The Effect of Superstar Firms on College Major Choice*

Darwin Choi
Chinese University of Hong Kong
dchoi@cuhk.edu.hk

Dong Lou
London School of Economics and CEPR
d.lou@lse.ac.uk

Abhiroop Mukherjee
Hong Kong University of Science and Technology
amukherjee@ust.hk

First Draft: November 2016
This Draft: December 2018

*We thank Ashwini Agrawal, Li An, Josh Angrist, Nick Barberis, Pedro Bordalo, James Choi, Xavier Gabaix, Robin Greenwood, David Hirshleifer, Daniel Ferreira, Nicola Gennaioli, Caroline Hoxby, Dirk Jenter, Theresa Kuchler, Daniel Metzger, Per Ostberg, Steve Pischke, Christopher Polk, Wenlan Qian, Antoinette Schoar, Kelly Shue, David Solomon, Johannes Stroebel, Constantine Yannelis, and seminar participants at Australian National University, CEMFI Madrid, Chinese University of Hong Kong, Durham Business School, Hong Kong Polytechnic University, Hong Kong University of Science and Technology, KAIST, London School of Economics, Loughborough Business School, New York University, Toulouse School of Economics, Tsinghua University, University of Hong Kong, University of Oxford, University of Toronto, Yale University, 2017 Adam Smith Finance Conference, 2017 European Finance Association Annual Meeting, 2017 Stanford Institute for Theoretical Economics (SITE) Labor and Finance, 2017 Labor and Finance Group Meeting, 2018 American Economic Association Annual Meeting, 2018 CEPR Spring Symposium in Financial Economics, and 2018 NBER Summer Institute Education/Labor Studies for helpful comments and suggestions. We are grateful for funding from the Paul Woolley Center at the London School of Economics.

The Effect of Superstar Firms on College Major Choice

Abstract

We study the effect of superstar firms on college students' major choice. The occurrence of superstar performers in an industry is followed by a significant rise in the number of college students choosing to major in related fields, after controlling for lagged industry returns and wages. The tendency to follow superstars, however, results in a temporary over-supply of human capital, as evidenced by the *lower* real wage earned by entry-level employees when students enter the job market. Further evidence from the National Survey of College Graduates shows that this adverse impact on career outcomes can last for decades.

JEL Classification: I21, I26, D81, D91

Keywords: College Major Choice, Human Capital Investment, Superstars, Salience, Skewness

1 Introduction

From Carnegie Steel to JP Morgan, from Microsoft to Tesla, economists have long been interested in the role of superstar firms and entrepreneurs in driving economic growth (Schumpeter, 1942). On the one hand, technological breakthroughs creating these superstar firms can lead to increases in productivity. Another possibility is that superstar firms gain monopolistic power in their respective industries, which then impedes competition and lowers future growth. Curiously, there has been little research on how the occurrences of superstar firms may affect individuals' education choice, despite the crucial role of education in determining individual well-being and economic growth. This paper empirically assesses the impact of superstar firms on the distribution of college major enrollment in the past five decades, and evaluates labor-demand-based vs. supply-based explanations for these findings.

There is plenty of anecdotal evidence that suggests a causal link between superstar firms and college major choice. For example, as reported by Stanford Daily, the number of Stanford undergraduate students who declared a Computer Science major in 2013 was nearly four times that in 2006, potentially attributable to the high-profile, extreme successes of a handful of mobile app and social media companies (a prominent example of which is Facebook). A *New York Times* article on June 15, 2011 indeed argues that "students are flocking to computer science because they dream of being the next Mark Zuckerberg." The objective of this paper is to bring data to bear on the claim that college students' attention is drawn to—and their expectations and decisions shaped by—the occurrences of superstar firms in related industries.

Intuitively, superstar firms can impact college students' major choice, and consequently labor supply in related industries, through two reinforcing channels. First, superstar firms and entrepreneurs attract disproportionate media coverage and social attention. For example, the story of Mark Zuckerberg, who dropped out of Harvard to work full-time on his Facebook project and became a self-made billionaire, has been a constant talking point both in the popular press and on college campuses. Given the substantial costs faced by college students in forming income expectations about different industries (e.g., Stigler, 1961; 1962), superstar firms are likely to play a disproportionately large role in shaping their expectations.

Second, occurrences of superstar firms often involve extreme payoffs. Mark Zuckerberg has been consistently named one of the world's wealthiest individuals since Facebook went public. A long-standing literature in labor economics, dating back to at least Rosen (1997), argues that individuals have a preference for skewed payoffs, possibly due to complementarities between taste and income.[1] As extreme payoffs and event salience often go hand-in-hand,

[1] The idea is that once income reaches some threshold, an individual's consumption bundle shifts, leading

these two channels—a) income expectations based on a small number of non-representative but highly visible observations and b) individuals' preferences for extreme payoffs—are likely to reinforce each other.

To operationalize our empirical analyses of whether and how superstar firms affect college major choice, we take the following steps. First, we measure the occurrence of superstar firms (as well as super-losers) in each industry by the *cross-sectional* return skewness in that industry. In our baseline results, we use employment-weighted skewness to give more weight to more important firms in the industry.[2] Positive cross-sectional skewness indicates that, holding the industry's average return and return volatility constant, a small number of firms in the industry have performed exceptionally well; these salient examples of extreme successes may draw college students to related majors. Negative cross-sectional skewness, on the other hand, indicates that a small number of firms in the industry have done exceptionally poorly, which is likely to drive students away from related fields. Undoubtedly, the occurrence of superstar firms (as well as its proxy, stock return skewness) could reflect changes in industry prospects and/or organization, and thus relate to labor demand. In our empirical test, we let the data inform us about the relative importance of shifts in labor demand vs. shifts in labor supply in explaining our results.

Second, we focus solely on the set of science and engineering majors (e.g., computer science vs. chemical engineering) that can be mapped relatively cleanly to one or more industry sectors (e.g., information technology vs. pharmaceutical). Third, since college students usually declare their majors by the end of their sophomore year, we focus on industry return skewness measured in calendar years $t-7$ to $t-3$ prior to the graduation year (i.e., from their junior year in high school to sophomore year in college) to explain major enrollment in year t.[3]

Our empirical analysis reveals a strong positive relation between the occurrence of superstar firms and enrollment in related college majors. Using college enrollment data compiled by the Integrated Postsecondary Education Data System (IPEDS), we find that a one-standard-deviation increase in within-industry (cross-sectional) return skewness in years $t-7$ to $t-3$ is associated with a 10.1% (t-statistic = 5.34) increase in the number of gradu-

to an increase in marginal utility, and thus a preference for positively skewed payoffs. In unreported tests, we show that cross-sectional stock return skewness is only weakly related to future return skewness, and insignificantly forecasts future wage skewness in the same industry.

[2]Employment-weighted skewness assigns a weight that is proportional to employment size to each firm in calculating the skewness of the distribution. We do this for two reasons. First, more important firms are more visible and should carry a higher weight. Second, other variables in our analyses, including average industry wage, average industry return and return volatility, are also weighted by the size of employment. Our results are also robust to using firm-size-weighted skewness.

[3]Our results are also robust to other return windows, e.g., $t-8$ to $t-3$ and $t-6$ to $t-3$.

ates in related subjects in year t. This result is robust to controlling for the average industry return and return volatility measured over the same period, as well as the lagged average wage and time and major fixed effects. Also, this result is stronger among elite private universities in states where the superstars' industry has a substantial presence, potentially because students from top universities are more likely to associate themselves with extreme successes.

The positive association between college major enrollment and industry return skewness can be consistent with both a labor-demand-based and a supply-based explanation. Put differently, students may be attracted by superstar performers because a) they rationally anticipate better job opportunities in related industries, or b) they are drawn by salient extreme observations that are in fact uninformative about job prospects. To empirically evaluate the relative importance of the two channels, we examine simultaneously the wage and number of employees in related industries when students enter the job market. By examining the *price-quantity* pair in the labor market, we can compare shifts in the labor-supply curve relative to shifts in the demand curve. The granularity of industry employment data from Bureau of Labor Statistics (BLS) allows us to focus squarely on the wage and total employment of entry-level employees with a college degree.

Our results indicate a relatively larger shift in labor supply than in labor demand with the occurrence of superstar firms. After controlling for year and industry fixed effects, a one-standard-deviation increase in industry return skewness in years $t-7$ to $t-3$ is associated with a 1.1% (t-statistic = 2.57) *drop* in the real wage earned by entry-level employees in related industries in year t.[4] To put this number in perspective, a one-standard-deviation increase in the industry average return is associated with a 0.6% (t-statistic = 2.86) increase in wages. Moreover, the effect of industry return skewness on the average entry-level wage declines with the "versatility" of the major, defined as the diversity of employment opportunities for graduates from that major in various industries. This could be because an increase in student supply is shared among many similar industries, leading to a smaller wage decline in each of them. Meanwhile, the effect of industry return skewness on the number of entry-level employees in year t is indistinguishable from zero. This is consistent with the view that labor demand is relatively inelastic in the short run; a sudden increase in labor supply thus lowers the average wage earned by entry-level employees without affecting the size of employment.

To understand the *long-term* impact of college students' major choice on their career

[4]Our empirical design is to compare the average market-adjusted entry-level wage of the same major across *different* cohorts. An alternative design would be to compare a student with his counterfactual-self had he chosen a different major. We choose not to go down this alternative route as individual major choice crucially depends on *unobservable* personal ability and interest. This is less of a concern at the cohort level—so long as the average ability and interest in each cohort does not vary systematically over time.

outcomes, we draw on survey evidence from the National Survey of College Graduates, available since 1993. The average respondent in this sample is 44 years old, roughly 20 years out of college. Our analysis reveals that after controlling for age, survey-year, and industry fixed effects, a one-standard-deviation increase in industry return skewness 3 to 7 years before graduation is associated with an 88bps (t-statistic = 3.03) lower real wage earned by the respondent at the time of the survey; it is also associated with a 4% (t-statistic = 2.86) higher likelihood, relative to the unconditional probability, that the respondent no longer works in industries related to his college major. These results suggest that an outward shift in labor supply without a similar outward shift in labor demand can have a long-lasting adverse impact on individuals' career outcomes.

We provide additional, potentially causal, evidence for the supply side of human capital investment by linking industry popularity/salience to student major choice. To start, we exploit structural breaks in industry valuation during the NASDAQ bubble period to identify superstar industries and their impact on college students. Our analysis follows closely the recent work of Charles, Hurst, and Notowidigdo (2018), who argue that sharp increases in local housing prices in the early 2000s are the result of speculative activity and are unlikely to be caused by abrupt changes in local economic conditions. Following a similar logic, we exploit the exact timing and magnitude of structural breaks in industry valuation in the 1990s to identify abrupt changes in the popularity of the industry. In an "event-study" centered around the time of the structural break in industry valuation, we find that a one-standard-deviation increase in the magnitude of the structural break is associated with a 12% (t-statistic = 3.12) increase in the number of graduates in related major fields; in the post-bubble period, however, the same variable forecasts a 6.4% (t-statistic = 2.17) decline in the number of graduates.

Second, we provide perhaps the cleanest evidence for the supply side of college major choice by zooming in on just one profession. Specifically, we use time variation in the viewership of one of the longest-running US TV series, *Law & Order*, to gauge the variation in popularity of the legal profession; we further tie it to the number of students applying to and enrolled in law schools, as well as the subsequent wages earned by entry-level lawyers. Our results reveal that a one-standard-deviation increase in the viewership of *Law & Order* in years $t-7$ to $t-3$ forecasts an 7.5% increase (t-statistic = 2.42) in the number of students taking the LSAT in year t and a 4.6% increase (t-statistic = 2.67) in the number of law school graduates in year $t+3$.[5] Most importantly, the rise in popularity of *Law & Order* in years $t-7$ to $t-3$ is associated with a 2.6% (t-statistic = 2.25) drop in real wages of entry-level lawyers in year $t+3$, when students graduate. Taken together, all our results suggest that

[5] Despite the increase in total enrollment, the law school admission rate in year t decreases.

individuals' education choice is importantly driven by salient, extreme events that are not informative about future job prospects.

An important premise in our empirical design is that cross-sectional return skewness of an industry reflects/captures the occurrences of superstar firms (as well as super-losers) in that industry. We corroborate this assumption by correlating industry return skewness with a more direct measure of extreme events—skewness in media coverage and tones. To this end, we obtain news sentiment data from RavenPack (available after 2000) and calculate a *news-tone* score for each firm in every year. News skewness of an industry is then defined as the cross-sectional skewness of news-tone across all firms in the industry. Intuitively, a positive (negative) news skewness measure indicates that, all else equal, a few firms in the industry have received a disproportionate amount of positive (negative) media coverage. Not surprisingly, the news skewness measure is strongly and positively correlated with contemporaneous stock return skewness. Moreover, when we repeat our analysis to forecast future college major enrollment, we find that a one-standard-deviation increase in news skewness in years $t-7$ to $t-3$ is associated with a 6.83% (t-statistic = 3.61) increase in the number of graduates in related majors in year t. This news-based skewness measure also negatively forecasts future industry wages; yet, it has no significant predictive power for the number of entry-level employees in related industries.

The remainder of the paper is organized as follows. Section 2 provides a background and literature review. Section 3 describes the data we use. Section 4 reports the main results of our empirical analyses. Section 5 provides additional evidence for the labor-supply-based interpretation of our results. Section 6 reports additional tests and robustness checks. Finally, Section 7 concludes.

2 Background and Literature Review

Fluctuations in the labor market and their relation to prevailing economic conditions have been a focal point of academic discussions since at least the post-War era (e.g., see Blank and Stigler, 1957; or Arrow and Capron, 1959 on the labor market for engineers). The shortage of engineers in the late 1950s and early 1960s was followed by a surplus in the late 1960s and early 1970s, and again a shortage in the latter half of the 1970s. This motivated Freeman (1971) to apply cobweb theory to labor demand and supply decisions in the market for new graduates. Freeman (1975, 1976) then assesses the predictions of cobweb theory in the market for new engineers and lawyers. Cobweb theory exploits the time delay between the decision to enroll in a major and the subsequent entrance into the labor market. Under this view, a lower salary in major M in year t attracts fewer freshmen and, ultimately, produces fewer graduates—but this change in supply manifests itself in the labor market four years later. Consequently, starting wages in year $t+4$ become higher, affecting in turn, major choice of the freshman cohort of that year, hence producing endogenous cycles in both enrollment and wages. While our paper also a) acknowledges the time lag between major choice and graduation and b) builds on the premise that students form expectations based on stale information, our focus is different: we are interested in the effect of superstar firms in an industry on the distribution of major enrollment, controlling for lagged wages.

We also contribute to the vast literature on students' education choice and on career outcomes (Hoxby, 2003 provides a comprehensive review).[6] Most prior studies on college major choice use a rational expectations framework in which students form expectations of future earnings using statistical modeling and Bayesian updating. Berger (1988) is an early example of this. Subsequent research complements this approach (e.g., Altonji, 1993) by incorporating uncertainties (e.g., uncertainties about ability, preference and academic progress) to the baseline model. Our paper contributes to and deviates from this literature by examining the role of salient extreme events—occurrences of superstar firms—in determining college students' earnings expectations, and consequently, their major choice. More broadly, our results speak to the literature on human capital investment. Given the near irreversibility of human capital investment at the college level, our results suggest that salient extreme events have a large, permanent impact on students' lifetime income.

Our paper further provides evidence for a growing theoretical literature on the impact of salience on human decision making. A series of recent papers have emphasized the idea that people do not consider all available information, and instead over-emphasize information that their minds focus on (Gennaioli and Shleifer, 2010; and Bordalo, Gennaioli, and Shleifer, 2012). The core idea of salience has been used to explain decisions in the context of consumer choice (Bordalo, Gennaioli, and Shleifer, 2013a), asset prices (Bordalo, Gennaioli, and Shleifer, 2013b), judicial decisions (Bordalo, Gennaioli, and Shleifer, 2013c), and tax effects (Chetty, Looney, and Kroft, 2009). In neuro-economics, Fehr and Rangel (2011) show that subjects evaluate choices by aggregating information about different attributes, with decision weights influenced by attention. While none of these papers have examined the role played by salience on education choice, like we do here, it is perhaps a natural application—given the complexity of the search process for information on future job prospects (e.g., Stigler, 1961; 1962).

[6] See also James, Alsalam, Conaty, and To (1989), Altonji (1993), Sacerdote (2001), Avery and Hoxby (2004), Hoxby (2004), Bhattacharya (2005), Dickson (2010), Blom (2012), Goldin (2014), Lemieux (2014), Stinebrickner and Stinebrickner (2014), Zafar (2014), Bordon and Fu (2015), Altonji, Arcidiacono, and Maurel (2015), Arcidiacono, Hotz, and Kang (2015), Fricke, Grogger, and Steinmayr (2015), Wiswall and Zafar (2015), among others.

Finally, our result that the occurrences of superstar firms in an industry forecast worse job outcomes for graduates from related major fields can be consistent with both preference- and belief-based explanations. On the preference side, Rosen (1997) presents a model of preferences for skewness based on state-dependent utility. In our context, students with a preference for skewed payoffs may be willing to accept a lower average wage for a small chance of having significantly better job opportunities.[7] A different explanation for this pattern is that it reflects students' mistaken beliefs: students who do not have the capacity or resources to go through detailed industry employment records might base their income expectations on just a few salient, non-representative observations. Theory and evidence on such mistaken beliefs leading to oversupply can be found as far back as in Kaldor (1934), or more recently, in Greenwood and Hanson (2015), although in contexts very different from ours.

3 Data

Our data on college enrollment are obtained from the Integrated Postsecondary Education Data System (IPEDS) and the National Science Foundation (NSF). NSF uses IPEDS Completions Surveys conducted by the National Center for Education Statistics (NCES) and reports the annual number of bachelor's and master's degrees in science and engineering fields. A list of the fields is presented in Online Appendix Table A1. These degrees were conferred between 1966 and 2015 by accredited institutions of higher education in the U.S., which includes the 50 states and the District of Columbia. Starting in 1987, IPEDS also provides the annual number of graduates from each institution.

We map a subset of the science and engineering degrees to 3-digit NAICS industry codes, as shown in online Appendix Table A2. This is modified from the merge of two maps: the 2010 Classification of Instructional Programs (CIP) to the 2010 Standard Occupational Classification (SOC) Crosswalk and the 2010 SOC to the 2012 NAICS map. Each industry code can be mapped to several degree fields. For example, Petroleum and Coal Products Manufacturing (NAICS = 324) is associated with degrees in Chemical Engineering, Industrial and Manufacturing Engineering, Materials Science, and Mechanical Engineering. Each degree field can also correspond to different industries: e.g., A degree in Health is linked to Ambulatory Health Care Services (NAICS = 621), Hospitals (NAICS = 622), Nursing and Residential Care Facilities (NAICS = 623), and Social Assistance (NAICS = 624).

[7] A preference for skewness is also a central theme in the non-standard utility literature, e.g., prospect theory (Kahneman and Tversky, 1979). Most prominent applications of this theory, however, have been in finance (e.g., Barberis and Huang, 2008; Conrad, Dittmar, and Ghysels, 2013; Barberis, Mukherjee, and Wang, 2016).

Aggregate wage and employment data between 1997 and 2016 are available from the Bureau of Labor Statistics (BLS) through the Occupational Employment Statistics (OES) program. Wage is defined as straight-time, gross pay, exclusive of premium pay. Wage and employment data are reported at the SOC code level in each industry. BLS provides projections of the job requirement (degrees and approximate number of years of experience required) of many SOC codes. We make use of the CIP-SOC Crosswalk and the BLS projections to define entry-level jobs for graduates of each major. These are jobs that are suitable for students of a particular major and that require a bachelor's degree but does not require prior work experience. We also use the National Survey of College Graduates sponsored by the NSF and conducted by the Census Bureau. From the survey, we can obtain information about survey respondents' graduation year, major, demographics, total earnings, and employment.[8]

Our news sentiment data are from RavenPack News Analytics, which quantifies positive and negative perceptions of news reports. We focus on the Composite Sentiment Score (CSS) constructed by RavenPack. CSS is calculated based on the number of positive and negative words in news articles, earnings evaluations, short commentary and editorials, mergers and acquisitions, and corporate action announcements. It ranges between 0 and 100 and typically hovers between 40 and 60, where 50 represents neutral sentiment, and is available between 2000 and 2015.

We get the data on IPOs in 1975–2008 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 in CRSP is between 400 and 490, or equal to 572 or 574. The sample period of delisting and default data is 1985–2015.

We present summary statistics for our variables of interest in Table 1. Panel A presents the median, standard deviation, and percentiles for our variables, while Panel B shows their pairwise Pearson correlations. The median number of bachelors in each major is 8,083 students per year, with males contributing approximately 80% of that number. We define industries at the 3-digit NAICS level. On average, our industry returns are positively skewed in the cross-section, with a median annual skewness of 0.7 to 0.8. The median cross-sectional skewness in news tone is 1.2. The employment-weighted average entry-level wage for workers with a bachelor's degree in science and engineering shows a median of $58,000 (in 1997

[8]The survey is conducted every two years since the 1970s. Data are available online beginning 1993. We require information on respondents' majors, which is publicly available in the years 1993, 2003, 2010, 2012, and 2015.

dollars). Note that we do not have data specifically on the first year of employment; the wage and employment figures include seasoned workers who are still in these entry-level positions and are not promoted. The median annual change in the log number of employees in these positions is 0.02, and the median change in the number of employees is 3,620. From Panel B, we can see that our proxies for the existence of superstar firms are positively correlated with one another. The measures of super-loser firms—Default Rate and Default and Delisted Rate—are usually negatively correlated with the superstar measures. These correlations are mostly significant at the 1% level.

4 Main Results

This section presents the main results of our paper. We start by examining the relation between the occurrence of superstar firms in an industry and the subsequent number of students choosing related major fields.

4.1 Number of Graduates in Different Majors

Our main hypothesis is that while deciding upon a major, students get disproportionately attracted to industries where a small number of superstars have been performing exceptionally well. For example, when Apple is "hot" in the headlines—maybe due to a series of successful releases of new iPhones—there is a general increase in excitement, drawing more and more students to the Computer Science major. More generally, given the difficulty in gathering and analyzing data on the actual distribution of work opportunities in different industries, students' expectations about these opportunities—and hence, major choices—are disproportionately influenced by these salient, easy-to-recall events.

To analyze the effect of occurrences of superstar performers (proxied by cross-sectional returns skewness) on major choice decisions, we estimate the following regression equation:

$$log(bachelor_{i,t}) = \alpha + \beta Skew_{i,t-3 \text{ to } t-7} + \gamma \mathbf{X}_{i,t-3} + \mu_i + \tau_t + \epsilon_{i,t}, \tag{1}$$

where $bachelor_{i,t}$ is the number of graduates in major category i in year t (t refers to the calendar year of graduation, all other time variables are expressed with respect to this; i.e., $t-k$ refers to k years before graduation). $Skew_{i,t-3 \text{ to } t-7}$ is our measure of salient, attention-grabbing events affecting firms in industries associated with that major category.[9] $\mathbf{X}_{i,t-3}$ is

[9]Each major category is associated with multiple industries. We first calculate the cross-sectional return skewness for each industry, and then take the equal-weighted average skewness across all industries. This is assuming students follow each industry equally. We repeat this for all industry-level variables. Our results

a vector of controls, and μ_i and τ_t are major and time (year) fixed effects, respectively. Our vector of controls includes the average return of firms in related industries between $t-7$ and $t-3$, a measure of volatility of firm performance, average industry wage, average firm age and size, and average industry valuation ratio (book-to-market, B/M). The inclusion of major fixed effects ensures that our identification of the coefficient of interest, β, comes from changes in the number of graduates, not its level. Inclusion of time fixed effects purges out any market-wide events from our estimate.

Two aspects of our test design are noteworthy. First, our skewness measures are sufficiently lagged to reflect that extreme salient events can only affect major choice if they occur *before the major is decided*, which for most students is, at the latest, their sophomore year in college. Second, as mentioned before, many of our majors can be stepping stones to careers in multiple industries and choosing to matriculate in a particular major does not necessarily limit the student to work in the industry most closely related to it. For example, Computer Science graduates can also work as librarians. All we assume for our analysis is that *at the time* the student chose to major in Computer Science, he was much more interested in a career in the Computing or Tech industry than he was interested in librarianship.

If our hypothesis—that college students' major choice is influenced by superstar firms—is indeed true in the data, we expect to see that various measures of industry skewness positively predict the number of graduates in related major fields in the future. That is, the coefficient on the *Skew* measure in the major choice regression, β, should be positive. We present these results in Table 2 Panel A.

In Columns 1 and 2, we measure salient events driving excitement about an industry based on the employment- or size-weighted annual skewness of stock returns for firms in that industry, averaged over years $t-7$ to $t-3$ ($Skew_{i,t-3 \text{ to } t-7}$, referred to as *Skew* in the following), where t is the cohort graduation year. In Column 1 each firm is weighted in proportion to its size (market capitalization), and in Column 2 the weights are proportional to employment (both weights reflect that larger firms are more important and visible). As can be seen from the table, *Skew* predicts major choice strongly, even after controlling for the average return in the industry and its cross-sectional dispersion. For example, a one-standard-deviation increase in employment-weighted *Skew* is associated with an increase in the number of students majoring in related fields by 10.1% (all explanatory variables are standardized for ease of comparison). This coefficient is statistically significant at the 1% level (t-statistic = 5.34). In comparison, a one-standard-deviation increase in the mean return to firms in that industry is associated with an increase in major popularity by 10.3% (t-statistic = 2.55); while a one-standard-deviation change in industry growth opportunities

are robust if we use weights based on industry total market capitalization or total employment instead.

(measured as the log of the industry-average B/M ratio following the literature) is associated with an increase in major popularity by 13% (t-statistic = 2.49). So, our measure of salient events at related industries seems to have similar predictive power for major choice decisions as other well-known determinants. In Columns 3 and 4 of the same table, we change our measure of return skewness to the average of monthly and quarterly cross-sectional (employment-weighted) return skewness within industry in years $t-7$ to $t-3$, and continue to find similar results.

Finally, in Column 5 we examine whether the relationship we document is distinct from the cycles of enrollment, employment and wages in Cobweb models. Recall that in Cobweb theory, college students decide majors by looking at wages when they make this choice (e.g., in years $t-5$ to $t-3$), which is well before when they actually start working (in year t). In order to understand whether our results are distinct from this channel, we directly control for real wages of graduates of that major in years $t-5$ to $t-3$. As our results show, the past average wage is indeed positively related to major choice. But, importantly, our skewness measure continues to predict major choice, even after controlling for the past average wage.

In Panel B of Table 2, we examine school-level data from four-year universities. We focus on 298 schools that offer at least 6 out of our 11 majors and study whether the effect of superstar firms is stronger at top schools, and especially those located in states with significant presence of related industries (e.g., California for Tech jobs). In Column 1, we add an interaction term for private schools that are within top 100 in the *US News 2018 Best Colleges* list, in Column 2 we include an interaction term for schools located in the state that hires the most people in industries related to the particular major, and in Column 3 we combine the two: that is, look at the differential effect at top private schools located in the state that hires the most people in related industries. As our results in Column 3 show, our effect is particularly strong in the last case; in other words, top school students are especially drawn by local superstar performers. This is in line with the media narrative that the best students in California—who might believe that they have the talent to become the next Zuckerberg—are especially attracted to these superstar-related majors.

4.2 Effects on Entry-Level Wages and Employment

The fact that students are drawn to industries with superstar performers can be consistent with both labor-demand-based and supply-based interpretations; that is, students are attracted to these majors either because a) they rationally anticipate improving job prospects in related industries, or b) they are simply drawn by extreme, salient events that are in fact uninformative about future job opportunities. To examine the relative importance of labor demand vs. supply channels, we simultaneously examine two quantities—wages (inflation-adjusted) and employment. By examining the price-quantity pair, we can disentangle the relative shifts in the labor supply vs. demand curves.

In particular, we focus on entry-level employment and wages for jobs that requires a bachelor's degree but no work experience. That is, we examine what happens to work opportunities at the time of graduation of our year t cohort in majors where a few related firms have performed exceptionally well, thus resulting in a significantly larger number of college graduates. Here, we estimate the following regression equation:

$$log(annual\_wage_{i,t}) = \alpha + \beta Skew_{i,t-3 \text{ to } t-7} + \gamma \mathbf{X}_{i,t-1} + \mu_i + \tau_t + \epsilon_{i,t}, \quad (2)$$

where $annual\_wage_{i,t}$ is the employment-weighted average annual wage for students in major i in year t, using a map between majors and occupation codes which typically employ students from that major. $Skew_{i,t-3 \text{ to } t-7}$ is our measure of salient, attention-grabbing events affecting firms in industries related to major i. We include the same set of controls as in Table 2, and further add to this list (the log of) the average number of bachelors graduating in related majors in years $t-1$ to $t-2$ to account for the effect of delayed absorption of previous years' graduates in that industry.

We also control for major and time fixed effects in our regressions, so one way of thinking about our empirical design is that we compare the average market-adjusted entry-level wage of the same major across different cohorts, depending on lagged industry return skewness. An alternative design would be to compare a student with his counterfactual-self had he chosen a different major. We do not go down this alternative route as individual major choice crucially depends on unobservable personal characteristics and interests. This is less of a concern at the cohort level—as long as the average ability and interest in each cohort does not vary systematically over time.

Table 3 reports results on wages and employment. In Column 1, we examine entry-level wages as a function of lagged industry skewness. There is some evidence of rationality in college major choice: a larger number of students choosing to major in related fields indeed is associated with higher wages at graduation, as indicated by the positive coefficient on $log(Number\_of\_Bachelors)$. Moreover, major fields whose related industries have had higher returns in years $t-7$ to $t-3$ indeed have higher wages at time t, as evidenced from the positive coefficient on $Mean\_Return$, so it is sensible to base major choice on lagged industry returns (as we see students doing in Table 2). Controlling for these two covariates, $Skew$ is significantly and negatively associated with future entry-level wages across all specifications. In terms of economic magnitude, a one-standard-deviation increase in lagged industry skewness is associated with a 1.08% (t-statistic = 2.57) lower real wage for entry-level jobs requiring a bachelor's degree.

In Column 2, we examine net new hires—i.e., year-on-year changes in the number of employees in entry-level jobs related to the major—as a function of lagged industry skewness. We use the *change* in the number of employees, rather than its level, to make our measure consistent with the major choice regressions in Table 2, where we also use the "flow" of new graduates as the dependent variable (rather than the "stock" of every working-age individual who graduated in that field). Given that our dependent variable is already defined in changes, we do not include major-fixed effects. As can be seen from Column 2, there is no significant relation between $Skew$ and future new hires. This suggests that even though salient events drive more students to major in related fields, entry-level job positions do not immediately expand to absorb these extra graduates, consistent with labor demand being inelastic in the short-run.

In Columns 3 and 4, we entertain the notion that the fungibility of employment opportunities varies across majors. Specifically, we argue that if graduates from a particular major have employment opportunities in a variety of industries, then part of the excess labor supply due to the presence of superstar firms can be absorbed more easily across these different industries, thus leading to less downward pressure on wages. We test this hypothesis using an interaction term between $Skew$ and $Versatility$, defined as the diversity of employment for graduates from a particular major. Column 3 reveals that industry skewness negatively affects real wages mostly for majors that have concentrated job opportunities in a small number of industries. Again, we do not find statistically significant differences in entry-level employment in Column 4.

Finally, in Columns 5 and 6, we examine whether our results on wages and employment are also distinct from predictions of a Cobweb model by incorporating lagged average wages in our regression. $Skew$ continues to predict wages negatively, controlling for past wages, and continues to be statistically unrelated to net new hires.

Overall, evidence presented in Table 3 indicates that the presence of salient superstar performers forecasts lower future wages but does not lead to additional entry-level jobs. Put differently, students' decision to follow superstars in their major choice does not seem to benefit them; if anything, it costs them in terms of starting out with a lower entry-level salary.

4.3 A Placebo Test

Up until this point, 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 placebo test by measuring *Skew* in years $t-2$ and $t-1$, i.e., the two calendar years right before graduation, but after major declaration. If within-industry skewness indeed captures time-varying industry prospects, and students base their major choice on rational expectations of future job opportunities, we expect *Skew* measured closer to the graduation year to have stronger predictive power for the year t major enrollment.

The results of the placebo test are shown in Table 4. Panel A examines the relation between industry skewness measured in different windows and future major enrollment. When included in the regression alone (Column 1), *Skew* measured in the last two years of college does not predict major choice. In a horse race between the two skewness measures (Column 2), the coefficient on *Skew* measured in years $t-2$ to $t-1$ is marginally significant, but its economic magnitude is much smaller compared to the coefficient on *Skew* measured in years $t-7$ to $t-3$ (4.5% vs. 10.6%). One reason that $Skew_{t-2 \text{ to } t-1}$ marginally predicts the number of graduates at time t could be that students working toward other—possibly related—majors, are attracted by these superstar firms and switch their majors in the last two years of college.

Panel B then examines industry wages and new hires. Similar to what we see in Panel A, *Skew* in the last two years of college is unrelated to entry-level wages upon graduation, while *Skew* measured in years $t-7$ to $t-3$ remains significantly negative in forecasting future wages. Both skewness measures are uncorrelated with the number of new hires. Taken together, the placebo test lends further support to our hypothesis that students are drawn to "hot" majors by extreme, salient events in related industries—rather than because they rationally anticipate better job opportunities.

4.4 Long-Term Effects

One possible concern thus far is that although results from immediate work opportunities do not seem to indicate students' response to superstars is demand-driven, industry prospects may improve in the longer term. Another concern is that our wage measure in the previous section does not adequately capture total earnings (which should also include bonuses and stock options). A third concern is that while we show some results consistent with employment not expanding in the short-term to keep pace with increased labor supply, we have not provided direct evidence as to how the extra supply is eventually absorbed by the labor market, possibly by other sectors not directly related to the chosen major. We explore all these issues by examining long-term survey data from the *National Survey of College Graduates* (NSCG).

Two-thirds of the NSCG respondents are male, and nearly three quarters are married. Respondents also report their total earnings, which include compensation other than salary. The average age of the respondents at the time of the survey is 44 years, so roughly 20 years out of college; thus the survey provides useful information on long-term outcomes. Another advantage of the survey is that it contains information on whether the graduate works in a sector which he/she considers typically unrelated to his/her field of study ($Job\_Outside\_Main\_Field\_of\_Study$). If there is indeed an excess supply of graduates looking for jobs in sectors with superstars, and these sectors do not expand employment to keep pace with labor supply, as we see in Tables 2 to 4, we should expect to see a positive correlation between $Skew$ and the propensity to work in a job outside the field of study.

The results are shown in Table 5. The first two columns report results from panel regressions with $\log(Total\_Earnings)$ as the dependent variable, while the last two columns report results from Logistic regressions with a categorical dependent variable indicating whether the graduate now works outside her field of study. Our results reveal that one-standard-deviation higher $Skew$ is associated with 0.57% to 0.88% lower earnings and 4% higher propensity to work in a job outside the field of study. This is consistent with an expanding literature on long-term effects of adverse initial labor market conditions on the lifetime earnings of college graduates (see, for example, Oyer, 2006, 2008; Oreopolous et al, 2012).

Overall, our results suggest a relatively larger shift in labor-supply in response to salient superstar performers in some sectors of the economy. In the short run, labor demand is relatively inelastic, as it takes times for firms to increase capacity; so this sudden increase in labor supply lowers the average wage earned by entry-level employees, without affecting the size of entry-level employment. This adverse effect on earnings lasts for years/decades: graduates continue to earn lower income and have a higher likelihood of having to take up jobs in sectors unrelated to their fields of study.

5 More Evidence on Labor Demand vs. Supply

Our evidence in the previous section on the joint dynamics of quantity (the number of graduates/new hires) and prices (wages) indicate a relatively larger shift in the labor supply rather than in the labor demand curve in response to 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 by extreme, salient events. In this section, we provide more tests to shed further light on this issue.

5.1 Structural Breaks in Industry Valuation

While the focus of the paper is on superstar firms within an industry, in this and the next sections, we provide additional causal evidence for the supply side of human capital investment by linking time variation in the relative popularity/salience of different industries to student major choice. To start, we exploit structural breaks in industry valuation during the NASDAQ bubble in the late 1990s to more cleanly identify superstar industries and their impact on college major choice. 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 abrupt 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 sharp 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:

$$R_{i,t} = \alpha_i + \tau_i t + \lambda_i (t - t_i^*) \mathbb{1}(t > t_i^*) + \epsilon_{i,t}, \tag{3}$$

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:

$$log(bachelor_{i,t}) = \alpha + \beta Post_{i,t} \times \lambda_i + \gamma \mathbf{X}_{i,t-3} + \mu_i + \tau_t + \epsilon_{i,t}, \tag{4}$$

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.

Table 6 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 (0.71, t-statistic = 6.73). Interestingly, Health-, and Earth and Ocean Science-related industries experience negative structural breaks, 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 structure 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 12% (t-statistic = 3.12) 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.

Panel C repeats the same exercise in the post-bubble period—from 2005 to 2010 (starting from a few years after the market peak). If the structural breaks indeed are the result of speculative demand, we expect a larger λ_i to be followed by a larger decline in student enrollment after the bubble burst, reverting to the normal level. Consistent with this prediction, as shown in Column 1 of Panel C, a one-standard-deviation increase in the magnitude of the structural break in the 1990s forecasts a 6.4% (t-statistic = 2.17) decline in the number of graduates in the post-2005 period relative to the boom period. In Column 2, we show that the difference in the number of college graduates from related fields between the post-bubble period and normal pre-bubble period (pre-1990) is not significantly related to λ_i. In sum, our results based on structural breaks in industry valuation provide further evidence for a plausibly causal impact of extreme, salient events on college major choice.

5.2 *Law & Order* and the Legal Profession

In this section, we provide more direct, and arguably cleaner, evidence for the supply side of education choice by zooming in on just one occupation. 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 schools, as well as the future wages earned by entry-level lawyers. Unlike the rest of the paper, which examine all NSF majors, here we focus on law for a couple of reasons. First, there has been no substantial change in the legal profession during our sample period, making reverse causality (TV series viewership is a reflection of salient changes in an occupation, and these changes caused prospective students to respond) less of a concern. Second, we have detailed data on law school test (LSAT) takers, applicants, graduates, as well as data on entry-level employment and wages, which allows us to do our tests.

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, law school applicants, and applicants that are admitted are provided by The Law School Admission Council. The median age of LSAT test takers is 23 to 24, and we study the impact of the popularity of *Law & Order* 3 to 7 years before students take LSAT.[10] 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.[11] In the application and enrollment analysis, we control for a linear time trend. In the analysis of the job opportunities, we adjust lawyers' salary and net new hires by the corresponding figures for other professional occupations.[12]

As can be seen from Table 7, 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 $t-7$ to $t-3$ is followed by an 7.5% increase (t-statistic = 2.42) in the number of students taking the LSAT in year t, and a 4.6% increase (t-statistic = 2.67) in the number of law school graduates in year $t+3$. Consistent with a supply-side channel, the rise in the popularity of *Law & Order* in years $t-7$ to $t-3$ is associated with a 2.6% (t-statistic = 2.25) drop in the average earnings of entry-level lawyers and an insignificant change in the net new hires in year $t+3$, when students graduate. Overall,

[10]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.

[11]Note that our data here are a time-series, so we cannot include year fixed effects. We obtain the number of LSAT takers from 1993 to 2017 and the number of applications and admitted applicants from 2000 to 2015.

[12]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 and PhDs.

our evidence from the case study of the law profession provides additional support for the supply-side interpretation of our earlier evidence.

5.3 Future Industry Operating Performance

One obvious concern with our industry skewness measure is that it may reflect unobserved industry performance dynamics. While we cannot (and do not intend to) rule this out completely, we correlate our lagged within-industry skewness measure with various proxies for industry operating performance. The regression setup is similar to equation (2) above, with $Industry\_avg\_performance_j$, the average operating performance for all firms in industry j, as our dependent variable.

The results are reported in Table 8. Across all three panels, 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). Panel A examines industry performance at the time of graduation, Panel B examines industry performance 5 years after graduation, and Panel C examines industry performance at an even longer horizon, 10 years after graduation.

As we see from the table, *Skew* measured in years -7 to -3 does not predict any of our industry performance measures in any specification. This makes it unlikely that our skewness measure is picking up some metric that is related to future industry performance. When viewed together with our evidence in Tables 2 through 7, these results suggest that the effect of *Skew* on college major choice is unlikely to be driven by students' rational expectations of future job prospects.

6 Additional Tests

6.1 More Direct Measures of Extreme, Salient Events

6.1.1 Skewness in Media Coverage

Up until now, our main measure of the occurrences of superstar firms in an industry is based on stock returns. However, it seems unlikely that high school students, or for that matter first and second year college students, follow the stock performance of all firms on a regular basis to be able to calculate or affected by stock return skewness. Indeed, we think of *Skew*, or any of our other return skewness measures in Table 2, as nothing more than a capture-it-all proxy for value-relevant information: salient events taking place in related industries that draw students' attention and shape their expectations and decisions.

While there could be many types of prominent events that affect just a few firms, contributing to $Skew$, one overarching outcome of any such event is media attention. Thus, an alternative way of capturing extreme, salient industry events is to exploit the cross-sectional skewness in media coverage and tones received by firms in the industry. In order to measure media skewness, we create a media-coverage positivity score supplied by RavenPack (which sifts through all news articles published by major financial news outlets starting in 2000). More specifically, we assign a score of -1 to 1 to each news article depending on the positivity or negativity of the tone, following Dang, Moshirian, and Zhang (2015).[13] For every firm, we then calculate the sum of all news scores in each year (similar to the cumulative stock return in a year). Finally, we calculate the employment-weighted cross-sectional skewness of this firm-level news tone measure for each industry in each year, labelled $News\_Skew$. As can be seen from Table 1, Panel B, this measure of news salience is strongly and positively correlated with various measures of return skewness.

We next run regressions similar to equation (1) but replace return skewness with the media skewness measure discussed above. We report these results in Table 9. In Panel A, we find that media skewness also predicts major choice, with substantial economic magnitudes. A one-standard-deviation increase in $News\_Skew$ in years $t-7$ to $t-3$ is associated with 6.8% (t-statistic = 3.61) more graduates from related majors in year t. This estimate is also highly statistically significant, despite the fact that our sample size drops substantially due to the lack of media coverage data in the earlier part of the sample.

In Panels B and C, we examine the relation between media skewness measured in years $t-7$ to $t-3$ and entry-level wages and net new hires in year t. Similar to the results in Table 3, we find that one-standard-deviation higher media-coverage skewness is associated with a 0.72% (t-statistic = 2.12) lower entry-level wage; once again, there is no significant relation between our news-tone skewness measure and net new hires.

6.1.2 Specific Events in the Equity Market

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 associated with large positive returns, likely drawing students to related majors, defaults are significant negative events, which are likely to drive students away.

[13]Also following their paper, only news articles with relevance = 100 (articles which can be definitely ascertained as referring to a certain firm) are counted.

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 10. In Column 1, our main independent variable of interest is the first-day average return of all IPOs in an industry (a common proxy for the popularity of the industry); in Column 2, it is the (log of) first day dollar return of all IPOs; in Column 3 it is the total number of firm defaults in the industry; and in Column 4 it is the number of delistings plus defaults in each industry. We find consistent evidence throughout Table 10: IPO returns are positively related to future major enrollment while firm defaults and delistings are negatively associated with major enrollment.

6.2 Expectational Errors or Preferences for Skewed Payoffs?

As discussed earlier (both in the Introduction and in Section 2), there are two related channels through which college students may be drawn to industries with superstar performers. One possibility is expectational errors: students may form income expectations based on a small number of non-representative but highly visible observations. For example, a student may decide to study Computer Science because he is attracted by the extreme success story of Facebook, and does not fully realize that a typical computer science graduate gets a far less glamorous job, earning a much lower salary. The other possibility is that students indeed form rational expectations about future job opportunities but are happy to accept a lower average wage for a small chance of hitting the jackpot—a preference for skewed payoffs which can stem from complementarities between taste and income.

Empirically, it is nearly impossible to differentiate between the two channels, as we do not observe individuals' income expectations, nor their preferences for skewed payoffs. To shed more light on this issue, we design and conduct our own survey of college graduates on the platform provided by *SurveyMonkey* (the survey was conducted in July 2018; original survey questions are included in an online Appendix A3). We screen our respondents using the following criteria: at the time of the survey, the respondent is a) a college graduate with one of the NSF majors that we examine throughout, b) between 21 and 65 years old, and c) employed full time. Out of the 1,169 individuals that start the survey, our screening procedure reduces the sample size to 516. In addition, we also screen 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.[14] We then match

[14]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"). The Survey Instrument is attached in the appendix.

the survey data to industry return skewness and other control variables used in earlier tests, leaving us with a final sample of 398 respondents with non-missing data.

Table 11 reports results from our own survey. To begin, we examine the consistency between our survey evidence and empirical results reported earlier on labor market outcomes. Column 1 in Panel A shows an ordered logistic regression with Household income (in 8 buckets: 7 buckets of size \$25,000, starting from \$25,000, and the last bucket for incomes $\$200,000+$) as the dependent variable. Column 2 reports the marginal effects from a Logistic regression with a dummy dependent variable indicating whether the graduate started his post-college career in an industry that he expected to work in when choosing his major. Column 3 reports marginal effects from a Logistic regression with a dummy dependent variable indicating whether the graduate still works in the same industry that he joined right after graduating from college.

We are interested primarily in the correlation between our stock return skewness measure used throughout the paper and these career outcomes. Note that we never ask the survey respondents about any return skewness: knowing their major and the year they decided on it (which we ask directly in the survey), we can back out the cross-sectional return skewness relevant to each respondent as the average skewness of related industries in the two prior years.[15] In all regressions, we control for major-, industry-, graduation-year-, gender-, and region-of-residence- fixed effects, as well as fixed effects based on categorical answers to a question regarding how worried the respondent was about paying back his student loans when choosing the major.

We find a significant, negative relation (Panel A, Column 1) between cross-sectional return skewness in related industries prior to major declaration and individuals' long-term household income. To be clear, we did not elicit household income; the platform asked respondents their household income when they first signed up. Given the potential for noise in this setting (household income is purely self-reported), the significant relationship is remarkable.

Columns 2 and 3 effectively repeat the $Job\_Outside\_Field$ test from the *National Survey of College Graduates* in Table 5. Here, we find that industry return skewness positively forecasts the likelihood that the respondent has to take up a job in a field unrelated to his major right after graduation. We also find that the respondent is less likely to have continued working in the same field throughout his career, although this last result is not statistically significant. Both results (job outcomes at graduation and later in the career) are consistent

[15] Note that here we do not need to average skewness over a longer time period like in the previous tests because we directly find out from the Survey the year each respondent decided on her major, which allows us to focus squarely on skewness in years relevant to the major decision.

with the idea that part of the excess labor supply due to the occurrence of superstar firms is gradually absorbed by other industries.

In Panel B, we examine the possible factors that drive students' decisions to follow superstar firms. The dependent variable is the industry return skewness described earlier. The main independent variable of interest in Column 1 is a dummy variable, $Expectation\_errors$, based on a question of whether the respondent thought his/her expectations of future job/income outcomes could have been more accurate had he/she done a bit more research. The main independent variable in Column 2 is another dummy variable, $Lottery\_preference$, which takes the value of 1 if the respondent answers that he/she would have chosen to play a fair lottery (with a small probability of earning a large income) over a stable, future income stream had he/she been given the choice in college. The last column presents a horse-race between these two explanatory variables. Our evidence from these tests suggests that expectation errors, rather than an inherent preference for skewness, is more likely to drive individuals' decisions to chase superstar performers in their major choice.

6.3 The Role of Gender

Recent research (e.g. Zafar, 2013) suggests that males and females differ substantially in their beliefs and preferences, with males caring more about pecuniary outcomes in the workplace than females. Under this view, if the occurrences of superstar firms in related industries affect students' major choice through their effect on pecuniary expectations like we hypothesize, we might observe a stronger effect for male than for female students. To examine this possibility, we repeat our major choice regression (1) separately for the male and the female subsamples. In results reported in Table 12, we show evidence consistent with the above view. Almost all of our observed effect of superstar firms on college major choice comes from the male sample, with industry return skewness having a significantly weaker effect on female students' major choice.

6.4 Robustness Tests

Finally, we examine the robustness of our main empirical findings. The results are presented in Table 13. In Panel A, we examine the number of graduates with a master's degree, instead of bachelor's, in related fields as a function of lagged within-industry return skewness. The results are similar to those reported in Table 2. For example, as shown in Column 2, a one-standard-deviation increase in *Skew* measured in years $t-7$ to $t-3$ is associated with an 8.4% (t-statistic = 3.90) increase in the number of students graduating with a master's degree in related fields in year t. (Again, this result is robust to *Skew* measured over different horizons, for example, $t-3$ to $t-6$ or $t-3$ to $t-8$.) In Panel B, we show that leaving out the Tech boom years (1990-2002) from our analysis does not change our results significantly, showing that our evidence does not come solely from the Computer Science major in one bubble episode. In untabluated tests, we also exclude the health industry from all our analyses, and the results are virtually unchanged: a one-standard-deviation increase in industry return skewness in years $t-7$ to $t-3$ is associated with a 10.2% (t-statistic = 5.12) rise in student enrollment in related major fields, a 1.5% (t-statistic = 3.24) drop in real entry-level wage, as well as an insignificant change in net new hires (t-statistic = -0.71) in year t.

7 Conclusion

This paper examines the effect of superstar firms on an important human capital decision—college students' major choice. Using cross-sectional skewness in stock returns or favorable news coverage as proxies for the occurrences of superstar firms in an industry, we find that they are associated with a disproportionately larger number of college students choosing to major in related fields. Students' tendency to follow superstars, however, results in a temporary over-supply of human capital. In particular, we find that upon entering the job market, students attracted by superstar firms earn lower real wages relative to their peers with the same major but from different cohorts. Coupled with the finding that the number of entry-level employees stays roughly constant, this result is consistent with the view that industry labor demand is relatively inelastic in the short run; a sudden increase in labor supply thus lowers the average wage earned by entry-level employees without affecting employment size.

Moreover, these adverse effects on career outcomes last for years/decades. Cohorts drawn into fields by superstar performers earn lower wages even 20 years after graduation and have a lower propensity to work in jobs related to their college majors.

In sum, our paper is the first to examine the role of salient, extreme events, such as the occurrences of superstar firms, in driving arguably the most important and irreversible decision in one's life: human capital investment. Our results have implications for both labor economists who study the substantial variation in individuals' education choice, as well as micro-economists who emphasize the role of salience and skewed payoffs in human decision making. Our paper also points to an additional channel—individual education choice—through which superstar firms may impact social welfare and economic growth.

References

Altonji, J. G., 1993, "The demand for and return to education when education outcomes are uncertain," Journal of Labor Economics 11, 48–83.

Altonji, J.G., Arcidiacono, P. and Maurel, A., 2015, "The analysis of field choice in college and graduate school: Determinants and wage effects," National Bureau of Economic Research Working Paper No. 21655.

Arcidiacono, P., Hotz, V. J. and Kang, S., 2012, "Modeling college major choices using elicited measures of expectations and counterfactuals," Journal of Econometrics 166, 3–16.

Arrow, K. and Capron, W., 1959, "Dynamic Shortages and Price Rises: The Engineer-Scientists Case," Quarterly Journal of Economics, Vol. 73, No. 2, pp. 292–308.

Avery, C. and Caroline M. Hoxby, 2004, "Do and Should Financial Aid Decisions Affect Students' College Choices?" in Caroline Hoxby, ed. College Choices: The New Economics of Choosing, Attending, and Completing College. University of Chicago Press.

Bai, Jushan, 1997, "Estimation of a change point in multiple regression models," Review of Economics and Statistics 79, 551–563.

Bai, Jushan, and Pierre Perron, 1998, "Estimating and testing linear models with multiple structural changes," Econometrica 66, 47–78.

Barberis, N. and M. Huang, 2008, "Stocks as Lotteries: The Implications of Probability Weighting for Security Prices, American Economic Review 98, 2066–2100.

Barberis, N., A. Mukherjee, and B. Wang, 2016, "Prospect theory and stock returns: an empirical test," Review of Financial Studies, forthcoming.

Beffy, M., Fougere, D. and Maurel, A., 2012, "Choosing the field of studies in postsecondary education: Do expected earnings matter?" Review of Economics and Statistics 94, 334–347.

Berger, M.C., 1988, "Predicted future earnings and choice of college major," Industrial & Labor Relations Review, 41(3), 418–429.

Bhattacharya, J., 2005, "Specialty selection and lifetime returns to specialization," Journal of Human Resources 15, 115–143.

Blank, David M. and George J. Stigler, 1957, "The demand and supply of scientific personnel," NBER Books.

Blom, E., 2012, "Labor market determinants of college major," Yale University Working Paper.

Bordon, P. and Fu, C., 2015, “College-major choice to college-then-major choice,” Review of Economic Studies.

Bordalo, P., Gennaioli, N. and Shleifer, A., 2012, “Salience theory of choice under risk,” Quarterly Journal of Economics 127 (3): 1243–1285.

Bordalo, P., Gennaioli, N. and Shleifer, A., 2013a, “Salience and consumer choice,” Journal of Political Economy 121(5): 803–843.

Bordalo, P., Gennaioli, N. and Shleifer, A., 2013b, “Salience and asset prices,” American Economic Review 103(3), 623–628.

Bordalo, P., Gennaioli, N. and Shleifer, A., 2013c, “Salience theory of judicial decisions,” The Journal of Legal Studies vol. 44(S1), S7–S33.

Campello, M. and J.R. Graham, 2013, “Do stock prices influence corporate decisions? Evidence from the technology bubble,” Journal of Financial Economics 107, 89–110.

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

Chetty, Raj, Adam Looney, and Kory Kroft, 2009, “Salience and Taxation: Theory and Evidence,” American Economic Review 99(4): 1145–77.

Conrad, J., R. Dittmar and E. Ghysels, 2013, “Ex-Ante Skewness and Expected Stock Returns,” Journal of Finance 68, 85–124.

Dang, T.L., Moshirian, F. and Zhang, B., 2015, “Commonality in News Around the World,” Journal of Financial Economics 116(1), 82–110.

Dickson, L., 2010, “Race and gender differences in college major choice,” The Annals of the American Academy of Political and Social Sciences, 627, 108–124.

Fehr, Ernst, and Antonio Rangel, 2011, “Neuroeconomic Foundations of Economic Choice—Recent Advances,” Journal of Economic Perspectives 25(4): 3–30.

Freeman, R.B., 1971, “The Labor Market for College-Trained Man-power” (Cambridge: Harvard University Press).

Freeman, R.B., 1975, “A Recursive Model of the Market for New Lawyers,” The Review of Economics and Statistics, Vol. 57, No. 2, pp. 171–179.

Freeman, R.B., 1976, “A cobweb model of the supply and starting salary of new engineers,” Industrial & Labor Relations Review 236.

Fricke, H., Grogger, J., Steinmayr, A., 2015, “Does exposure to economics bring new majors to the field? Evidence from a natural experiment,” NBER Working Paper.

Fougere, D. and Maurel, A., 2012, "Choosing the field of studies in postsecondary education: Do expected earnings matter?" Review of Economics and Statistics 94, 334–347.

Gennaioli, N. and Shleifer, A., 2009, "What comes to mind," Quarterly Journal of Economics 125(4): 1399–1433.

Goldin, C., 2014, "A grand gender convergence: Its last chapter," American Economic Review 104, 1–30.

Green, T. Clifton and Byoung-Hyoun Hwang, 2012, "Initial public offerings as lotteries: Skewness preference and first-day returns," Management Science 58, no. 2: 432–444.

Greenwood, R. and Hanson, S.G., 2015, "Waves in ship prices and investment," The Quarterly Journal of Economics, 55, p.109.

Hastings, J., Neilson, C., Ramirez, A. and Zimmerman, S., "(Un)informed college and major choice: evidence from linked survey and administrative data," Economics of Education Review, forthcoming.

Hausman, Jerry A., and Gregory K. Leonard, 1997, "Superstars in the National Basketball Association: Economic value and policy," Journal of Labor Economics 15, no. 4: 586-624.

Hoxby, Caroline M., ed., "The Economics of School Choice," Chicago: University of Chicago Press, 2003.

Hoxby, Caroline M., ed., 2004, "College Choices: The Economics of Where to Go, When to Go, and How to Pay for It," Chicago: University of Chicago Press.

James, E., Alsalam, N., Conaty, J. C., To, D. L., 1989, "College quality and future earnings: Where should you send your child to college?" American Economic Review 79, 247–252.

Kaldor, Nicholas, 1934, "A Classificatory Note on the Determination of Equilibrium," Review of Economic Studies, 1, 122–136.

Lazear, E. P. and Sherwin Rosen, 1981, "Rank-Order Tournaments as Optimum Labor Contracts," The Journal of Political Economy 89, no. 5: 841–864.

Lemieux, T., 2014, "Occupations, fields of study and returns to education," Canadian Journal of Economics 47(4), 1–31.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, 2008, "The Short- and Long-Term Career Effects of Graduating in a Recession: Hysteresis and Heterogeneity in the Market for College Graduates," IZA Discussion Paper 3578.

Oyer, Paul, 2006, "The Macro-Foundations of Microeconomics: Initial Labor Market Conditions and Long-Term Outcomes for Economists," National Bureau of Economics Working Paper 12157.

Oyer, Paul, 2008, “The Making of an Investment Banker: Stock Market Shocks, Career Choice, and Lifetime Income,” Journal of Finance, 63(6): 2601–28.

Pallais, A., 2015, “Small differences that matter: Mistakes in applying to college,” Journal of Labor Economics 33, 493–520.

Rosen, S., 1981, “The economics of superstars,” The American Economic Review, 71(5), 845–858.

Rosen, S, 1997, “Manufactured Inequality,” Journal of Labor Economics 15, no. 2: 189–196.

Sacerdote, B., 2001, “Peer effects with random assignment: Results for Dartmouth roommates,” Quarterly Journal of Economics 116, 681–704.

Schumpeter, Joseph, 1942, “Socialism, capitalism and democracy,” Harper and Brothers.

Stigler, George J., 1961, “The economics of information,” Journal of Political Economy. 69 (3): 213–225.

Stigler, George J., 1962, “Information in the labor market,” Journal of Political Economy. 70 (5): 94–105.

Stinebrickner, T. and Stinebrickner, R., 2014, “A major in science? Initial beliefs and final outcomes for college major and dropout,” Review of Economic Studies 81, 426–472.

Taylor, S.E. and Thompson, S.C., 1982, “Stalking the elusive “vividness” effect,” Psychological review, 89(2), p.155.

Wiswall, M. and Zafar, B., “Determinants of college major choice: identification using an information experiment,” Review of Economic Studies, forthcoming.

Yuen, J., 2010, “Job-education match and mismatch: Wage differentials,” Perspective on Labour and Income 11, 1–26.

Zafar, Basit, 2013, “College major choice and the gender gap,” Journal of Human Resources 48.3: 545–595.

Table 1
Summary Statistics and Correlations

Panel A provides summary statistics of our major variables. Number of Bachelors is the annual number of bachelor degrees awarded for a major. Number of Male and Female Bachelors, as well as Masters are also reported. Size- and Employment-Weighted Skew are the cross-sectional skewness of annual returns in a industry, weighted by market cap and number of employees of firms, respectively. Skew_Monthly and Skew_Quarterly are similar to Employment-Weighted Skew; they are the employment-weighted cross-sectional skewness of monthly returns and quarterly returns, respectively, and then averaged across the year.

News Skew is the employment-weighted cross-sectional skewness of annual sum of news scores, based on RavenPack CSS scores. Mean IPO First Day Return and Log IPO First Day Dollar Return are the employment-weighted average IPO first day return and the log total dollar amount of IPO first day return. Default Rate and Default and Delisted Rate are the number of defaults (as defined by S&P issuer ratings) and the number of defaults and delisted firms, divided by the total number of rated firms in a industry.

Annual Wage is the employee-weighted average wage across occupation codes that are mapped to the major and that require bachelor s degree and do not require prior experience, inflation-adjusted (1997 level). Net new hires is the net change in the number of employees in these positions. Our industry control variables include Mean Return (in a industry) and Return Coefficient of Variation (standard deviation divided by the mean). Both are weighted by the number of employees of firms.

Panel A: Summary Statistics					
	Sample Period	Median	25th Pctl	75th Pctl	Std Dev
Number of Bachelors	1966-2015	8083	3420	18814	24175
Number of Bachelors (Male)	1966-2015	6848	2630	13369	8310
Number of Bachelors (Female)	1966-2015	1459	298	2977	19924
Number of Masters	1966-2015	2506	1276	4640	10260
Size-Weighted Skew	1959-2015	0.684	0.084	1.542	1.362
Employment-Weighted Skew	1959-2015	0.831	0.176	1.791	1.551
Skew_Monthly	1959-2015	0.414	0.099	0.762	0.557
Skew_Quarterly	1959-2015	0.590	0.092	0.968	0.798
News Skew	2000-2015	1.208	0.156	2.355	2.555
Mean IPO First Day Return	1975-2008	0.072	0.029	0.153	0.212
Log IPO First Day Dollar Return	1975-2008	5.606	0.000	17.381	8.897
Default Rate (%)	1985-2015	0.000	0.000	0.000	0.239
Default and Delisted Rate (%)	1985-2015	0.000	0.000	0.113	0.452
Mean Return	1959-2015	0.115	-0.071	0.301	0.309
Return Coefficient of Variation	1959-2015	0.945	-0.837	1.960	34.896
Annual Wage (1997 Dollars)	1997-2016	58168	55370	63324	7994
Net New Hires (Log Change)	1998-2016	0.0249	-0.0095	0.0547	0.3141
Number of Net New Hires	1998-2016	3620	-620	12090	264917

Table 1 (continued)

Panel B presents the correlations between different measures of the existence of superstar firms. *** denotes 1% significance.

Panel B: Correlations Between Different Measures of Superstar Firms					
	#1	#2	#3	#4	
1 Size-Weighted Skew	1	0.624***	0.325***	0.362***	
2 Employment-Weighted Skew		1	0.445***	0.527***	
3 Skew_Monthly			1	0.708***	
4 Skew_Quarterly				1	

	#6	#7	#8	#9	#10
2 Employment-Weighted Skew	0.058**	0.214***	0.156***	0.028	0.026
6 News Skew	1	0.181***	0.382***	-0.119***	-0.107***
7 Mean IPO First Day Return		1	0.377***	-0.012	-0.036
8 Log IPO First Day Dollar Return			1	-0.108***	-0.009
9 Default Rate				1	0.749***
10 Default and Delisted Rate					1

Table 2
Regressions of Number of Bachelors on Return Skewness

This table reports the results of regressions of Log Number of Bachelors on skewness measures (averaged across years t-3 to t-7) and other controls. Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major. Aggregate numbers of graduates are used in Panel A. Skew is the size-weighted or employment-weighted cross-sectional skewness of annual returns in a industry. Skew_Monthly and Skew_Quarterly are similar to Skew; they are the employment-weighted cross-sectional skewness of monthly returns and quarterly returns, respectively, and then averaged across the year. All skewness measures are then averaged across years t-3 to t-7, relative to the graduation year t.

Our industry control variables include Mean Return (in a industry), Return Coefficient of Variation (standard deviation divided by the mean). Both are size- or employment-weighted and are averaged across years t-3 to t-7. Log Average Wage is the log average wage of graduates of the major in years t-3 to t-5. Other controls are Log Total Market Cap, Log Mean Book-to-Market, and Log Mean Firm Age, measured at year t-3. 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 2015.

	Log Number of Bachelors				
Weighting of RHS Variables	Size	Employment	Employment	Employment	Employment
	(1)	(2)	(3)	(4)	(5)
Skew	0.0948***	0.1010***			0.0524***
	(0.0301)	(0.0189)			(0.0167)
Skew_Monthly			0.1003***		
			(0.0371)		
Skew_Quarterly				0.0876**	
				(0.0389)	
Mean Return	0.0518*	0.1027**	0.0886**	0.1052***	0.0785**
	(0.0310)	(0.0402)	(0.0393)	(0.0389)	(0.0327)
Return Coefficient of Variation	-0.0533***	0.0016	-0.0003	0.0077	0.0096
	(0.0204)	(0.0154)	(0.0141)	(0.0146)	(0.0120)
Log Average Wage					0.2835***
					(0.0737)
Log Total Market Cap	0.0358	0.0201	-0.1787**	-0.0423	-0.0012
	(0.0783)	(0.0564)	(0.0783)	(0.0752)	(0.0512)
Log Mean Book-to-Market	0.0723*	0.1301**	0.0206	0.0341	0.0063
	(0.0432)	(0.0523)	(0.0413)	(0.0433)	(0.0394)
Log Mean Firm Age	-0.1627***	-0.1641***	-0.1078***	-0.1413***	0.0257
	(0.0304)	(0.0330)	(0.0287)	(0.0291)	(0.0395)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes	Yes
# Observations	521	521	521	521	150
Adj. R-Squared	0.87	0.88	0.88	0.88	0.99

Table 2 (continued)

School-level numbers of bachelors of each major are used in Panel B. There are 298 schools in total. These are 4-year universities in the U.S., offering at least 6 out of our 11 majors. Top is a dummy variable, indicating that the school is a private school that is in the top 100 in US News Rankings in 2018 (Column (1)), the school is located in the state that hires the most people in the major-related industries (Column (2)), and a combination of these conditions (Column (3)). The sample period is from 1987 to 2015.

	Log Number of Bachelors		
Top =	Top Private	Location	Top Private + Location
	(1)	(2)	(3)
Skew	0.0433***	0.0474***	0.0446***
	(0.0141)	(0.0141)	(0.0138)
Skew * Top	0.0154	-0.0186	0.0966**
	(0.0204)	(0.0249)	(0.0465)
Mean Return	0.0275	0.0331**	0.0317*
	(0.0180)	(0.0163)	(0.0169)
Mean Return * Top	0.0306	-0.0255	-0.0073
	(0.0229)	(0.0387)	(0.0578)
Return Coefficient of Variation	0.0292**	0.0274**	0.0279**
	(0.0131)	(0.0120)	(0.0121)
Return Coefficient of Variation * Top	-0.0051	-0.0054	-0.0961*
	(0.0185)	(0.0194)	(0.0565)
Log Total Market Cap	-0.0428	-0.0642	-0.0534
	(0.0507)	(0.0463)	(0.0475)
Log Total Market Cap * Top	-0.0451	0.2099*	0.2004
	(0.0635)	(0.1153)	(0.1876)
Log Mean Book-to-Market	0.0098	0.0080	0.0101
	(0.0279)	(0.0262)	(0.0274)
Log Mean Book-to-Market * Top	0.0049	0.0067	-0.1139
	(0.0426)	(0.0658)	(0.0946)
Log Mean Firm Age	0.0131	0.0112	0.0103
	(0.0422)	(0.0389)	(0.0399)
Log Mean Firm Age * Top	-0.0186	0.0225	0.0851
	(0.0528)	(0.0648)	(0.1189)
Year * Top Fixed Effects	Yes	Yes	Yes
Major * Top Fixed Effects	Yes	Yes	Yes
# Observations	69078	69078	69078
Adj. R-Squared	0.18	0.19	0.18

Table 3

Regressions of Wage and Net New Hires Upon Graduation

This table reports the results of regressions of Log Annual Wage and Net New Hires, both in graduation year t, on skewness measures (averaged across years t-3 to t-7) and other controls. Annual Wage is the employment-weighted average wage across occupation codes that are mapped to the major and that require bachelor s degree and do not require prior experience, inflation-adjusted (1997 level). Net New Hires is the log change in the number of employees in these positions. Skew is the employment-weighted cross-sectional skewness of annual returns in a industry. It is then averaged across from years t-3 to t-7. Versatility is a dummy variable indicating that the concentration of employment in various industries is low for the major. The concentration is measured by the Herfindahl index of employment in different industries. Lagged Log Annual Wage is the log average wage of graduates of the major in years t-3 to t-5. Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major, averaged across years t-1 to t-2.

Our industry control variables include Mean Return (in a industry), Return Coefficient of Variation (standard deviation divided by the mean). Both are employment-weighted and are averaged across years t-3 to t-7. Other controls are Log Total Market Cap, Log Mean Book-to-Market, and Log Mean Firm Age, measured at year t-1. Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables (except dummy variables) are standardized with zero mean and unit standard deviation. The sample period is from 1997 to 2016.

	Log Annual Wage (1)	Net New Hires (2)	Log Annual Wage (3)	Net New Hires (4)	Log Annual Wage (5)	Net New Hires (6)
Skew	-0.0108**	-0.0113	-0.0213***	0.0232	-0.0068*	-0.0253
	(0.0042)	(0.0243)	(0.0071)	(0.0428)	(0.0037)	(0.0193)
Skew * Versatility			0.0142**	-0.0422		
			(0.0060)	(0.0372)		
Mean Return	0.0063***	0.0279	0.0059***	0.0305	0.0060***	0.0333
	(0.0022)	(0.0287)	(0.0021)	(0.0334)	(0.0023)	(0.0315)
Return Coefficient of Variation	-0.0014	-0.0240	-0.0021	-0.0249	-0.0017	-0.0198
	(0.0016)	(0.0228)	(0.0016)	(0.0225)	(0.0016)	(0.0180)
Lagged Log Annual Wage					0.0141	-0.0452
					(0.017)	(0.0356)
Log Number of Bachelors	0.0823***	0.0261	0.0733***	0.0275	0.0709***	-0.0020
	(0.0130)	(0.0168)	(0.0106)	(0.0248)	(0.016)	(0.0104)
Log Total Market Cap	0.0128*	-0.0182	0.0106	-0.0179	0.0169**	0.0283
	(0.0076)	(0.0458)	(0.0077)	(0.0445)	(0.0064)	(0.0412)
Log Mean Book-to-Market	0.0036	0.0017	0.0022	0.0012	0.0072*	0.0109
	(0.0043)	(0.0206)	(0.0045)	(0.0149)	(0.0040)	(0.0332)
Log Mean Firm Age	0.0050	0.0497	0.0049	0.0474	0.0047	0.0226
	(0.0074)	(0.0545)	(0.0072)	(0.0531)	(0.0075)	(0.0210)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	No	Yes	No	Yes	No
# Observations	200	190	200	190	160	160
Adj. R-Squared	0.97	0.06	0.97	0.06	0.98	0.09

Table 4

Regressions with Skewness Measures of Different Horizons

Panel A of this table reruns regressions of Log Number of Bachelors in year t, while Panel B reruns regressions of Log Annual Wage and Net New Hires, both in year t. In addition to our return measures measured over years t-3 to t-7 in Tables 2 and 3, we include skewness, mean, and coefficient of variation that are measured over years t-1 to t-2. All other variables are the same as Tables 2 and 3. 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 2015 in Panel A and from 1997 to 2016 in Panel B.

Panel A: Log Number of Bachelors, with t-1 to t-2 Measures		
	(1)	(2)
Skew t-1 to t-2	0.0392	0.0446*
	(0.0292)	(0.0229)
Skew t-3 to t-7		0.1058***
		(0.0203)
Mean Return t-1 to t-2	0.0075	0.0010
	(0.0328)	(0.0296)
Mean Return t-3 to t-7		0.0982**
		(0.0387)
Return Coefficient of Variation t-1 to t-2	-0.0183	-0.0205**
	(0.0116)	(0.0096)
Return Coefficient of Variation t-3 to t-7		0.0041
		(0.0154)
Log Total Market Cap	0.3215***	0.1846**
	(0.0963)	(0.0782)
Log Mean Book-to-Market	0.0827	0.1599**
	(0.0501)	(0.0721)
Log Mean Firm Age	-0.1710***	-0.1690***
	(0.0277)	(0.0292)
Year Fixed Effects	Yes	Yes
Major Fixed Effects	Yes	Yes
# Observations	521	521
Adj. R-Squared	0.87	0.88

Table 4 (continued)

Panel B: Entry-Level Positions, with t-1 to t-2 Measures				
	Log Annual Wage (1)	Log Annual Wage (2)	Net New Hires (3)	Net New Hires (4)
Skew t-1 to t-2	0.0000	0.0003	-0.0164	-0.0142
	(0.0027)	(0.0028)	(0.0227)	(0.0223)
Skew t-3 to t-7		-0.0142***		-0.0101
		(0.0047)		(0.0192)
Mean Return t-1 to t-2	-0.0092*	-0.0146***	0.0112	0.0096
	(0.0053)	(0.0049)	(0.0254)	(0.0260)
Mean Return t-3 to t-7		0.0021		0.0296
		(0.0027)		(0.0310)
Return Coefficient of Variation t-1 to t-2	-0.0001	-0.0015	-0.0024	-0.0077
	(0.0014)	(0.0019)	(0.0100)	(0.0133)
Return Coefficient of Variation t-3 to t-7		-0.0033**		-0.0234
		(0.0015)		(0.0249)
Log Number of Bachelors	0.0479***	0.0722***	0.0262	0.0265
	(0.0112)	(0.0124)	(0.0159)	(0.0161)
Log Total Market Cap	0.0107*	0.0118*	-0.0035	-0.0180
	(0.0063)	(0.0068)	(0.0359)	(0.0483)
Log Mean Book-to-Market	-0.0033	-0.0077	-0.0008	-0.0014
	(0.0053)	(0.0054)	(0.0295)	(0.0258)
Log Mean Firm Age	0.0057	0.0111	0.0400	0.0502
	(0.0065)	(0.0070)	(0.0445)	(0.0564)
Year Fixed Effects	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	No	No
# Observations	200	200	190	190
Adj. R-Squared	0.97	0.97	0.06	0.06

Table 5
Regressions Using Data from the National Survey of College Graduates

This Table reports results from the National Survey of College Graduates. The first 2 columns report results from fixed effects panel regressions with log(Total Earnings) as the dependent variable, while the last 2 columns report results from Logistic regressions with a dummy dependent variable indicating whether the graduate now works in a field outside his domain of study. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. The sample period is from 1993 to 2015.

	Log(Earnings)	Log(Earnings)	1(Job Outside Main Field of Study)	1(Job Outside Main Field of Study)
	(1)	(2)	(3)	(4)
Skew	-0.0057**	-0.0088***	0.0460***	0.0478***
	(0.0028)	(0.0029)	(0.0161)	(0.0164)
Mean Return	0.0109***	0.0138***	-0.0078	0.0068
	(0.0025)	(0.0025)	(0.012)	(0.0122)
Return Coefficient of Variation	0.0178***	0.0201***	-0.0249*	-0.0247*
	(0.0026)	(0.0026)	(0.012)	(0.013)
Age-related Controls	Age, Age-squared	Age Decile Fixed Effects	Age, Age-squared	Age Decile Fixed Effects
Minority Status Fixed Effect	Yes	Yes	Yes	Yes
Gender Fixed Effect	Yes	Yes	Yes	Yes
Marital Status Fixed Effect	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes
Survey Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
# Observations	93,633	93,633	109,860	109,860
Adj. R-Squared (%)	20.40%	20.20%	12.10%	12.18%

Table 6
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 cumlative 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 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 Log Total Market Cap, Log Mean Book-to-Market, and Log Mean Firm Age, measured at year t-3 in Column (1), and t-1 in Columns (2) to (5). Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

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	96.07%	0.1032	0.7110	(6.73)	199704
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	96.07%	0.1032	0.7110	(6.73)	199704
Health	88.91%	0.0628	-0.2385	(-13.60)	199704
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	0.4169***	-0.3869	-0.0253	-0.0756	0.0782
	(0.1336)	(1.2896)	(0.0432)	(0.0971)	(0.0790)
Log Total Market Cap	-0.0568***	0.4852	-0.0147	0.0078	-0.0290
	(0.0187)	(0.7139)	(0.0148)	(0.0308)	(0.0324)
Log Mean Book-to-Market	0.0422	0.9359	0.0219	0.0518	0.0672
	(0.1120)	(1.6515)	(0.0242)	(0.0693)	(0.0494)
Log Mean Firm Age	-0.1691	3.7998	0.0532	0.1732	0.0400
	(0.1614)	(3.3374)	(0.0508)	(0.1236)	(0.0414)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes	Yes
# Observations	143	143	143	143	143
Adj. R-Squared	0.98	0.07	0.26	0.18	0.44

Table 6 (continued)

In this panel, the dependent variable is the log number of bachelors in each major in each of the years in the crash period (2005 to 2012) minus the average log number of bachelors in the boom period (3 years after the structural break up to 2002) (Column (1)) or minus the average log number of graduates in the normal period (1980-1989).

Panel C: Crash Period		
	Log Number of Bachelors (Crash - Average in Boom Period)	Log Number of Bachelors (Crash - Average in Normal Period)
	(1)	(2)
Lambda	-0.2159**	0.1097
	(0.0994)	(0.1594)
Log Total Market Cap	0.0242	-0.0448
	(0.0379)	(0.0287)
Log Mean Book-to-Market	0.1916	-0.4461***
	(0.1714)	(0.1800)
Log Mean Firm Age	-0.2468***	-0.4679***
	(0.0590)	(0.0492)
Year Fixed Effects	Yes	Yes
Major Fixed Effects	No	No
# Observations	66	66
Adj. R-Squared	0.19	0.36

Table 7
Analysis of the Legal Profession

This table reports the analysis of the legal profession. Log Test Takers and Percentage of Applicants Admitted are the log number of LSAT takers and the percentage of law school applicants that are admitted, respectively, in year t. Log Number of Graduates is the log number of JD graduates in year t+3. Log Average Salary and Net New Hires are the log employment-weighted average wage and the log change in the number of entry-level lawyers, respectively, in year t+3. Annual Salary and Net New Hires are adjusted by the corresponding numbers of other professional occupations. The dependent variable is Log Viewers, the log average number of viewers of Law & Order in years t-7 to t-3. In columns (1) to (3), 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.

	Log Test Takers	Percentage of Applicants Admitted	Log Number of Graduates	Log Average Salary	Net New Hires
	(1)	(2)	(3)	(4)	(5)
Log Viewers	0.0753**	-0.0616***	0.0463***	-0.0262**	-0.0045
	(0.0311)	(0.0237)	(0.0173)	(0.0117)	(0.0283)
Time Trend	0.0024	0.0081***	0.0008		
	(0.0044)	(0.0025)	(0.0028)		
# Observations	24	16	21	18	17
Adj. R-Squared	0.15	0.70	0.29	0.19	-0.06

Table 8
Regressions of Industry Average Operating Performance Measures

This table reports the results of regressions of industry average operating performance measures on skewness measures (averaged across years t-3 to t-7) and other controls. RoE is the return on equity, defined as earnings divided 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. In Panel A, these performance measures are measured in year t. In Panels B and C, these measures are measured in year t+5 and t+10, respectively. Skew is the employment-weighted cross-sectional skewness of annual returns in a industry. It is then averaged across from years t-3 to t-7. Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major, averaged across years t-1 to t-2.

Our industry control variables include Mean Return (in a industry), Return Coefficient of Variation (standard deviation divided by the mean). Both are employment-weighted and are averaged across years t-3 to t-7. Other controls are Log Total Market Cap, Log Mean Book-to-Market, and Log Mean Firm Age, measured at year t-1. 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 2015.

Panel A: Upon Graduation				
	RoE	RoA	NPM	Sales Growth
	(1)	(2)	(3)	(4)
Skew	0.0003	-0.0001	0.0002	0.0044
	(0.0028)	(0.0011)	(0.0017)	(0.0046)
Mean Return	-0.0100***	-0.0039**	-0.0017	-0.0134
	(0.0038)	(0.0016)	(0.0020)	(0.0087)
Return Coefficient of Variation	0.0031**	0.0010**	0.0018***	0.0013
	(0.0014)	(0.0004)	(0.0005)	(0.0022)
Log Number of Bachelors	-0.0162**	-0.0035	-0.0038	0.0041
	(0.0073)	(0.0030)	(0.0046)	(0.0184)
Log Total Market Cap	0.0049	0.0065**	0.0113*	-0.0334**
	(0.0099)	(0.0032)	(0.0066)	(0.0154)
Log Mean Book-to-Market	-0.0452***	-0.0151***	-0.0162***	-0.0496***
	(0.0074)	(0.0025)	(0.0041)	(0.0060)
Log Mean Firm Age	0.0067	0.0020	0.0088***	-0.0086
	(0.0043)	(0.0019)	(0.0032)	(0.0111)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
# Observations	1598	1598	1598	1598
Adj. R-Squared	0.29	0.43	0.30	0.31

Table 8 (continued)

Panel B: 5 Years After Graduation				
	RoE	RoA	NPM	Sales Growth
	(1)	(2)	(3)	(4)
Skew	0.0010	0.0010	-0.0198	0.0020
	(0.0028)	(0.0012)	(0.0355)	(0.0057)
Mean Return	-0.0011	0.0008	0.0730	0.0125*
	(0.0042)	(0.0018)	(0.0791)	(0.0066)
Return Coefficient of Variation	-0.0039*	-0.0007	0.0240	-0.0086*
	(0.0023)	(0.0010)	(0.0253)	(0.0050)
Log Number of Bachelors	-0.0019	-0.0014	0.2505	-0.0510***
	(0.0125)	(0.0057)	(0.2478)	(0.0149)
Log Total Market Cap	0.0046	-0.0042	-0.2845	-0.0086
	(0.0044)	(0.0029)	(0.2791)	(0.0120)
Log Mean Book-to-Market	0.0016	0.0004	-0.0653	-0.0008
	(0.0057)	(0.0021)	(0.0705)	(0.0086)
Log Mean Firm Age	-0.0099	-0.0025	0.0186	0.0088
	(0.0055)	(0.0022)	(0.0298)	(0.0089)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
# Observations	1269	1269	1269	1269
Adj. R-Squared	0.12	0.07	-0.01	0.23

Panel C: 10 Years After Graduation				
	RoE	RoA	NPM	Sales Growth
	(1)	(2)	(3)	(4)
Skew	-0.0044	0.0025	0.4150	0.0006
	(0.0069)	(0.0049)	(0.4394)	(0.0086)
Mean Return	0.0018	0.0027	0.1352	0.0096
	(0.0057)	(0.0026)	(0.1512)	(0.0080)
Return Coefficient of Variation	-0.0006	0.0002	0.0357	0.0071**
	(0.0025)	(0.0011)	(0.0399)	(0.0033)
Log Number of Bachelors	0.0289*	0.0171**	-0.1803	0.0412**
	(0.0157)	(0.0068)	(0.2187)	(0.0172)
Log Total Market Cap	0.0086	-0.0004	-0.5666	0.0131
	(0.0057)	(0.0024)	(0.4190)	(0.0178)
Log Mean Book-to-Market	0.0003	-0.0024	-0.0848	0.0053
	(0.0051)	(0.0019)	(0.0921)	(0.0082)
Log Mean Firm Age	-0.0294***	-0.0066**	-0.0298	0.0039
	(0.0065)	(0.0027)	(0.0809)	(0.0110)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
# Observations	899	899	899	899
Adj. R-Squared	0.12	0.04	-0.01	0.18

Table 9

Regressions Using News Skewness

Panel A reports the results of regressions of Log Number of Bachelors on news skewness (averaged across years t-3 to t-7) and other controls. Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major. News Skew is the employment-weighted cross-sectional skewness of annual sum of news scores, based on RavenPack CSS scores. It is then averaged across years t-3 to t-7, relative to the graduation year t.

Panel B reports the results of regressions of Log Annual Wage and Net New Hires, both in graduation year t, on news skewness (averaged across years t-3 to t-7) and other controls. Annual Wage is the employment-weighted average wage across occupation codes that are mapped to the major and that require bachelor s degree and do not require prior experience, inflation-adjusted (1997 level). Net New Hires is the log change in the number of employees in these positions. Log Number of Employees is the log number of employees in these occupation codes. In Panel B, Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major, averaged across years t-1 to t-2.

Our industry control variables include Mean Return (in a industry), Return Coefficient of Variation (standard deviation divided by the mean). Both are employment-weighted and are averaged across years t-3 to t-7. Other controls are Log Total Market Cap, Log Mean Book-to-Market, and Log Mean Firm Age, measured at year t-3 in Panel A, and t-1 in Panel B. 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 2007 to 2015.

Panel A: Log Number of Bachelors	
News Skew	0.0683***
	(0.0189)
Mean Return	0.0141
	(0.0187)
Return Coefficient of Variation	-0.0036
	(0.0119)
Log Total Market Cap	-0.0258
	(0.0187)
Log Mean Book-to-Market	0.0513**
	(0.0213)
Log Mean Firm Age	0.0520
	(0.0316)
Year Fixed Effects	Yes
Major Fixed Effects	Yes
# Observations	99
Adj. R-Squared	0.99

Table 9 (continued)

Panel B: Entry-Level Positions		
	Log Annual Wage	Net New Hires
	(1)	(2)
News Skew	-0.0072**	0.0132
	(0.0034)	(0.0372)
Mean Return	0.0022	0.0537
	(0.0030)	(0.0668)
Return Coefficient of Variation	0.0023	-0.0322
	(0.0023)	(0.0408)
Log Number of Bachelors	0.1309***	0.0204
	(0.0302)	(0.0158)
Log Total Market Cap	0.0183	-0.0386
	(0.0164)	(0.0526)
Log Mean Book-to-Market	0.0085	-0.0287
	(0.0067)	(0.0296)
Log Mean Firm Age	0.0054	0.0539
	(0.0087)	(0.0607)
Year Fixed Effects	Yes	Yes
Major Fixed Effects	Yes	No
# Observations	100	100
Adj. R-Squared	0.98	0.09

Table 10

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 (averaged across years t-3 to t-7). Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major. Mean IPO First Day Return and Log IPO First Day Dollar Return are the employment-weighted average IPO first day return and the log total dollar amount of IPO first day return. Default Rate and Default and Delisted Rate are the number of defaults (as defined by S&P issuer ratings) and the number of defaults and delisted firms, divided by the total number of rated firms in a industry. All these right-hand-side measures are then then averaged across years t-3 to t-7, relative to the graduation year t.

Our industry control variables include Mean Return (in a industry), Return Coefficient of Variation (standard deviation divided by the mean). Both are averaged across years t-3 to t-7. Other controls are Log Total Market Cap, Log Mean Book-to-Market, and Log Mean Firm Age, measured at year t-3. 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 1992 to 2015 in Columns (3) and (4).

	Log Number of Bachelors			
	(1)	(2)	(3)	(4)
Mean IPO First Day Return	0.0645***			
	(0.0175)			
Log IPO First Day Dollar Return		0.1352***		
		(0.0410)		
Default Rate			-0.0522**	
			(0.0261)	
Default and Delisted Rate				-0.0427*
				(0.0240)
Log Total Market Cap	-0.0469	-0.0940	-0.1028***	-0.0904***
	(0.0582)	(0.0518)	(0.0183)	(0.0255)
Log Mean Book-to-Market	-0.1048**	-0.0475	-0.0038	0.0046
	(0.0395)	(0.0528)	(0.0451)	(0.0453)
Log Mean Firm Age	-0.0257	-0.1486***	-0.0353	-0.0443*
	(0.0626)	(0.0491)	(0.0253)	(0.0268)
Year Fixed Effects	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes
# Observations	232	299	264	264
Adj. R-Squared	0.98	0.98	0.98	0.98

Table 11

Regressions Using Data from Survey of College Graduates

This Table reports results from the Survey of College Graduates that we conducted. The first column in Panel A reports results from an fixed effects ordered logistic regression with Household income (in 8 buckets -- 7 buckets of size $25,000, starting from $25,000, and one for incomes $200,000+) as the dependent variable. The second column reports marginal effects from a Logistic regression with a dummy dependent variable indicating whether the graduate started his post-College career in an industry he was expecting to work in when he chose his major. The third column reports marginal effects from a Logistic regression with a dummy dependent variable indicating whether the graduate still works in the same industry that he joined right after graduating from College.

In Panel B, we examine what factors correlate with skewness. In the first column we look at a dummy variable measuring Expectation_errors, based off a question on whether the graduate thought his expectations of future job/income outcomes could have been more accurate had she done a bit more research. In the second column, we look at a dummy variable measuring Lottery_preference, which takes the value 1 if the graduate answered that she would have chosen to play a fair lottery over a stable, future income stream had she been given th echoice in College. The last column presents a horse-race between these two explanatory variables.

Loan-importance fixed effects reflect categorical answers to a specific question on how worried the graduates were about paying back their student loans). Standard errors are clustered by industry throughout. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Income and Employment			
	HH Income (Ordered Logit)	1 (First job post-graduation in target industry=1)	1 (Still works in the industry where she started her career=1)
	(1)	(2)	(3)
Skew	-0.3792***	-0.0473*	-0.0149
	(0.1164)	(0.0271)	(0.0292)
Mean Return	1.3133**	0.0137	0.0571
	(0.6434)	(0.2467)	(0.1394)
Return Coefficient of Variation	0.0066	0.0020	-0.0025
	(0.0079)	(0.0026)	(0.0025)
Major Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Graduation Year Fixed Effects	Yes	Yes	Yes
Loan-importance Fixed Effects	Yes	Yes	Yes
Gender Fixed Effect	Yes	Yes	Yes
Region of Residence Fixed Effects	Yes	Yes	Yes
Effective # Observations	362	286	352
Pseudo R-Squared (%)	12.15%	31.10%	21.90%

Table 11 (continued)

Panel B: Skewness			
		Skew	
	(1)	(2)	(3)
Expectation_errors	0.1270**		0.1401**
	(0.0618)		(0.0691)
Lottery_preference		-0.0744	-0.0932
		(0.0963)	(0.102)
Mean Return	1.5615**	1.5368**	1.5626**
	(0.5937)	(0.6047)	(0.5894)
Return Coefficient of Variation	0.0011	0.0013	0.0009
	(0.0019)	(0.0019)	(0.0019)
Major Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Major choice Year Fixed Effects	Yes	Yes	Yes
Loan-importance Fixed Effects	Yes	Yes	Yes
Gender Fixed Effect	Yes	Yes	Yes
Region of Residence Fixed Effects	Yes	Yes	Yes
Effective # Observations	398	398	398
Adj. R-Squared (%)	53.47%	53.20%	53.53%

Table 12

Regressions of Number of Male and Female Bachelors on Return Skewness

This table reports the results of regressions of Log Number of Bachelors (male and female as separate observations) on skewness measures (averaged across years t-3 to t-7) and other controls. Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major. Skew is the employment-weighted cross-sectional skewness of annual returns in a industry. It is then averaged across years t-3 to t-7, relative to the graduation year t. Female is a dummy variable indicating the number of bachelors is for female graduates.

Our industry control variables include Mean Return (in a industry), Return Coefficient of Variation (standard deviation divided by the mean). Both are employment-weighted and are averaged across years t-3 to t-7. Other controls are Log Total Market Cap, Log Mean Book-to-Market, and Log Mean Firm Age, measured at year t-3. Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables (except dummy variables) are standardized with zero mean and unit standard deviation. The sample period is from 1966 to 2015.

	Log Number of Bachelors
Skew	0.1043***
	(0.0204)
Skew * Female	-0.0770***
	(0.0285)
Mean Return	0.0946**
	(0.0410)
Mean Return * Female	-0.0705
	(0.0617)
Return Coefficient of Variation	-0.0073
	(0.0158)
Return Coefficient of Variation * Female	0.0439*
	(0.0228)
Log Total Market Cap	0.2387***
	(0.0872)
Log Total Market Cap * Female	-0.2987**
	(0.1288)
Log Mean Book-to-Market	0.1642**
	(0.0755)
Log Mean Book-to-Market * Female	-0.3096***
	(0.1112)
Log Mean Firm Age	-0.2125***
	(0.0346)
Log Mean Firm Age * Female	0.0255
	(0.0659)
Year * Female Fixed Effects	Yes
Major * Female Fixed Effects	Yes
# Observations	1042
Adj. R-Squared	0.95

Table 13
Robustness Tests

Panel A repeats Table 2, Panel A using Log Number of Masters. Panel B reruns Table 2 and drops graduation years that are between 1990 and 2002. All other variables are the same as Table 2. Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. The sample period is from 1966 to 2015.

Panel A: Log Number of Masters				
Weighting of RHS Variables	Size	Employment	Employment	Employment
	(1)	(2)	(3)	(4)
Skew	0.1178***	0.0843***		
	(0.0234)	(0.0216)		
Skew_Monthly			0.1053***	
			(0.0321)	
Skew_Quarterly				0.1036***
				(0.0328)
Mean Return	0.0120	0.0682*	0.0509	0.0670**
	(0.0270)	(0.0351)	(0.0326)	(0.0326)
Return Coefficient of Variation	-0.0121	-0.0112	-0.0162	-0.0077
	(0.0153)	(0.0136)	(0.0111)	(0.0112)
Log Total Market Cap	-0.0967	0.0514	0.0590	0.0246
	(0.0591)	(0.0764)	(0.0776)	(0.0745)
Log Mean Book-to-Market	0.0629	0.1056*	0.0653	0.0692
	(0.0396)	(0.0579)	(0.0525)	(0.0499)
Log Mean Firm Age	-0.1362***	-0.1764***	-0.1840***	-0.1645***
	(0.0268)	(0.0299)	(0.0309)	(0.0331)
Year Fixed Effects	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes
# Observations	521	521	521	521
Adj. R-Squared	0.91	0.91	0.91	0.91

Panel B: Exclude 1990-2002				
Weighting of RHS Variables	Size	Employment	Employment	Employment
	(1)	(2)	(3)	(4)
Skew	0.1158***	0.1219***		
	(0.0367)	(0.0238)		
Skew_Monthly			0.1088*	
			(0.0562)	
Skew_Quarterly				0.1315**
				(0.0540)
Mean Return	0.0545	0.0842	0.0840	0.0859*
	(0.0469)	(0.0531)	(0.0547)	(0.0512)
Return Coefficient of Variation	-0.0923***	0.0083	0.0246	0.0288
	(0.0257)	(0.0214)	(0.0196)	(0.0207)
Log Total Market Cap	0.0944	0.2115**	0.2771***	0.1917**
	(0.0726)	(0.0952)	(0.0946)	(0.0777)
Log Mean Book-to-Market	0.1030*	0.1436*	0.1635**	0.1283*
	(0.0588)	(0.0855)	(0.0825)	(0.0744)
Log Mean Firm Age	-0.1519***	-0.1890***	-0.2100***	-0.1621***
	(0.0323)	(0.0327)	(0.0330)	(0.0362)
Year Fixed Effects	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes
# Observations	378	378	378	378
Adj. R-Squared	0.85	0.85	0.85	0.85