

Superstar Firms and 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

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Abstract

We study the relation between the presence of superstar firms and college students' major choice. Salient occurrences of superstar performers in an industry are followed by a sharp rise in the number of college students choosing to major in related fields. This cohort effect remains significant after controlling for lagged industry returns and wages. Students' tendency to follow superstars, however, is met with lower real wages earned by entry-level employees when these students enter the job market. Further evidence from two college-graduate surveys shows that such adverse career outcomes can last for decades.

JEL Classification: D81, D91, G40, I23, J24

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1 Introduction

Education choice and human capital investment are of great importance to both individual well-being and social-economic development (Hoxby 2003, 2004). An integral part of this decision is college major choice.¹ In this paper, we study a potentially important but understudied determinant of major choice that is frequently referred to in the popular press: the link between college major enrollment and the presence of superstar performers — that is, a small number of firms that have done exceptionally well — in related industries. For example, Stanford Daily reports that the number of Stanford undergraduate students who declared a Computer Science major in 2013 was nearly four times that in 2006, possibly due to the high-profile successes of a handful of mobile-app and social-media companies such as Facebook. A *New York Times* article argues that “students are flocking to computer science because they dream of being the next Mark Zuckerberg.”

One possible account for this casual observation is that college students’ attention is often drawn to—and their expectations and decisions shaped by—salient occurrences of superstar performers.² For one, superstar firms and entrepreneurs attract disproportionate media coverage and social attention (Hirshleifer, 2019): the story of Mark Zuckerberg, one of the youngest self-made billionaires, is a constant talking point in the popular press and on college campuses. In addition, the occurrences of superstar firms and entrepreneurs are often accompanied by extreme payoffs: Mr. Zuckerberg is consistently named one of the world’s wealthiest and most influential individuals. A combination of these two salient features—disproportionate social attention coupled with extreme payoffs—make superstar firms particularly influential in college students’ major choice.

The importance of salience in driving human decisions, given limited cognitive resources, has been extensively studied in the psychology literature. As Taylor and Thompson (1982) put it, “salience refers to the phenomenon that when one’s attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments.” Kahneman (2011) goes on to argue that “our mind has a useful capability to focus on whatever is odd, different

¹Prior literature links the decision of college major choice (Computer Science vs. Economics, for example) to individuals’ perceptions of lifetime income of each major, personal interest in the subject, and innate ability.

²Note that “superstar firms/performers” in our context refer to a handful of firms with exceptional recent performance. This definition differs from the one often used in the industrial organization literature, where “superstar firms” refer to the largest firms (in terms of market value, employment or sales) in an industry (e.g., Autor et al., 2020). For example, a superstar performer in the tech sector in the early 2010s was Facebook, while the largest firm in the tech sector in the same period was Microsoft, which was struggling in its competition against Apple and Google. We argue that salient superstar performers like Facebook, rather than large firms like Microsoft in the 2010s, attract student attention.

or unusual.” Applying this insight to the setting of college major choice, we argue that salient occurrences of superstar firms and entrepreneurs—albeit non-representative of the whole industry—can play a substantial role in shaping students’ expectations and decisions. This force is particularly relevant given the substantial search costs faced by college students in their major choice (see, e.g., Hoxby, 2004; Altonji, Blom and Meghir, 2012; Hastings et al., 2016; Huntington-Klein, 2016).

To analyze the empirical relation between superstar firms and college major choice, we take the following steps. First, as defined in Rosen (1981) and Malmendier and Tate (2009), a superstar system is characterized by a highly skewed distribution of payoffs and public attention. We measure the presence of superstar performers in each industry by the *cross-sectional* stock return skewness in that industry. By definition, positive (negative) cross-sectional skewness in an industry reflects a small number of firms performing exceptionally well (poorly) relative to the industry peers.³ For example, Pan American World Airways (Pan Am) outperformed its peers by over 250% in the 1960s, leading to large positive cross-sectional skewness in the Air Transportation industry; Lockheed and Chrysler outperformed their peers by more than 300% in the early 1980s, giving rise to high return skewness in the Manufacturing industry. In our baseline results, we use employment-weighted skewness to give more weight to more important/visible firms in the industry.

We also use a more intuitive, approximate measure of skewness, $tail_N$: $(|top_N - median| - |bottom_N - median|)/stdev$, i.e., the distance between the top N firms in the return distribution and the median firm minus the distance between the bottom N firms and the median firm, divided by the standard deviation of returns. This measure is designed to capture the presence of N extreme winners and/or losers in the industry. The correlation between our main measure of industry return skewness and this more intuitive measure is well over 50%, and all our main results go through with this approximate definition of skewness.

Second, we focus on a set of science and engineering majors (computer science vs. chemical engineering, for example) that can be easily mapped to one or more industry sectors (information technology vs. pharmaceutical). Third, since college students usually declare their majors by the end of the sophomore year, we focus on industry return skewness measured in years $t-7$ to $t-3$ prior to the graduation year (from their junior year in high school to sophomore year in college) to explain college major distribution at graduation in year t .

Our empirical results reveal a strong positive relation between the presence of superstar firms and enrollment in related college majors. Using cohort-level college degree data from

³We do not claim that high school or college students regularly follow the stock market. Instead, we think of return skewness as a proxy for salient events taking place in related industries that draw students’ attention, and shape their expectations and decisions. We also use a more direct measure of salient events – skewness in media coverage and tones – and find very similar results.

the National Science Foundation (NSF) and controlling for both year- and major-fixed effects, we find that a one-standard-deviation increase in within-industry return skewness in years $t-7$ to $t-3$ is associated with a 15.74% (t -statistic = 4.89) increase in the number of graduates in related major fields in year t . For reference, a one-standard-deviation increase in the average industry return (wage) in years $t-7$ to $t-3$ forecasts an increase in graduates in year t by 7.55% (4.99%). This relation between industry skewness and major choice extends well beyond any particular industry or time-period. Going back to our earlier examples, the large positive cross-sectional return skewness in the Air Transportation industry in the 1960s was indeed followed by the popularity of the Aeronautical and Astronautical Engineering major; likewise, the positive skewness in the manufacturing sector in the early 1980s was followed by rising popularity of the Industrial and Manufacturing Engineering major.

A positive relation between college major enrollment and the presence of superstar performers is consistent with two general mechanisms. On the one hand, occurrences of superstar firms may indicate brighter industry prospects, so students choose related major fields in anticipation of more and better job opportunities (labor-demand based). On the other hand, although the presence of superstar performers is uninformative about future industry prospects, students are attracted by these salient, non-representative observations (labor-supply based).⁴ To empirically evaluate the relative importance of labor-demand- vs. supply-based channels, we examine the wage and net hiring (the price-quantity pair) at the time the cohort enters the job market. A relatively larger outward shift in labor supply (demand) should result in lower (higher) entry-level wages.

Our results favor a supply-based mechanism. After controlling for year- and major-fixed effects, a one-standard-deviation increase in industry return skewness in years $t-7$ to $t-3$ is associated with a 1.44% (t -statistic = 4.97) *drop* in the real wage earned by entry-level employees in related majors in year t . In contrast, within-industry return skewness in years $t-7$ to $t-3$ is uncorrelated with the average wage of advanced positions in year t , consistent with recent college graduates not competing for these types of jobs.⁵

Further, we find that the relation between lagged industry skewness and net hiring of entry-level employees in year t is indistinguishable from zero. This is consistent with the view

⁴A related possibility is that within-industry return skewness is informative about future industry prospects, but students overreact to this information; consequently, shifts in labor supply outweigh shifts in labor demand.

⁵Our 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 her counterfactual-self, had she chosen a different major. An obvious issue with this second approach is that individual major choice crucially depends on *unobservable* personal characteristics, such as ability and interest in the subject-matter. This is less of a concern at the cohort level, as long as the distribution of personal characteristics in each cohort does not vary systematically with the distribution of industry skewness over time.

that labor demand is relatively inelastic in the short run, as it takes time for firms to expand operations and production. An increase in labor supply (in the form of a larger number of college graduates in related fields) thus lowers the average wage earned by entry-level employees, without affecting the size of employment.

As a natural extension, we also examine changes in the composition of labor supply, that is, the type of students more likely to be attracted by salient occurrences of superstar performers. First, we find that the positive effect of industry return skewness on college major choice is significantly stronger among elite universities in states where the superstar’s industry has a substantial presence. Second, the negative effect of industry skewness on subsequent entry-level wages is stronger for occupation codes that pay above-median wages within a major (e.g., a larger effect on the wages of software developers than on that of database administrators, for Computer Science majors). Both results suggest that superstar performers attract more able students to related fields, potentially because better students are more likely to associate themselves with extreme success.

After providing evidence at the cohort level, we next examine granular, individual-level data from the National Survey of College Graduates (NSCG). The average respondent in this survey is 43.9 years old, roughly 20 years out of college, allowing us to examine career outcomes over a long horizon. The survey also contains information on total earnings, which includes wage as well as other sources of income, allowing a more complete measurement of job prospects. Moreover, the survey reports how closely a respondent’s current job is related to her main field of study, allowing us to study whether a part of the excess supply of graduates related to superstars gets absorbed in unrelated fields.

Our analysis reveals that after controlling for a host of fixed effects for different demographic characteristics, cohort, survey-year, industry, and major, a one-standard-deviation increase in industry return skewness of the respondent’s declared major forecasts 1.51–2.73% lower real annual earnings (including wages and bonuses) at the time of the survey. We also find that higher skewness is associated with a 4.69–5.18% higher propensity that the respondent works in a job outside her field of study, typically associated with worse outcomes. Working outside one’s field of study is associated with significantly worse outcomes—respondents who work in unrelated fields earn 16.7% less, and have 57-percentage-points higher odds of reporting job dissatisfaction, compared to their peers. These results suggest that an outward shift in labor supply not accompanied by a similar shift in labor demand can have a long-lasting, adverse impact on individuals’ career outcomes.

Our evidence, put together, points to a strong relation between superstar performers and increasing labor supply in related industries. Throughout the paper, we interpret this relation through the lens of industry salience – superstar performers increase industry salience, which

helps attract students to related majors. An alternative interpretation of this relation is that the presence of superstar firms does not by itself increase an industry’s attractiveness; instead, it is a reflection of an underlying industry trend/theme, which is unrelated to the industry’s labor demand but attracts student attention. For instance, during the internet bubble, there was an over-hyped narrative that the information technology sector alone was going to dominate our economy; consequently, a) a few internet companies achieved spectacular stock performance and b) students flocked to Computer Science. Although we cannot rule out this (omitted-variable) possibility, it is broadly consistent with our industry-salience-based interpretation: the occurrence of superstar performers still remains a *proxy* for industry salience, except that in this case salience stems from a narrative around the entire industry, rather than around a few firms in the industry.

In the last part of the paper, we provide more detailed evidence on the role of industry salience in driving college students’ major choice. We start by presenting evidence from a survey of college graduates we conducted for this paper using the SurveyMonkey platform, to answer questions that cannot be addressed using public data. For example, neither the NSF nor NSCG data contain information on the type of industries that college students want to work in at the time of major declaration. So it is unclear whether the relation between high-skewness majors and working in unrelated fields is driven by respondents who always wanted to work in different fields (computer science students longing for a career in investment banking) or by respondents who could not get a job in their target industry due to excess supply of graduates. We ask this question directly in our survey, and the evidence clearly favors the latter possibility. Moreover, our survey helps distinguish between the two previously-mentioned channels through which college students may be drawn to industries with superstar performers: a) belief errors—i.e., students form income expectations (or more generally, expectations of future successes) based on a small number of non-representative but highly visible observations; b) preferences for positively skewed payoffs—that is, students are happy to accept a lower average wage for a small chance of hitting the jackpot. Our survey evidence indicates that skewness-driven major choice is strongly correlated with self-reported expectation errors, but not with lottery preferences.

Second, motivated by the analysis in Charles, Hurst, and Notowidigdo (2018), we exploit structural breaks in industry valuation during the NASDAQ bubble at the turn of the 21st century to identify superstar industries. Computer Science-related industries experience the largest structural break in industry valuation among all science-engineering majors in our sample; moreover, the size of the structural break is significantly and positively associated with subsequent changes in major enrollment.

Finally, we provide more direct evidence for the effect of industry salience on human

capital investment by honing 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 salience/popularity of the legal profession among prospective students. Consistent with the salience interpretation, we find that lagged viewership of *Law & Order* strongly and positively forecasts students' interest and enrollment in law schools, but negatively forecasts future wages of entry-level lawyers.

In sum, our set of analyses provides novel evidence that the presence of superstar performers in an industry forecasts higher college major enrollment in related fields, but lower entry-level wages and a higher likelihood of working outside target industries at the time of graduation; moreover, these adverse career outcomes last for decades. These results are in favor of an outward shift in labor supply (more so than that in labor demand) in relation to superstar performers. Together, our evidence suggests an additional channel—education choice—through which superstar firms may impact social welfare and economic growth.

2 Related Literature

Our paper contributes to a large labor-finance literature on human capital investment. For example, several papers study the consequences of shocks to labor supply. Ouimet and Zarutskie (2014) show that an increase in regional supply of younger workers increases the rate of new firm creation. Agarwal et al. (2019) use the Chinese superstition of giving birth in “Dragon” years to identify the effect of labor supply shocks on earnings. Gupta and Hacamo (2018) study early career choices and subsequent long-run career outcomes of elite engineers. Bena and Simintzi (2019) show that the ability to access labor cheaply affects firm innovation. A related literature studies the impact of sectoral booms and busts on workers' choices and outcomes (Oyer, 2008; Charles, Hurst, and Notowidigdo, 2018; Hombert and Matray, 2019).

This paper is also related to the growing literature on the impact of salience on human decisions (Chetty, Looney, and Kroft, 2009; Bordalo, Gennaioli, and Shleifer, 2012, 2013a, 2013b; Han, Hirshleifer, and Walden, 2022; Hirshleifer and Plotkin, 2021; Cosemans and Frenhen, 2021). In neuroeconomics, Fehr and Rangel (2011) show that subjects evaluate choices by aggregating information about different attributes, with decision weights influenced by attention. Recent theoretical research has also developed novel ways of incorporating limited attention in economic decisions (Gabaix, 2014). While none of these papers have examined the role of salience in education choice, like we do here, it is perhaps a natural application—given the complexity of the search process for information about job prospects (Stigler, 1961; 1962).

While superstar firms have been studied at least since Rosen (1981), our result that the occurrence of superstars forecasts worse outcomes is reminiscent of Malmendier and Tate (2009), although both the context of the studies (CEOs vs students) and the channels (CEO actions vs oversupply) are markedly different. Our result itself 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; more generally, a preference for skewness is also a central theme in the non-standard utility literature (Kahneman and Tversky, 1979; Barberis and Huang, 2008, Kahneman, 2011). On the belief side, theory and evidence on mistaken beliefs leading to oversupply can be found as far back as in Kaldor (1934), or more recently, in Greenwood and Hanson (2015).

Fluctuations in labor markets have also been studied through the lens of Cobweb theory, by Freeman (1971, 1975, 1976). Under Cobweb theory, a lower salary in a major attracts fewer freshmen and, ultimately, produces fewer graduates—but this change in supply manifests itself in the labor market only a few years later. Consequently, starting wages become higher, affecting in turn, major choice of the freshman cohort of the future year—hence producing endogenous cycles in both enrollment and wages. While our paper also a) emphasizes the time lag between major choice and graduation and b) builds on the premise that students form expectations based on stale, non-representative information, our focus is on the effect of salient occurrences of superstar firms in an industry on the distribution of major enrollment.

Finally, we also contribute to the broader literature on individuals' education choice and on career outcomes (Hoxby, 2003).⁶ Most prior studies on college major choice (Berger, 1988) use a framework in which students form rational expectations of future earnings using Bayesian updating. Subsequent research has added various dimensions to this approach, from uncertainties (Altonji, 1993) to heterogeneity (Patnaik et al., 2020). Our paper contributes to and deviates from this literature by examining the role of salient occurrences of superstar firms in determining college students' expectations and major choice.

⁶See also James, Alsalam, Conaty, and To (1989), Altonji (1993), Sacerdote (2001), Avery and Hoxby (2004), Hoxby (2004), Bhattacharya (2005), Blom (2012), Goldin (2014), Lemieux (2014), Stinebrickner and Stinebrickner (2014), Bordon and Fu (2015), Altonji, Arcidiacono, and Maurel (2016), Arcidiacono, Hotz, and Kang (2012), Fricke, Grogger, and Steinmayr (2015), Wiswall and Zafar (2015, 2022), among others.

3 Data

3.1 College Majors and Related Industries

Our data on college degrees are obtained from the National Science Foundation (NSF) and the Integrated Postsecondary Education Data System (IPEDS). 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. NSF groups the 2010 Classification of Instructional Programs (CIP), a taxonomy of academic disciplines, into different major fields. The full list of the major fields is presented in Online Appendix Table A1. We use an online NSF document, which lists the number of degrees that were conferred between 1966 and 2012 by accredited institutions of higher education in the US, including the 50 states and the District of Columbia. For degrees that were conferred between 2013 and 2017, we download the number of degrees for each 6-digit CIP code from NSF’s Data Explorer and aggregate them into the corresponding major fields.⁷ IPEDS provides the annual number of bachelor degrees for each CIP awarded by each institution, starting in 2001.⁸

We then map the science and engineering degrees from Appendix Table A1 to 3-digit NAICS industry codes. We focus on the set of majors that can be readily mapped to one or more industry sectors (e.g., computer science). In other words, we exclude some physical science and social science majors (e.g., physics, sociology) from our analysis, because students choosing these majors are unlikely to be targeting any specific *industry jobs*. For instance, during our sample period, many physics majors later become high school teachers.⁹

This mapping is carried out through merging two crosswalks, the 2010 Classification of Instructional Programs (CIP) to the 2010 Standard Occupational Classification (SOC) Crosswalk and the 2010 SOC to the 2012 NAICS map. The detailed mapping is shown in Online Appendix Table A1. Each major field can correspond to multiple 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

⁷The online NSF document is available from the NSF website: <https://www.nsf.gov/statistics/2015/nsf15326/pdf/nsf15326.pdf>. The number of degrees provided by NSF’s Data Explorer at the 6-digit CIP level starts in 1997. While NSF’s Data Explorer also provides other useful statistics such as enrollment and race composition, we opt for a longer sample period and use the NSF document, which only lists the number of degrees awarded. As shown in Figure 1, this sample period sees the rise of different popular majors and superstar firms.

⁸For the school-level analysis, we sum the number of first majors and second majors to get the number of graduates. Between 1987 and 2000, IPEDS only reports the number of first majors from each school. We do not use these years as they are not comparable to the post-2001 data.

⁹Our analysis compares the science and engineering majors we focus on with each other, but not with majors that are excluded.

Assistance (NAICS = 624). Each industry code can also be mapped to several major 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.¹⁰

3.2 Return Skewness

To construct our skewness measure, we first calculate the employment-weighted cross-sectional return skewness within each NAICS 3-digit industry.¹¹ Since students may follow multiple industries when deciding their majors, we then take the equal-weighted average skewness across all industries associated with the major. Our approach assumes that students are equally exposed to salient events in all industries related to each major. We aggregate other industry-level variables to the major level in the same way. Our results are robust to other ways to aggregate industry-level variables (e.g., focusing on the industry with the maximum absolute skewness measure, or computing skewness by pooling firms across all related industries).

Figure 1 shows episodes of high major skewness, and the superstar firms in each episode that were the top contributors to the skewness measure. Specifically, we calculate the five-year residual skewness (after adjusting for the mean and standard deviation of returns in corresponding industries) for each major in each year. The solid line shows the maximum residual skewness across all majors in each year, and the shaded areas depict episodes of particularly high maximum residual skewness. The firms shown in the figure are those that contribute the most to the skewness of the related major in each episode, calculated as the difference between the skewness of the corresponding major with and without that firm.

Besides the internet bubble episode, we identify superstars in other periods as well. For example, in the late 1960s, Pan American World Airways (Pan Am) outperformed its industry peers by 250% in terms of stock returns, contributing to the high return skewness of the Air Transportation industry, and possibly the high enrolment in the Aeronautical and Astronautical Engineering major shortly after.¹² The early 1980s saw high returns to companies like Chrysler and Lockheed, and Industrial and Manufacturing Engineering was

¹⁰Two of the majors, Computer Sciences and Electrical Engineering, are mapped to the same set of industry codes as they are closely related.

¹¹The employment-weighted return skewness is given by $\frac{\sum_i^n w_i (\frac{r_i - \bar{r}}{\hat{\sigma}})^3}{\sum_i^n w_i}$, where n is the number of firms in the industry, w_i is the number of employees in firm i , r_i is the return of firm i , and \bar{r} and $\hat{\sigma}$ are the employment-weighted mean and standard deviation of return, respectively. The stock and firm data are obtained from CRSP and Compustat.

¹²Although Pan Am went into bankruptcy in 1991, it was a highly successful and visible company in the 1960s. This is evidenced by the Hollywood movie, *Catch Me If You Can* (2002), which was based on the life of a con-artist who impersonated a Pan Am pilot in the 1960s.

a popular major in the following years. The early 2010s saw high returns to "bulge-bracket" banks, followed by the popularity of the Economics major. In the last few years, Tesla had spectacular returns and made auto manufacturing glamorous.

3.3 Aggregate Wage and Employment

Aggregate wage and employment data between 1997 and 2017 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 requirements (degrees and approximate number of years of experience required) for the majority of the SOC codes. We use 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 do not require prior work experience. Note that the aggregate wage and employment for each major is calculated from the employment-weighted wage and total employment across all relevant SOCs. Each SOC (e.g., Computer Programmers) can appear in multiple industries, some of which (e.g., Financial Services) can be different from our major-NAICS map in Appendix Table A1. In other words, our measures of aggregate wage and employment are derived from the actual employment data and do not rely on any major-NAICS map.

Our tests focus on engineering and applied science majors that can be readily mapped to industry sectors. In our analysis of aggregate-level data (from NSF, IPEDS, and BLS), we exclude Biological Sciences and Health majors. Although students of these majors can follow superstars in specific industries (e.g., in the Health sector), many biology- and health-related jobs require an advanced degree and students often go to graduate schools before entering the job market (health and bio majors are 26.9% more likely to have higher degrees, relative to other majors in our sample). Lacking information on the actual starting year of their careers, our skewness measure constructed from years $t - 7$ to $t - 3$ is less precise. Nevertheless, our conclusion remains unchanged if we include Biological Sciences and Health majors in the aggregate-level analysis, as reported in Appendix Table A2. In the analysis of individual-level data, we include these two majors in our analyses, because there we do have detailed information on respondents' education and career paths, which allows us to avoid the aforementioned issue.

3.4 Individual-Level Wage and Employment

We also use the National Survey of College Graduates, sponsored by the National Center for Science and Engineering Statistics (NCSES) and the NSF and conducted by the Census Bureau. The survey provides data on college graduates, focusing on those in the science and engineering workforce. It is conducted every two years since the 1970s and samples individuals who live in the U.S., have at least a bachelor’s degree, and are younger than 76. Eligible individuals are identified by the education attainment responses to the U.S. Census long form and the American Community Survey (ACS). The data are collected through online surveys, paper questionnaires, and computer-assisted telephone interviews. From the survey, we can obtain information about individual survey respondents’ graduation year, major, demographics, total earnings (including variable compensation, e.g., bonuses), and employment status. Data are available online beginning 1993. We require information on respondents’ majors, which is publicly available in the years 1993, 2003, 2010, 2012, 2015 and 2017.

3.5 News Sentiment

Our news sentiment data are from RavenPack News Analytics, which quantifies positive and negative contents of news reports. We focus on the Event Sentiment Score (ESS) constructed by RavenPack. ESS is determined by matching stories typically categorized by financial experts as having positive or negative financial or economic impact. It ranges between 0 and 100, where 50 represents neutral sentiment, and is available between 2000 and 2017.

3.6 Summary Statistics

We present summary statistics for our variables of interest in Table 1. The median number of bachelors in each major is 6,921 students per year. We define industries at the 3-digit NAICS level. On average, firm returns in an industry are positively skewed in the cross-section, with a median annual skewness of 0.86. The median cross-sectional skewness in news tone, measured from the Ravenpack news analytics data, is 1.52. The correlation between the return-based and news-based skewness measures is roughly 30%. The employment-weighted average entry-level wage for workers with a bachelor’s degree in science and engineering has a median of \$58,070 (in 1997 dollars).¹³ The median annual net new hiring of these positions is 3,102, or 2.3% of the number of employees in the previous year.

¹³Note 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 have not been promoted.

4 Main Results at the Major Level

This section presents the main results of our paper. We start by examining the relation between occurrences of superstar firms in an industry and the subsequent number of students choosing related major fields. Note that in contrast to standard major choice regressions typically run at the individual level using survey data, in this section we are mostly interested in variation at the cohort level, as a function of related-industry characteristics.

4.1 Number of Graduates in Different Majors

Our main hypothesis is that given the substantial cognitive costs faced by college students in figuring out job prospects, personal ability and interest in various industries, students' expectations—and hence major choice—are disproportionately influenced by salient, easy-to-recall events. To analyze the effect of occurrences of superstar performers (measured by cross-sectional returns skewness) on major choice decisions at the cohort level, we estimate the following regression equation:

$$\log(bachelor_{i,t}) = \alpha + \beta LaggedSkew_{i,t-3} + \gamma \mathbf{X}_{i,t-3} + \mu_i + \tau_t + \epsilon_{i,t}, \quad (1)$$

where $\log(bachelor_{i,t})$ is the natural logarithm of the number of graduates in major 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). $LaggedSkew_{i,t-3}$ is the cross-sectional return skewness relevant to that major, calculated using returns data from $t-7$ to $t-3$.¹⁴ Note that our skewness measure is 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 by their sophomore year in college.¹⁵

$\mathbf{X}_{i,t-3}$ is a vector of controls, suitable to our setting of analyzing major choice at the cohort level. Our vector of controls includes the average industry return and industry return volatility between $t-7$ and $t-3$. These two controls ensure that our skewness measure picks up differences between industries that have performed similarly in the recent past, and have had similar variability in performance. Next, we include as a control the average size (market

¹⁴Our results are also robust to other return windows, e.g., $t-8$ to $t-3$ and $t-6$ to $t-3$.

¹⁵Further, Table A3 in the Online Appendix conducts a test using skewness measured in years $t-2$ and $t-1$, i.e., the two years that are likely after major declaration and hence mostly reflect those who switch majors. As expected, $LaggedSkew$ in these two years has a much more muted effect on major choice, and in a horse race has virtually no impact on the coefficient on $LaggedSkew$ in years $t-7$ to $t-3$, suggesting that switching majors is far less popular than sticking to a declared major. For example, in our own survey using SurveyMonkey, we ask each respondent the year she decided on her major, and find that about 80% decide their majors by the end of their sophomore year in college.

capitalization) of firms in that industry. We also account for the average firm age and industry valuation ratio (book-to-market, B/M), which are typically regarded as proxies for firm growth within an industry. μ_i and τ_t are major and time (year) fixed effects, respectively. 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 fluctuation from our estimate. We cluster the standard errors at the year level and not at the major level because of the small number of majors; our results remain highly statistically significant with block-bootstrapped standard errors (see Online Appendix Table A2).

If our hypothesis—that college students’ major choice is influenced by superstar firms—is true in the data, we expect skewness to positively predict the number of graduates in related major fields in the future. That is, the coefficient on *LaggedSkew*, β , should be positive. We present the results in Table 2. As we can see from Column (1), *LaggedSkew* predicts major choice strongly, even after controlling for the average industry return and industry return volatility.¹⁶ A one-standard-deviation increase in *LaggedSkew* is associated with an increase in the number of students majoring in related fields by 15.74% with a *t*-statistic of 4.89 (all explanatory variables are standardized). For comparison, a one-standard-deviation increase in the lagged average industry return is associated with a 7.11% (*t*-statistic = 1.96) increase in the number of students choosing the major in a univariate regression (omitted for brevity) and the coefficient estimate becomes statistically insignificant once we control for *LaggedSkew* and other industry characteristics.

We also control for the average wage earned by each major (*Lagged Log Average Wage*). This is to examine whether the empirical relation we document above is distinct from the cycles of major enrollment, employment and wages as described in Cobweb models. Following prior literature on Cobweb theory (e.g., Freeman, 1976), we control for the average real wage of each major in the past three years. While past wages indeed positively predict future major enrollment, our skewness measure shows strong predictive power—both in terms of the economic magnitude and statistical significance.

To put our discussion above in perspective, we would like to highlight two key aspects of our empirical design. First, many of our majors can be stepping stones to careers in multiple industries; so choosing to graduate with 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 in our analysis is that *at the time* the

¹⁶Moreover, we also find that the relationship between $\log(\textit{bachelor})$ and *LaggedSkew* holds even if we drop the Tech Bubble period (shown in Online Appendix Table A2). These results are also robust to using cohort-level data on Masters degrees instead of Bachelors (Appendix Table A2).

student chooses to major in Computer Science, he is much more interested in a career in the Computing or Tech industry than he is interested in librarianship.

Second, we use skewness in stock returns, rather than concentration in firm size or sales (e.g., Autor et al., 2020), to reflect the fact that students are more likely to be attracted by what is “exciting” at that time. This notion of salience is more closely captured by a handful of superstar firms performing exceptionally well and thereby capturing public imagination and media attention, and is less so by the presence of a few dominant firms in the industry. Note that even though such exciting firms may lead a student to choose a major field, there is often a small chance of actually working for these dream companies. For example, even though Facebook’s success was (and perhaps still is) capturing social attention from college campuses to movie studios, the firm accounted for a tiny fraction of all jobs for Computer Science majors. We revisit this issue in Section 5.

4.2 Entry-Level Wages and Employment

The fact that students are drawn to industries with superstar performers can be consistent with both increased labor demand and increased labor supply. In other words, 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 (or less informative than they expect). To examine the relative importance of labor demand vs. supply channels, we simultaneously examine two quantities: wages (inflation-adjusted) and employment. Examining the price-quantity pair allows us to evaluate the relative magnitude of shifts in the labor supply vs. demand curves.

Note that in these wage/employment tests, while our skewness measure is based on related industries that students likely think about while making their major choice decisions, the wage data are from actual occupations that absorb graduates from various majors (from the CIP to SOC Crosswalk). Each occupation code can appear in multiple industries (e.g., computer programmers in the tech industry vs. financial services industry); we take an employment-weighted average across all industries to quantify employment opportunities more accurately. In our baseline result, we focus on entry-level employment and wages for jobs that require a bachelor’s degree but no prior work experience.

We examine what happens to job opportunities at the time our year t cohort enters the job market. Specifically, we estimate the following regression equation:

$$\log(\text{annual_wage}_{i,t}) = \alpha + \beta \text{LaggedSkew}_{i,t-3} + \gamma \mathbf{X}_{i,t-3} + \mu_i + \tau_t + \epsilon_{i,t}, \quad (2)$$

where $annual_wage_{i,t}$ is the employment-weighted average entry-level wage for major i in year t . $LaggedSkew_{i,t-3}$ is our employment-weighted salience measure of industries related to major i , as explained earlier (our results are robust if we use size-weighted $LaggedSkew$ instead). We also control for major and time fixed effects in our regressions, so one way of thinking about our empirical design is that we relate the average market-adjusted entry-level wage of the same major across different cohorts to lagged industry return skewness. Other control variables are similar to those in equation (1). In particular, we control for lagged wages of related majors to distinguish our results from predictions of a Cobweb model, and add two additional controls: a) the average number of graduates in related majors in years $t-1$ and $t-2$, to ensure that the delayed absorption of previous graduates is not driving our results, and b) the ratio of male to female graduates, to account for changes in gender balance.

Table 2 reports results on wages and employment. As shown in Column (2), $LaggedSkew$ is significantly and negatively associated with future entry-level wages. A one-standard-deviation increase in lagged industry skewness is associated with a 1.44% (t -statistic = 4.97) lower real wage for entry-level jobs requiring a bachelor’s degree. In Column (3), we find an insignificant relation between $LaggedSkew$ and future new hires. This suggests that even though salient events drive more students to related major fields, entry-level job positions do not immediately expand to absorb these extra graduates. This is consistent with labor demand being relatively inelastic in the short-run. In the Online Appendix Table A4, we show that industry turnover, defined as total separations minus hires (as a percentage of employment), is also unrelated to $LaggedSkew$.¹⁷

In Columns (4) and (5) we conduct a placebo test by repeating our analysis in Columns (2) and (3) using data on *advanced* job positions that require a Doctoral or Professional degree or substantial prior work experience. If our results are driven by $Skew$ reflecting changes in demand for labor, we should see a similar pattern with these advanced positions. If, instead, our results are driven by increased supply of fresh graduates, this should mostly affect entry-level jobs, and not advanced positions. Our evidence supports the latter: $LaggedSkew$ is unrelated to wages and net new hires of advanced positions. In contrast, the lagged average industry return significantly and positively forecasts future wages of both entry-level and advanced positions, consistent with the view that industry returns are forward looking and informative about future career prospects.

Combined, the evidence presented in Table 2 suggests that the presence of salient super-

¹⁷There 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 entry-level wages at graduation, as indicated by the positive coefficient on *Lagged Log Number of Bachelors* (consistent with the findings in Wiswall and Zafar, 2022).

star performers forecasts larger enrollment in related major fields, and yet lower future wages when these students enter the job market, and is uncorrelated with the number of entry-level jobs.¹⁸ Put differently, students’ decision to follow superstars in their major choice is subsequently met with worse job opportunities.

4.3 Alternative Measures of Superstar Performers

4.3.1 A More Intuitive Measure of Skewness

The main skewness variable we use is the standard definition in the literature, designed to capture the presence of outliers in a smooth and continuous fashion exploiting the entire distribution. To provide more intuition for skewness, we use an alternative, more discrete definition of distribution asymmetry: the distance between the right tail of a distribution and its median, minus the distance between the left tail and the median. More formally, we define $tail_N = (|top_N - median| - |bottom_N - median|)/stdev$.¹⁹ Take $N = 1$ for example, a large and positive $tail_1$ indicates that the best performing firm in the industry does spectacularly better than the median firm while the worst performing firm only mildly worse—which intuitively captures our definition of an industry with superstar performers.

We repeat our analyses in Table 2 using $tail_N$ in place of cross-sectional skewness. Again, the measure is constructed using return data from $t-7$ to $t-3$. The results are shown in Table 3, Panel A.²⁰ Column (1) shows that this alternative measure positively predicts the number of bachelors. A one-standard-deviation increase in $tail_N$ forecasts a 19% (t -statistic = 4.99) higher number of graduates in related major fields. Column (2) shows that the effect of $tail_N$ mainly operates through superstar firms ($top_N - median$) attracting more students, and less so through super losers ($bottom_N - median$) repelling students (the difference between the coefficients on $top_N - median$ and $bottom_N - median$ is significant at the 1% level). The evidence in Column (3) suggests that a one-standard-deviation increase in our return asymmetry measure predicts 1.66% (t -statistic = 4.88) lower entry-level wages in related industries when the cohort graduates. Column (4) shows that this wage effect—in line with the effect on the supply of graduates in Column (2)—is also coming solely from superstars, and not super losers. As before, $tail_N$ does not predict future changes in entry-

¹⁸In Online Appendix Table A2, we repeat the exercises in Table 2 by using alternative ways to aggregate industry return skewness to the major level, specifically by focusing on the industry with the maximum absolute skewness and computing one skewness measure by first pooling firms across all related industries. The results are by and large unchanged.

¹⁹We exclude firms below the 50th percentile of the size distribution when selecting the top and bottom N firms in each industry so that the measure is not dominated by small firms.

²⁰In our baseline result, we pick $N = 10$ to reduce noise in the measure, but as shown in Online Appendix Table A2, our results are robust to other choices of N (e.g., 1, 3, 5).

level employment size in related industries (Columns (5) and (6)).

4.3.2 Skewness in Media Tones

Until now, we measure salient occurrences of superstar firms in an industry using cross-sectional return skewness. As mentioned earlier, this is not to suggest that high school students, or first and second year college students, follow the stock performance of all firms on a regular basis. Indeed, we think of *LaggedSkew* as a proxy for salient events in related industries that draw students' attention and shape their expectations and decisions.

These salient events are also likely to be accompanied by significant media attention. Thus, an alternative way of capturing extreme, salient industry events is to exploit variation in media coverage and tones. Here, we use a media-coverage positivity score supplied by RavenPack (which sifts through all news articles published by major financial news outlets starting in 2000), and assign a score of -1 to 1 to each news article depending on the positivity or negativity of the tone (see Dang, Moshirian, and Zhang, 2015).

We then run regressions similar to equation (1) but replace return skewness with media skewness, and report these results in Table 3, Panel B. In Column (1), we find that media skewness positively predicts major choice; a one-standard-deviation increase in *Lagged News Skew* is associated with 15.70% (t -statistic = 3.55) more graduates in related majors in year t .²¹ In Columns (2) and (3), we show that a one-standard-deviation increase in news skewness is associated with a 1.48% (t -statistic = 2.96) lower entry-level wage, and an insignificant relation between news-tone skewness and net new hires.²²

4.4 Heterogeneity in the Cross Section

4.4.1 Composition Changes in Labor Supply

Our focus so far has been on the shifts in the entire labor supply curve, without explicitly considering the composition of the supply; in other words, we implicitly assume that the *types of students* choosing each major are unrelated to the presence of superstar firms.²³

²¹In Online Appendix Table A5, we zoom in on two specific types of salient events in the equity market: initial public offerings (IPOs) and firm defaults and delistings, both of which can attract substantial media and public attention to the relevant industry. While IPOs are salient positive events, likely drawing students to related majors, defaults and delistings are salient negative events, which are likely to turn students away. We find consistent evidence: IPO returns are positively related to future major enrollment while firm defaults and delistings are negatively associated with it.

²²The results on the number of students choosing the major and those on wages and new hires are similar if we also control for the industry mean and standard deviation of news tones.

²³A related possibility is that salient occurrences of superstar firms lead to an overall increase in enrollment in science and engineering. In other words, students that would not go to college or would not choose science and engineering majors are now attracted to do so. In Online Appendix Table A6, we show that neither the

In this section, we discuss two related variants of the labor-supply channel that allows for changes in supply composition.

The first variant is that less capable students disproportionately select into high-skewness majors. If these students drive up labor supply, then the observed lower entry-level wage partly reflects their lower marginal productivity. We take this possibility to the data and examine whether our results are stronger among students of lower versus higher overall quality.

Our first test looks at college reputation. In Table 4, Panel A we examine dis-aggregated school-level data from four-year universities. We focus on 336 schools that offer at least 5 out of our 10 majors and study whether the effect of superstar firms is any different among top schools, especially those located in states with significant presence of related industries (e.g., California for Tech jobs). To this end, we construct a dummy variable, *TopSchool*, which equals one if a school is in the top 50 in the *US News 2018 Best Colleges* list and is located in the state that hires the most people in related industries (e.g., Stanford University for Computer Science), and zero otherwise (under this definition, there are 20 Top schools). Our results show that top school students are especially drawn by local superstar performers. Specifically, the effect of lagged industry skewness on subsequent major enrollment among top schools is more than thrice as large as that for non-top schools (0.369 vs. 0.112).

Our second test exploits wage differences for jobs within a major (e.g., software developers vs. database administrators, for Computer Science majors). Specifically, for each major-year, we separate combinations of occupation codes and industries into those offering wages above and below the sample median in year $t-3$. The former (latter) group represents higher-(lower-) skilled jobs within the major. We calculate the average wage and change in net hiring in each of these major-wage groups, and add an interaction term between *LaggedSkew* and *Lowskilled*, where *Lowskilled* indicates the lower-wage group. (We further include in the regression specification *Major-Wage-group* fixed effects to subsume (time-invariant) differences between high- vs. low-skilled jobs within each major.) Column (1) of Table 4 Panel B shows that *LaggedSkew* strongly and negatively predicts wages of high-skilled occupations but not wages of low-skilled occupations (-0.0279 vs. -0.0114). Column (2) shows that *LaggedSkew* is not systematically related to the net new hires in either group.

In sum, the evidence shown above—a) that top school students react more to local superstar firms and b) that the wage decline in relation to superstar firms is present only in high-skilled occupations—suggests that the documented drop in average entry-level wage in relation to superstar performers is unlikely to be reflection of an influx of less capable

max skewness nor the average skewness across all majors predicts total enrollment in science and engineering majors, so this is an unlikely possibility.

students.

A second variant of the baseline labor-supply mechanism is that although students of good overall quality are attracted to majors with superstar firms, the matching quality between students' skills and those required by the major declines (for example, a student who would make a good mechanical engineer now chooses to study computer science.) As a result, the lower entry-level wage partly reflects poor matching. While this variant also provides an additional explanation for the lower entry-level wage, it still operates through the labor supply channel: talented students are attracted to potentially unsuitable majors by the presence of superstar performers in related industries.

4.4.2 Major Versatility

Next, we investigate the notion that the fungibility of employment opportunities is different across majors. Specifically, if graduates from a particular major have employment opportunities in a variety of industries, then part of the excess labor supply can be shared among those industries, leading to less downward pressure on wages in each industry. We test this hypothesis using an interaction term between *LaggedSkew* and *Versatility*, defined as the Herfindahl index of employment for graduates from a particular major in different industries. Our evidence in the first column of Table 4, Panel C reveals that industry skewness negatively affects real wages mostly for majors that have concentrated job opportunities in a small number of industries. (We do not find statistically significant differences in entry-level employment size in Column (2) of the same panel.)

5 Granular Data from Surveys

5.1 National Survey of College Graduates

One important concern regarding our result that following superstar firms seems to hurt college students at graduation is that job prospects may improve in the longer term. Another concern is that our wage measure does not adequately capture total earnings (which should also include bonuses and other payments). A third issue 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 shown how this excess supply is eventually absorbed by the labor market. Finally, the evidence we have presented is based on aggregate, macro-level data; it is useful to show that our wage results also hold up at the individual level, after controlling for age, gender, and other well-known determinants whose distributions might also shift across cohorts. We explore all these issues using granular survey data from the *National*

Survey of College Graduates (NSCG). First, the average age of respondents (67.7% male, 71.7% married) in the NSCG surveys is 43.9 years—roughly 20 years out of college; thus the survey provides useful information on long-term outcomes. Second, NSCG respondents report their total earnings including bonuses and stock grants. Third, NSCG data allow us to explore whether college graduates from high-skew majors have to accept jobs unrelated to their majors. Finally, this dataset is at the *individual* level, allowing us to add various non-parametric controls, e.g., a host of fixed effects for majors, survey-cohorts, graduation-years, gender, marital status, minority status, work industry, highest degree attained, and highest degree fields (see, e.g., Macpherson and Hirsch, 1995; Johnson and Neal, 1997; Dickson, 2010).

Table 5 shows our regression results. The first three columns of Panel A report results from panel regressions with $\log(\text{Earnings})$ as the dependent variable. Columns (1) and (3) examine the full sample, while Column (2) examines students whose highest degree is bachelors. In Column (3), we further control for the highest degree attained by the respondent, the field of the highest degree through fixed effects, and high dimensional fixed effects for each major-survey year, industry-survey year and major-industry pair.

As can be seen from Columns (1)–(3), one-standard-deviation higher *LaggedSkew* is associated with 1.5% to 2.7% lower total earnings (comparable to the effect on starting wages in Table 2). This is consistent with adverse initial labor market conditions affecting long-term income of college graduates (also see Oyer, 2006, 2008; Oreopolous et al. 2012). In sum, the wage effect we document earlier is neither short-lived, nor is it an artifact of leaving out non-wage compensation.

The last two columns of Table 5, Panel A report the odds ratios from Ordered Logistic regressions of how closely the graduate’s current job is related to her field of study in college. Closeness is reported in three levels: “closely related,” “somewhat related” and “unrelated,” with higher values indicating decreasing relatedness. We find that a one-standard-deviation higher *LaggedSkew* is associated with a 4.7–5.18% higher propensity to work in a job outside the field of study, indicating the absorption of excess supply of graduates by other industries.

In Panel B, we examine the long-term consequences of working in an industry unrelated to one’s field of study. We find significant negative career outcomes associated with having to take a job outside one’s field: earnings are lower by 16.7–23.0%, and the odds of reporting lower job satisfaction are higher by 57.3–78.8% for those working in less related sectors.

5.2 Evidence from Our Own Survey

In this section, we provide evidence from a survey of college graduates we conducted on the SurveyMonkey platform, specifically designed for the purpose of this paper. While the NSCG survey shows that students influenced by superstar performers are more likely to work in industries outside their fields of study, that evidence may not reflect oversupply of graduates. For example, some engineering students may have hoped to work for investment banks when choosing their major. Further, we do not know from NSCG whether a graduate’s first job was in a different industry, or whether she changed her jobs later due to a change in interest or learning about job contents.²⁴

Moreover, the survey allows us to contrast two channels underlying student attraction to superstar-related majors: a) belief errors—students form income expectations (or more generally, expectations of future successes) based on a small number of non-representative but highly visible observations; and b) skewness preference—students are happy to accept a lower average wage for a small chance of hitting a jackpot.

Note that we never asked the survey respondents about salient extreme events or industry return skewness: knowing their major and the year they declared the major, we can back out the cross-sectional return skewness relevant to each respondent’s major choice decision. In all regressions, we control for major, industry, graduation-year, student debt status (e.g., Chakrabarti et al., 2020), and gender fixed effects. Further details on our survey are presented in the Internet Appendix.

Table 6 reports results from this survey. Column (1) in Panel A shows an ordered logistic regression with Household income buckets as the dependent variable. Column (2) reports the marginal effect from a logistic regression with a dummy dependent variable indicating whether the graduate started her post-college career in an industry that she expected to work in when choosing the major. In Columns (3)–(5), we examine consequences of taking up a job not in the graduate’s target industry. Our results here indicate that Lagged Skew is associated with a higher likelihood that the student’s first job is not in her target industry, which also corresponds to a higher probability of switching to yet another industry afterwards due to dissatisfaction of layoff. Other results on household income are consistent with those in Table 5.

In Panel B, we examine the two channels that could potentially drive respondents’ decisions to follow superstar firms. To understand the role of expectation errors, we construct two dummy variables from questions in the survey. First, we asked each respondent if she chose her major based on knowledge about a small number of well-performing firms, or

²⁴In our sample, 29% of the respondents change industries after graduation, similar to the figure reported by Ellul, Pagano, and Scognamiglio (2020).

by gathering thorough information on all job prospects. Second, we asked whether the respondent thought her expectations of future job/income outcomes could have been more accurate had she done a bit more research. *Expectation_Errors* is the average of the two dummy variables. Column (1) shows that respondents who chose a major associated with salient superstar performers are more likely to report having made a mistake in their expectations. Column (2) then examines *Lottery_Preference*, a dummy variable that equals one if the respondent would have preferred a lottery-like payoff over a stable future income stream had she been given that option in college. We do not find any significant relation between lottery preferences and tendencies to chase superstar performers. The last column shows that including *Expectation_Errors* and *Lottery_Preference* in the same regression does not change our conclusions.

Overall, our evidence suggests that belief errors, rather than an inherent preference for skewness, are associated with individuals' decisions to chase superstar performers in their college major choice.

6 Discussions of Our Results

6.1 Further Discussions of Labor Demand

As discussed earlier, the increase in major enrollment associated with superstar performers can be also consistent with increased labor demand; that is, occurrences of superstar performers are indicative of brighter future industry prospects, and students choose related major fields in anticipation of more and better job opportunities. This labor-demand mechanism, however, is unable to account for our findings a) that industry return skewness negatively forecasts entry-level wages when students enter the job market, b) that high industry skewness is not followed by an increase in entry-level hiring, and c) survey evidence that a disproportionate number of graduates in superstar-related majors have to accept jobs in industries different from where they wanted to join, which is costly in terms of both lower wages and job dissatisfaction. Further, we show in Online Appendix Table A4 that industry return skewness is uncorrelated with a list of observable measures of future industry performance, such as profitability and sales, which should reflect changes in future labor market opportunities (see Online Appendix Section 1.3 for more details).

Changes in the Composition of Labor Demand A more nuanced version of the labor-demand mechanism is that occurrences of superstar performers are associated with changes in the composition of labor demand. More specifically, industry skewness may forecast higher

demand for low-quality employees but lower demand for high-quality employees, thus keeping the total employment constant while driving down entry-level wages. First, this mechanism is inconsistent with our earlier finding that both entry-level net hiring and wages for low-skilled jobs are unrelated to the presence of superstar firms. Moreover, it cannot explain why a larger number of students (especially those from elite universities) choose to major in related fields in response to industry return skewness, knowing that future job opportunities are worse.

Changes in Bargaining Power Another related possibility is that return skewness reflects changes in the industry structure, which impacts firm bargaining power vis-a-vis employees. Specifically, superstar performers gain market power as they grow, which they then exploit to negotiate wages down. First, this mechanism does not explain the finding that industry return skewness negatively predicts entry-level wages, but not wages earned by occupations in the same industry that require prior experience. Second, and more importantly, this mechanism also fails to explain why more students are attracted to related major fields by superstar firms, knowing that their job prospects are going to be worse.

In sum, our evidence points to a strong relation between superstar performers and a subsequent increase in labor supply in related industries. Throughout the paper, we interpret this relation through the lens of industry salience: superstar performers increase industry salience, which helps attract students to related majors. An alternative interpretation of this relation is that the presence of superstar firms may reflect an underlying industry trend/theme, which is unrelated to the industry's labor demand but attracts student attention. During the NASDAQ bubble, for instance, there was an overly-exciting belief that internet was going to transform our economy; this led to both the occurrence of superstar performers and increased enrollment in Computer Science. Although we cannot rule out this possibility, it is broadly consistent with our industry-salience-based interpretation: here, the occurrence of superstar performers is still a *proxy* for industry salience, except that now salience stems from a narrative around the entire industry, rather than around a few firms in it.

6.2 More Evidence on Industry Salience

In this section, we provide further evidence for the role of industry salience in driving student major choice. Our evidence so far on the joint dynamics of quantities (the number of graduates/new hires) and prices (the average wage) points to a relatively larger shift in labor supply than in labor demand with the occurrences of superstar firms. In other words, college students are attracted by superstar firms in deciding their majors, not because they

rationally anticipate improved job prospects, but because they are drawn to extreme, salient events. In Online Appendix Section 2, we provide more evidence on the effect of salience on college major choice.

Our first test, motivated by the analysis in Charles, Hurst, and Notowidigdo (2018), exploits structural breaks in industry valuation during the NASDAQ bubble in the late 1990s to identify superstar industries. The results are reported in Online Appendix Table A7. Not surprisingly, Computer Science-related industries experience the largest structural break in industry valuation among all science-engineering majors in our sample; moreover, the size of the structural break is significantly and positively associated with subsequent changes in major enrollment.

Our second test provides more direct evidence on the role of salience by honing in on just one sector. More specifically, we exploit time variation in the viewership of one of the longest-running TV series in the US, *Law & Order*, to gauge the popularity/salience of the legal profession among prospective students. Our results in Online Appendix Table A8 show that the lagged viewership of *Law & Order* positively forecasts students' interest and enrollment in law schools, but negatively forecasts future wages of entry-level lawyers.

7 Conclusion

This paper studies the relation between superstar firms and college major choice. Using cross-sectional skewness in stock returns, as well as that in favorable news coverage, to capture the occurrences of superstar performers in each industry, we show that such occurrences are associated with larger college enrollment in related fields. However, students attracted by superstar performers earn lower real wages upon entering the job market. Coupled with the finding that entry-level hiring does not vary with the presence of superstar performers, the wage result is consistent with the view that an increase in labor supply, without an accompanying shift in the labor demand curve, lowers the average wage earned by entry-level employees without affecting employment size.

Further evidence from both the National Survey of College Graduates and our own survey indicates that many graduates from these high-skewness majors have to take up jobs in fields outside their target industries at graduation. Moreover, these adverse career outcomes last for decades: cohorts drawn into major fields by superstar performers earn lower wages 20 years after graduation, and have a lower probability of working in fields related to their college majors. In sum, our paper is the first to examine the role of salient extreme events, i.e., the occurrences of superstar firms, in driving one of the most important and irreversible decisions in life—human capital investment.

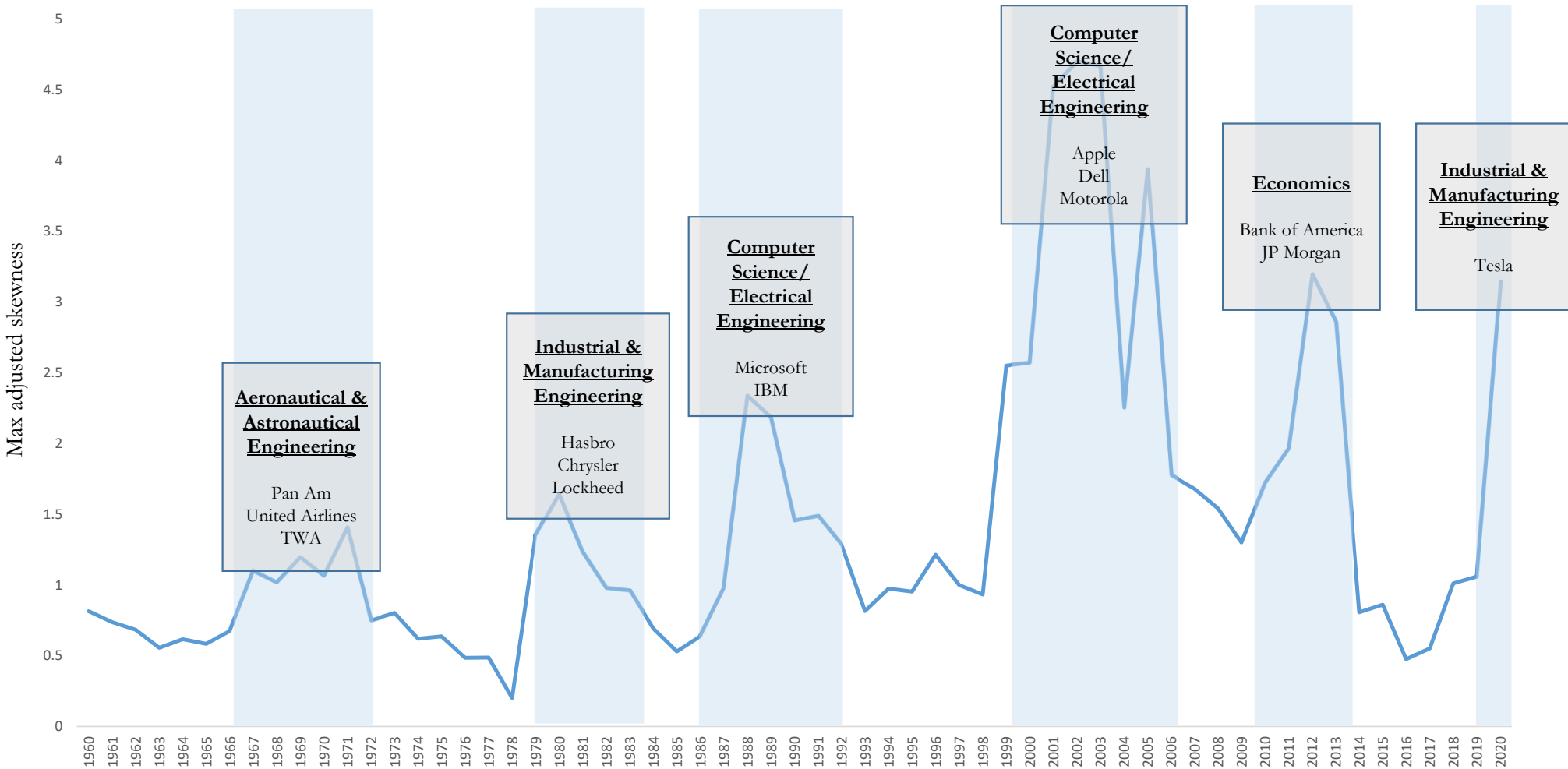
References

- Agarwal, Sumit, Qian, Wenlan, Sing, Tien Foo, and Tan, Poh Lin, 2019, “Dragon Babies,” National University of Singapore Working Paper.
- Altonji, J.G., 1993, “The demand for and return to education when education outcomes are uncertain,” *Journal of Labor Economics*, 11(1), pp.48-83.
- Altonji, J. G., Blom, E. and Meghir, C., 2012, “Heterogeneity in human capital investments: High school curriculum, college major, and careers,” *Annual Review of Economics* 4, 185-223.
- Altonji, J.G., Arcidiacono, P. and Maurel, A., 2016, “The analysis of field choice in college and graduate school: Determinants and wage effects,” in *Handbook of the Economics of Education*, Elsevier.
- 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.
- Autor, D., Dorn, D., Katz, L.F., Patterson, C., Van Reenen, J., 2020, “The fall of the labor share and the rise of superstar firms,” *Quarterly Journal of Economics* 135, 645-709.
- Avery, Christopher 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.
- Barberis, N. and M. Huang, 2008, “Stocks as Lotteries: The Implications of Probability Weighting for Security Prices,” *American Economic Review* 98, 2066–2100.
- Bena, J. and Simintzi, E., 2019, “Machines Could Not Compete with Chinese Labor: Evidence from U.S. Firms’ Innovation,” Working Paper.
- Berger, M.C., 1988, “Predicted future earnings and choice of college major,” *Industrial & Labor Relations Review*, 41, 418–429.
- Bhattacharya, J., 2005, “Specialty selection and lifetime returns to specialization,” *Journal of Human Resources* 15, 115–143.
- 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*, 82, 1247-1288.
- Bordalo, P., Gennaioli, N. and Shleifer, A., 2012, “Salience theory of choice under risk,” *Quarterly Journal of Economics* 127, 1243–1285.

- Bordalo, P., Gennaioli, N. and Shleifer, A., 2013a, “Salience and consumer choice,” *Journal of Political Economy* 121, 803–843.
- Bordalo, P., Gennaioli, N. and Shleifer, A., 2013b, “Salience and asset prices,” *American Economic Review* 103, 623–628.
- Chakrabarti, Rajashri, Vyacheslav Fos, Andres Liberman and Constantine Yannelis, 2020, “Tuition, Debt, and Human Capital,” Working paper.
- Charles, Kerwin Kofi, Erik Hurst and Matthew J. Notowidigdo, 2018, “Housing Booms and Busts, Labor Market Opportunities, and College Attendance,” *American Economic Review*, 108, 2947–94.
- Chetty, Raj, Adam Looney, and Kory Kroft, 2009, “Salience and Taxation: Theory and Evidence,” *American Economic Review* 99(4): 1145–77.
- Cosemans, Mathijs, and Rik Frehen, 2021, “Salience theory and stock prices: Empirical evidence,” *Journal of Financial Economics* 140, no. 2, 460-483.
- 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.
- Ellul, Andrew, Marco Pagano, and Annalisa Scognamiglio, 2020, “Careers in Finance,” Working Paper.
- 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*, 57, 171–179.
- Freeman, R.B., 1976, “A cobweb model of the supply and starting salary of new engineers,” *Industrial & Labor Relations Review*, 29, 236–248.
- 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.
- Gabaix, Xavier, 2014, “A sparsity-based model of bounded rationality”, *The Quarterly Journal of Economics*, 129(4), pp.1661-1710.
- Goldin, C., 2014, “A grand gender convergence: Its last chapter,” *American Economic Review* 104, 1091–1119.

- Gupta, N. and Hacamo, I., 2018, “(Mis)matching Superstar Engineers to Finance Jobs,” Working Paper.
- Greenwood, Robin, and Hanson, Samuel, 2015, “Waves in ship prices and investment,” *The Quarterly Journal of Economics*, 130, 55–109.
- Han, B., Hirshleifer, D., and Walden, J., 2022, “Social Transmission Bias and Investor Behavior,” *Journal of Financial and Quantitative Analysis*, 57(1), pp.390-412.
- Hastings, J.S., Neilson, C.A., Ramirez, A. and Zimmerman, S.D., 2016, “(Un) informed college and major choice: Evidence from linked survey and administrative data,” *Economics of Education Review*, 51, 136-151.
- Hirshleifer, David, 2019, “Attention, Psychological Bias, and Social Interactions,” Finance Theory Working Group Paper, Wharton.
- Hirshleifer, D. and Plotkin, J.B., 2021, “Moonshots, investment booms, and selection bias in the transmission of cultural traits,” *Proceedings of the National Academy of Sciences*, 118(26).
- Hombert, J. and Matray, A., 2019, “Technology Boom, Labor Reallocation, and Human Capital Depreciation,” HEC Paris Working Paper.
- Hoxby, Caroline M., ed., 2003, “The Economics of School Choice,” Chicago: University of Chicago Press.
- 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.
- Huntington-Klein, Nick, 2016 “(Un) informed College and Major Choice: Verification in an alternate setting.” *Economics of Education Review* 53: 159–163.
- 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.
- Johnson, W.R. and Neal, D.A., 1997, “Basic skills and the black-white earnings gap,” University of Virginia, Thomas Jefferson Center for Political Economy.
- Kahneman, D., 2011, “Thinking, fast and slow,” Macmillan.
- Kahneman, D. and A. Tversky, 1979, “Prospect Theory: An Analysis of Decision Under Risk, *Econometrica* 47, 263–291.
- Kaldor, Nicholas, 1934, “A Classificatory Note on the Determination of Equilibrium,” *Review of Economic Studies*, 1, 122–136.
- Lemieux, T., 2014, “Occupations, fields of study and returns to education,” *Canadian Journal of Economics* 47(4), 1047–1077.

- Macpherson, D.A. and Hirsch, B.T., 1995, "Wages and gender composition: why do women's jobs pay less?" *Journal of Labor Economics*, 13(3), pp.426-471.
- Malmendier, U. and Tate, G., 2009, "Superstar CEOs," *Quarterly Journal of Economics*, 124(4), pp.1593-1638.
- Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, 2012, "The Short- and Long-Term Career Effects of Graduating in a Recession: Hysteresis and Heterogeneity in the Market for College Graduates," *American Economic Journal: Applied Economics* 4, 1–29.
- Ouimet, Paige and Rebecca Zarutskie, 2014, "Who Works for Startups? The Relation between Firm Age, Employee Age and Growth," *Journal of Financial Economics* 112, 386-407.
- 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, 2601–28.
- Patnaik, A., Venator, J., Wiswall, M. and Zafar, B., 2020, "The role of heterogeneous risk preferences, discount rates, and earnings expectations in college major choice," *Journal of Econometrics*.
- Rosen, S., 1981, "The economics of superstars," *American Economic Review*, 71(5), pp.845-858.
- Rosen, S, 1997, "Manufactured Inequality," *Journal of Labor Economics* 15, 189–196.
- Sacerdote, B., 2001, "Peer effects with random assignment: Results for Dartmouth roommates," *Quarterly Journal of Economics*, 116, 681–704.
- Stigler, George J., 1961, "The economics of information," *Journal of Political Economy*, 69, 213–225.
- Stigler, George J., 1962, "Information in the labor market," *Journal of Political Economy*, 70, 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, 155.
- Wiswall, M. and Zafar, B., 2015, "Determinants of college major choice: identification using an information experiment," *Review of Economic Studies* 82, 791-824.
- Wiswall, M. and Zafar, B., 2022, "Human Capital Investments and Expectations about Career and Family," *Journal of Political Economy*, forthcoming.



This figure shows majors with the maximum five-year skewness after adjusting for year fixed effects, and the mean and standard deviation of returns. Shaded areas reflect episodes of high relative skewness. The firms indicated are among the top-3 contributors to the skewness of the related major during that period, calculated as the difference between the skewness of its major with and without that firm.

Figure 1. Superstar firms, and corresponding high skewness majors

Table 1
Summary Statistics

This table provides summary statistics of our major variables. Number of Bachelors is the annual number of bachelor degrees awarded for a major. Skew is the cross-sectional skewness of annual returns in an industry, weighted by the number of employees of firms. Tail₁₀ is the sum of Top₁₀ and Bottom₁₀. Top₁₀ (Bottom₁₀) is the average return of the top (bottom) 10 firms in an industry minus the median, divided by the standard deviation of returns, after dropping firms in the lowest 50th size percentile. News Skew is the employment-weighted cross-sectional skewness of annual sum of weekly news scores, based on RavenPack ESS scores.

Mean Return and Standard Deviation of Return (based on monthly returns in an industry), Average Market Cap, Average Book-to-Market, and Average Firm Age are weighted by the number of employees of firms. All industry measures are aggregated to the major level using the map in Appendix Table A1. 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 new hires in these positions.

	Sample Period	Median	25th Pctl	75th Pctl	Std Dev
Number of Bachelors	1966-2017	6921	3298	16196	11314
Skew	1959-2017	0.861	0.166	1.818	1.555
Tail₁₀	1959-2017	0.377	0.044	0.775	0.646
News Skew	2000-2017	1.519	0.330	2.942	2.665
Mean Return	1959-2017	0.013	0.008	0.018	0.010
Standard Deviation of Return	1959-2017	0.069	0.056	0.088	0.031
Average Market Cap (\$ millions)	1959-2017	682	194	2448	4519
Average Book-to-Market	1959-2017	0.592	0.415	0.891	0.518
Average Firm Age	1959-2017	17	12	29	11
Annual Wage (1997 Dollars)	1997-2017	58070	53346	64994	7818
Net New Hires	1998-2017	0.0231	-0.0130	0.0491	0.2917
Number of Net New Hires	1998-2017	3102	-658	12070	256172

Table 2
Number of Bachelors, Wage, and New Hires

This table reports the results of regressions of Log Number of Bachelors, Log Annual Wage, and Net New Hires on skewness measures (measured in years t-7 to t-3, relative to the graduation year t) and other controls. Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major. 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 net new hires in these positions. In Columns (4) and (5), we examine advances positions that typically require a Doctoral or Professional degree or substantial prior work experience. Skew is the employment-weighted cross-sectional skewness of annual returns in an industry.

Our control variables are all measured at year t-3 and include Log Average Wage, the industry-level 3-year average wage obtained from Compustat (up to 1998) or major-level 3-year average wage from BLS (1999 and onward); Mean Return and Standard Deviation of Return, both are employment-weighted. Other industry controls are Log Average Market Cap, Log Average Book-to-Market, and Log Average Firm Age, weighted by employment. In Columns (2) through (5), we also control for Log Number of Bachelors, the log annual number of bachelor degrees awarded for a major, averaged across years t-1 to t-2; and Lagged Male/Female Ratio, the ratio of male to female graduates in the major in years t-1 to t-2. All industry measures are aggregated to the major level using the map in Appendix Table A1.

Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables are standardized with zero mean and unit standard deviation. The sample period is from 1966 to 2017 in Column (1) and from 1997 to 2017 in Columns (2) to (5).

	Log Number of Bachelors	Log Annual Wage	Net New Hires	Log Annual Wage (Advanced Positions)	Net New Hires (Advanced Positions)
	(1)	(2)	(3)	(4)	(5)
Lagged Skew	0.1574*** (0.0322)	-0.0144*** (0.0029)	0.0089 (0.0292)	-0.0028 (0.0077)	-0.0184 (0.0600)
Lagged Mean Return	0.0755 (0.0555)	0.0061*** (0.0021)	0.0294 (0.0187)	0.0178** (0.0067)	0.0115 (0.0454)
Lagged Standard Deviation of Return	-0.0617 (0.0556)	-0.0057 (0.0048)	-0.0424 (0.0650)	-0.0171** (0.0077)	0.0326 (0.0437)
Lagged Log Average Wage	0.0499** (0.0230)	0.0063* (0.0039)	-0.0166 (0.0211)	0.0034 (0.0046)	-0.0139 (0.0215)
Lagged Log Number of Bachelors		0.0981*** (0.0198)	-0.0256 (0.1741)	0.0265 (0.0286)	0.1752 (0.3497)
Other Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes	Yes
# Observations	501	210	200	204	192
Adj. R-Squared	0.84	0.96	0.28	0.91	0.11

Table 3
Alternative Return Skewness Measures

This table reports the results of regressions of Log Number of Bachelors, Log Annual Wage, and Net New Hires on skewness measures (measured in years t-7 to t-3, relative to the graduation year t) and other controls. Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major. 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 net new hires in these positions. Tail₁₀ is the sum of Top₁₀ and Bottom₁₀. Top₁₀ (Bottom₁₀) is the average return of the top (bottom) 10 firms in an industry minus the median, divided by the standard deviation of returns, after dropping firms in the lowest 50th size percentile. News Skew is the employment-weighted cross-sectional skewness of annual sum of weekly news scores, based on RavenPack ESS scores.

Our control variables are Mean Return and Standard Deviation of Return, both are employment-weighted and measured at year t-3. Other controls are the same as those in the corresponding regressions in Table 2. Standard errors are clustered at the year level. *, **, and *** denote 10%, 5%, and 1% significance, respectively. All independent variables are standardized with zero mean and unit standard deviation.

Panel A: Tail Measures						
	Log Number of Bachelors	Log Number of Bachelors	Log Annual Wage	Log Annual Wage	Net New Hires	Net New Hires
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Tail₁₀ (Top₁₀+Bottom₁₀)	0.1905*** (0.0382)		-0.0166*** (0.0034)		0.0188 (0.0376)	
Lagged Top₁₀		0.3036*** (0.0674)		-0.0233*** (0.0054)		-0.0041 (0.0437)
Lagged Bottom₁₀		0.0679** (0.0312)		-0.0068 (0.0069)		0.0817 (0.0912)
Lagged Mean Return and Standard Deviation of Return	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Major Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	508	508	210	210	200	200
Adj. R-Squared	0.85	0.85	0.96	0.96	0.28	0.28
Panel B: News Skew						
	Log Number of Bachelors		Log Annual Wage		Net New Hires	
	(1)		(2)		(3)	
Lagged News Skew	0.1570*** (0.0442)		-0.0148*** (0.0050)		0.0657 (0.0986)	
Lagged Mean Return and Standard Deviation of Return	Yes		Yes		Yes	
Other Controls	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Major Fixed Effects	Yes		Yes		Yes	
# Observations	150		150		150	
Adj. R-Squared	0.99		0.98		0.03	

Table 4
Composition Changes in Labor Supply and Concentration of Employment

In Panel A, Log Number of Bachelors is the log annual number of bachelor degrees awarded for a major at the school-level. There are 336 schools in total. These are 4-year universities in the US, offering at least 5 out of our 10 majors. Top School is a dummy variable, indicating that the school is in the top 50 in US News Rankings in 2018 and is located in the state that hires the most employees in the major-related industries. Skew is the employment-weighted cross-sectional skewness of annual returns in an industry. In Panel B, the dependent variables are Log Annual Wage and Net New Hires of high- and low-skilled occupations. Low Skilled is a dummy variable indicating the low-skilled occupations, which are the occupation codes and industries that offer below median wage within a major in year $t-3$.

In Panel C, the dependent variables are Log Annual Wage and Net New Hires. Annual Wage is the employment-weighted average wage across occupation codes that are mapped to the major and that require bachelors degree and do not require prior experience, inflation-adjusted (1997 level). Net New Hires is the log net new hires in these positions. 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.

Panel A: Number of Bachelors		
	School-level Log Number of Bachelors	
	(1)	
Lagged Skew	0.1123***	
	(0.0244)	
Lagged Skew * Top School	0.2567***	
	(0.0921)	
Lagged Mean Return and Standard Deviation of Return	Yes	
Other Controls	Yes	
Various Fixed Effects	Yes	
# Observations	33301	
Adj. R-Squared	0.21	
Panel B: Wage and Net New Hires		
	Log Annual Wage	Net New Hires
	(1)	(2)
Lagged Skew	-0.0279***	0.0341
	(0.0072)	(0.0635)
Lagged Skew * Low Skilled	0.0165*	-0.0038
	(0.0088)	(0.0899)
Lagged Mean Return and Standard Deviation of Return	Yes	Yes
Other Controls	Yes	Yes
Various Fixed Effects	Yes	Yes
# Observations	354	332
Adj. R-Squared	0.90	-0.03
Panel C: Major Versatility		
	Log Annual Wage	Net New Hires
	(1)	(2)
Lagged Skew	-0.0149***	-0.0192
	(0.0042)	(0.0224)
Lagged Skew * Versatility	0.0095**	0.0006
	(0.0034)	(0.0325)
Lagged Mean Return and Standard Deviation of Return	Yes	Yes
Other Controls	Yes	Yes
Year and Major Fixed Effects	Yes	Yes
# Observations	180	180
Adj. R-Squared	0.98	0.03

Table 5

Individual-Level Analysis Using the National Survey of College Graduates

This table reports results from the National Survey of College Graduates. In Panel A, the first 3 columns report results from fixed effects panel regressions with $\log(\text{Earnings})$ as the dependent variable, while the last 2 columns report marginal effects on the odds ratios from Ordered Logistic regressions of a variable indicating the graduate's current job area is from her field of study (which is measured in 3 levels: "closely related", "somewhat related" and "unrelated", with higher values indicating decreasing relatedness). Columns (2) and (5) examine only those whose highest degree is bachelors, while Column (3) controls for high-dimensional fixed effects. In the full sample, job unrelated to field is defined directly for those who are either only graduates (no higher degrees), or those who got higher degrees but in the same field as their UG major. For those who got higher degrees in fields different from their UG majors, we determine their jobs to be unrelated to their UG major if they work in areas related to their highest-degree field. We exclude respondents working outside their fields of study if the switch of industry is due to changes in interest or family-related reasons. In Panel B, we examine the consequences of having a job unrelated to field of study. The first 3 columns examine $\log(\text{Earnings})$ as the dependent variable, while the next two columns examine Job satisfaction. The sample and fixed effect specifications in each column of Panel B are analogous to those in Panel A. We also report below each column the impact of our variables of interest on the Odds Ratios for all ordered logit regressions. Standard errors are clustered by year of graduation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Earnings and Job Unrelatedness					
	Log Earnings	Log Earnings	Log Earnings	Odds of job unrelated to UG major (Ordered logit)	Odds of job unrelated to UG major (Ordered logit)
	(1)	(2)	(3)	(4)	(5)
Lagged Skew	-0.0159** (0.0064)	-0.0273*** (0.008)	-0.0151*** (0.0065)	0.0469** (0.0228)	0.0518* (0.03)
Lagged Mean Return and Standard Deviation of Return	Yes	Yes	Yes	Yes	Yes
Various Fixed Effects	Yes	Yes	Yes	Yes	Yes
Impact on Odds Ratios	-	-	-	1.048**	1.053*
Sample	Full	Highest degree is Bachelors	Full	Full	Highest degree is Bachelors
# Observations	153,738	84,352	153,737	168,459	92,525
Adj./ Pseudo R-Squared	0.27	0.25	0.28	0.39	0.15
Panel B: Earnings and Job Dis-satisfaction					
	Log Earnings	Log Earnings	Log Earnings	Odds of Job dis-satisfaction (Ordered logit)	Odds of Job dis-satisfaction (Ordered logit)
	(1)	(2)	(3)	(4)	(5)
Job unrelatedness to UG major	-0.167*** (0.01)	-0.230*** (0.013)	-0.219*** (0.011)	0.453*** (0.025)	0.581*** (0.032)
Various Fixed Effects	Yes	Yes	Yes	Yes	Yes
Impact on Odds Ratios	-	-	-	1.573***	1.788***
Sample	Full	Highest degree is Bachelors	Full	Full	Highest degree is Bachelors
# Observations	154,809	81,311	153,967	154,375	82,043
Adj./Pseudo R-Squared	0.25	0.22	0.26	0.03	0.03

Table 6
Survey of College Graduates Using *SurveyMonkey*

In Panel A, Columns (1) and (3) report results from 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 income above \$200,000) as the dependent variable. Column (2) reports results from a logistic regression with a dummy dependent variable indicating whether the graduate started her post-College career in an industry she was expecting to work in when she chose her major. In Column (4) we examine a dummy dependent variable, which is 1 if the graduate currently works in an industry that is different from the industry she started after graduation. In Column (5) we measure whether the graduate switched her job industry because of a negative experience, i.e., dissatisfaction with pay/promotions or working conditions in original job or due to a layoff. Starting job not in target industry is a dummy variable indicating whether the graduate's first job was not in an industry she was targeting.

In Panel B, the dependent variable is Skew, the return skewness associated with the chosen major of each respondent. Expectation Errors, which is an average of two dummy variables. The first dummy is 1 if a respondent indicated that they formed expectations about job prospects in an industry only through information on a small number of firms, and the second is 1 if they thought that their expectations of future job/income outcomes could have been more accurate had they done more research. Lottery Preference is 1 if the graduate answered that she would have chosen to play a fair lottery over a stable, future income stream.

We report in each column the marginal effects for all logistic regressions, and below each column the impact of our variables of interest on the Odds Ratios for all ordered logit regressions. Standard errors are clustered by industry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Income and Employment					
	Odds of higher HH Income (Ordered Logit) (1)	First job in target industry (Logistic) (2)	Odds of higher HH Income (Ordered Logit) (3)	Job change to yet another different industry (Logistic) (4)	Change industry due to dis- satisfaction or layoff (5)
Lagged Skew	-0.5396** (0.225)	-0.0769** (0.031)			
Starting job not in target industry			-0.692*** (0.228)	0.108** (0.045)	0.1445* (0.079)
Lagged Mean Return and Standard Deviation of Return	Yes	Yes	Yes	Yes	Yes
Various Fixed Effects	Yes	Yes	Yes	Yes	Yes
Impact on Odds Ratio	0.582**	-	0.501***	-	-
# Observations	351	292	351	337	223
Pseudo R-Squared	0.12	0.29	0.11	0.20	0.26
Panel B: The Choice of a High-Skew Major					
	(1)		Skew (2)		(3)
Expectation Errors	0.271** (0.105)				0.267** (0.106)
Lottery Preference			0.076 (0.102)		0.068 (0.096)
Lagged Mean Return and Standard Deviation of Return	Yes		Yes		Yes
Various Fixed Effects	Yes		Yes		Yes
# Observations	385		385		385
Adj. R-Squared	0.30		0.29		0.30