Effects	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes
# Observations	273	273	330	330
Adj. R-Squared	0.97	0.98	0.97	0.97

Table A6
Change in the Total Number of Bachelors

This table reports the results of regressions of Log Change in Total Number of Bachelors on skewness measures (measured in years t-7 to t-3, relative to the graduation year t) and other controls. Log Change in Total Number of Bachelors is the log change in the annual total number of bachelor degrees across all the 10 majors in Table A1. Skew is the employment-weighted cross-sectional skewness of annual returns in an industry.

Our control variables are all measured at year t-3 and include Log Average Wage, the industry-level 3-year average wage obtained from Compustat (up to 1998) or major-level 3-year average wage from BLS (1999 and onward); Mean Return and Standard Deviation of Return, both are employment-weighted. Other industry controls are Log Average Market Cap, Log Average Book-to-Market, and Log Average Firm Age, weighted by employment. All industry measures are aggregated to the major level using two methods: averaging across all majors (weighted by the number of bachelors in year t-3) in Column (1) and picking the industry measure with the maximum absolute value in Column (2).

Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables are standardized with zero mean and unit standard deviation. The sample period is from 1966 to 2017.

Log Change in Total Number of Bachelors		
Aggregating Method	Bachelor-weighted Average	Max Absolute Value
	(1)	(2)
Lagged Skew	0.0029	0.0065
	(0.0124)	(0.0124)
Lagged Mean Return	0.0060	0.0332
	(0.0106)	(0.0218)
Lagged Standard Deviation of Return	-0.0027	0.0120
	(0.0084)	(0.0129)
Lagged Log Average Wage	-0.0040	0.0018
	(0.0272)	(0.0071)
Lagged Log Average Market Cap	0.0438	0.0118
	(0.0310)	(0.0225)
Lagged Log Average Book-to-Market	0.0332	0.0273*
	(0.0212)	(0.0150)
Lagged Log Average Firm Age	-0.0338***	-0.0333
	(0.0099)	(0.0334)
Intercept	0.0285***	0.0388***
	(0.0071)	(0.0124)
# Observations	45	51
Adj. R-Squared	0.38	0.17

Table A7

Structural Breaks in Industry Valuation

This table uses the NASDAQ bubble period in the 1990s to identify structural breaks in industry valuation. In Panel A, time series regressions are run for every major-related industry using the cumulative quarterly industry return from 1990 to 1999. Time Trend is the base time trend of the period, and Lambda is the change in time trend after the structural break. The structural break is identified by the time series regression that has the maximum adjusted R^2. The t-stats of the Lambda estimates are also reported.

In Panel B, Post is a dummy variable indicating the time is 3 years after the structural break of the major. The dependent variables are Log Number of Bachelors, RoE, RoA, NPM, and Sales Growth. Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major. RoE is the return on equity, defined as earnings divided by equity. RoA is the return on assets, defined as earnings divided by total assets. NPM is the net profit margin, that is, earnings divided by sales. Sales growth is the percentage growth in sales. The sample period for this panel is from 1990 to 2002. Other controls are all measured at year t-3 and include Log Average Wage, the industry-level 3-year average wage obtained from Compustat (up to 1998) or major-level 3-year average wage from BLS (1999 and onward); Log Average Market Cap, Log Average Book-to-Market, and Log Average Firm Age, weighted by employment. Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables (except Post and Lambda) are standardized with zero mean and unit standard deviation.

Panel A: Identifying Structural Break

Major	Max Adj. R^2	Time Trend	Lambda	t-stat	Break YearQtr
Aeronautical and astronautical eng.	84.32%	0.0181	0.0475	(3.39)	199404
Chemical engineering	95.22%	0.0301	0.0449	(6.77)	199402
Civil engineering	82.53%	0.0197	0.0242	(2.44)	199501
Computer sciences	97.62%	0.0740	0.3235	(8.95)	199701
Earth and ocean sciences	11.93%	0.0049	-0.0283	(-2.35)	199703
Economics	97.13%	0.0615	0.1854	(10.88)	199502
Electrical engineering	97.62%	0.0740	0.3235	(8.95)	199701
Industrial and manufacturing eng.	92.97%	0.0336	0.0322	(4.04)	199404
Materials science	93.42%	0.0324	0.0376	(4.80)	199404
Mechanical engineering	92.57%	0.0330	0.0319	(3.90)	199404

Panel B: Regressions on Structural Break

	Log Number of Bachelors	RoE	RoA	NPM	Sales Growth
	(1)	(2)	(3)	(4)	(5)
Post * Lambda	0.6186***	-0.1315	-0.0576	-0.0379	-0.0104
	(0.1694)	(0.1419)	(0.0436)	(0.0563)	(0.0733)
Lagged Log Average Wage	0.0355	-0.0167***	-0.0048***	-0.0072***	-0.0177**
	(0.0221)	(0.0051)	(0.0012)	(0.0014)	(0.0066)
Lagged Log Average Market Cap	0.0709	-0.0821**	-0.0183***	-0.0145*	-0.1129***
	(0.0430)	(0.0373)	(0.0060)	(0.0078)	(0.0337)
Lagged Log Average Book-to-Market	0.0977	-0.0353	-0.0054	-0.0063	0.0015
	(0.0553)	(0.0239)	(0.0046)	(0.0044)	(0.0224)
Lagged Log Average Firm Age	-0.1670**	0.0202	0.0065	0.0092	-0.0139
	(0.0731)	(0.0275)	(0.0071)	(0.0074)	(0.0217)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes	Yes
# Observations	130	130	130	130	130
Adj. R-Squared	0.98	0.29	0.49	0.56	0.47

Table A8

Analysis of the Legal Profession

This table reports the analysis of the legal profession. The median age of LSAT test takers is 23 (i.e., about one year after they receive their undergraduate degree), and we study the impact of the popularity of Law & Order 4 to 8 years before students take LSAT. Log Test Takers, Log Number of Applicants, and Log Number of Applications are the log number of LSAT takers, number of law school applicants, and number of law school applications, respectively. Log Number of Graduates is the log number of JD graduates. Log Average Wage and Net New Hires are the log employment-weighted average wage and the log net new hires of entry-level lawyers, respectively. Average Wage and Net New Hires are adjusted by the corresponding numbers of adjusted by the corresponding numbers of other professional occupations. The independent variables are Log Viewers, the log average number of viewers of Law & Order, measured in year t-8 to t-4; and Log Average Wage, the 3-year average median starting salary of lawyers in large law firms (up to 1998) or the employment-weighted average lawyer salary from BLS (1999 and onward) measured at year t-4. In columns (1) to (4), a linear time trend is also controlled for.

*, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables are standardized with zero mean and unit standard deviation. Law & Order viewership data are available between 1990 and 2010.

	Detrended Log Test Takers in Year t	Detrended Log Number of Applicants in Year t	Detrended Log Number of Applications in Year t	Detrended Log Number of Graduates in Year t+3	Log Adjusted Average Wage in Year t+3	Adjusted Net New Hires in Year t+3
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Log Viewers	0.0449*	0.1240**	0.2620***	0.0516***	-0.0353***	-0.0253
	(0.0229)	(0.0548)	(0.0710)	(0.0146)	(0.0106)	(0.0383)
Lagged Log Average Wage	0.1137***	0.0928***	0.1023***	0.0438***	-0.0052	0.0319
	(0.0235)	(0.0249)	(0.0322)	(0.0117)	(0.0106)	(0.0274)
# Observations	23	16	16	20	18	17
Adj. R-Squared	0.62	0.70	0.70	0.63	0.32	0.02