Gender Differences in Job Search and the Earnings Gap: Evidence from Business Majors*

Patricia Cortés† Jessica Pan‡ Laura Pilossoph§ Basit Zafar ¶

May 5, 2021

Abstract

To understand gender differences in the job search process, we collect rich information on job offers and acceptances from past and current undergraduates of Boston University's Questrom School of Business. We document two novel empirical facts: (1) there is a clear gender difference in the timing of job offer acceptance, with women accepting jobs substantially earlier than men, and (2) the gender earnings gap in accepted offers narrows in favor of women over the course of the job search period. Using survey data on risk preferences and beliefs about expected future earnings, we present empirical evidence that the patterns in job search can be partly explained by the higher levels of risk aversion displayed by women and the higher levels of overoptimism (and slower belief updating) displayed by men. We develop a job search model that incorporates these gender differences in risk aversion and (over)optimism about prospective offers. Our counterfactual exercises show that simple policies such as eliminating "exploding offers" by allowing students to hold onto offers for an additional month, or providing them with accurate information about the labor market, can reduce the gender gap significantly.

*We thank conference and seminar participants at Boston University, Brown, Cornell, Duke, Loyola Marymount University, Monash University, New York University, Northwestern Kellogg, Rady School of Management, Rochester, Sciences Po, Singapore Management University, Southern Methodist University, University College London, UCLA, UC Santa Barbara, UC Merced, University of Chicago, University of Essex, University of Exeter, University of Florida, University of Nebraska, University of Oxford, University of Pennsylvania, UT Austin, University of Wisconsin Madison, Yale, the 2019 ASSA Meetings, and the 2020 NBER Labor Studies Summer Institute for numerous helpful comments and suggestions. Jacob French, Maria Paola Ugalde Araya, Kevin Winseck, and Zhi Hao Lim provided excellent research assistance. We would also like to gratefully acknowledge the generous financial support from the National Science Foundation through Grant SES-1824469 and the Singapore Ministry of Education (MOE) Academic Research Fund (Tier 1). All errors that remain are ours.

†Questrom School of Business, Boston University and NBER. Email: pcortes@bu.edu

‡National University of Singapore, IZA, and CEPR. Email: jesspan@nus.edu.sg

§Federal Reserve Bank of New York. Email: laura.pilossoph@ny.frb.org

¶University of Michigan and NBER. Email: basitak@gmail.com

1 Introduction

Despite the significant advances that women have made in terms of reversing the gender gap in education, labor market attachment, and representation in professional spheres, gender gaps in earnings remain remarkably persistent, even among the highly-skilled (Blau and Kahn, 2017). The persistence of these gaps, even among groups of women who are arguably as skilled and well-trained as men, has led researchers to consider "new classes of explanations," such as the role of gender differences in psychological attributes, in order to explain the observed labor market disparities (Bertrand, 2011). Along these lines, a large experimental literature has documented robust differences in risk preferences and overconfidence between men and women, with women exhibiting a greater degree of risk aversion (see surveys by Croson and Gneezy (2009) and Eckel and Grossman (2008a)) and men displaying a greater degree of overconfidence in their relative ability (Barber and Odean, 2001; Niederle and Vesterlund, 2007). Recent work also finds that these differences in risk preferences and overconfidence can explain part of the gender gap in educational choices and earnings expectations (Buser et al., 2014; Reuben et al., 2017).

One particular aspect of the labor market where one might expect risk preferences and beliefs about relative ability to matter is job search. Since searching for a job is an inherently dynamic process that involves a considerable amount of uncertainty, systematic differences in preferences and beliefs across gender are likely to lead to differences in job search behavior and outcomes.[1] This is particularly true for the job market of fresh college graduates, where job offers with relatively short deadlines and exploding offers are common.[2] Nevertheless, we know surprisingly little about gender differences in labor market search behavior and its impacts on (early-career) gender wage gaps. A likely reason for this is that researchers usually have limited information on job search behavior and the offers that people receive. The few exceptions focus on the job search behavior of unemployed workers (Krueger and Mueller, 2011; Spinnewijn, 2015), less commonly on employed workers (Faberman et al., 2017), and the role of learning in labor market search (Conlon et al., 2018). To our knowledge, few studies have systematically documented and examined gender differences in job search behavior.

In this paper, we draw on rich retrospective survey data that we collected on job offers and acceptances from recent undergraduate alumni from Boston University's Questrom School of Business to document novel facts about gender differences in the job search process. Specifically, we

[1]Standard models of job search that incorporate heterogeneity of risk preferences show that individuals who are more risk tolerant will have higher reservation wages (Pissarides, 1974; Feinberg, 1977; Acemoglu and Shimer, 1999).

[2]Although most universities have guidelines that require employers to provide students with sufficient time to consider an offer (typically at least 14 days), "exploding offers" are relatively common (see, for example, https://hbr.org/2014/04/15-rules-for-negotiating-a-job-offer). In our data, approximately three-quarters of job offers to undergraduate business majors from Questrom required students to decide within two weeks of receiving the offer. In slightly more than 40% of job offers, students were only given about a week to consider the job offer. Once a student formally accepts a job offer, reneging the offer is highly frowned upon. See http://www.bu.edu/careers/for-employers/policies/ for information on BU's recruiting policies.

ask graduates from the 2013–2019 graduating classes details about the job search process that led to their first job after graduating from Questrom, such as the characteristics of their accepted offer (e.g. salary components, job characteristics, timing of the offer, and when the offer was accepted). We also asked similar questions about the characteristics of up to three job offers that were rejected, as well as the reasons for rejecting the offer. The survey also included questions on demographic and academic background, negotiation behavior, perceived relative ability, beliefs about the salary of their peers, and measures of risk preferences. To understand how expectations about the job search process evolve, we supplement the alumni survey with a prospective survey of current students from the graduating classes of 2018 and 2019. For these students, we surveyed them at three points in time – twice before they graduated – to ask about their earnings expectations and (intended) job search behavior, as well as eight months post-graduation to ask about the outcomes of their job search process (e.g. timing and nature of job offers and accepted job).

We begin by establishing two novel facts regarding gender differences in the job search process. First, we document a clear gender difference in the timing of acceptance of the first job after graduation – women, on average, accept jobs about one month earlier than their male counterparts (60% of women have accepted a job before graduation, compared to 52% of males). This difference is observed in the raw data and is robust to controlling for concentration (e.g. finance, marketing, etc.), GPA, and standard demographics such as race, cohort, country of birth, and parental education. In addition, this gap does not appear to be driven by gender differences in industry choice. Second, we find that the gender gap in accepted offers *narrows* in favor of women over the course of the job search period. For example, the average gender gap across all accepted offers starts at around 17% in August of the senior year and declines to about 10% by the following October and thereafter. These patterns are taking into account the aforementioned controls. In addition, we provide evidence suggesting that gender differences in outside options, expected duration at the first job, marriage market considerations, and locational preferences are unlikely to be driving the observed gender differences in job search behavior that we document.

In the second part of the paper, we develop a model of job search that can account for these empirical facts. We show how a model of job search that incorporates gender differences in risk aversion, overoptimism about the mean of the offer distribution, and learning (that is, updating of beliefs) – all assumptions which our data support – can rationalize the observed data patterns.[3]

[3]In principle, biased beliefs in the job search process can be modeled as biases in expectations of the mean of the offer distribution (like we do in this paper) or biases in beliefs about the arrival rate of offers. Previous work on unemployed workers has focused on biases in the job finding probability (e.g. Spinnewijn, 2015), which in itself is a function of both earnings expectations and beliefs about the job arrival rate. Conceptually, both types of biases are likely to generate qualitatively similar dynamics in the model since they operate through reservation wages. In terms of understanding the job search behavior of college students, we chose to focus on potential biases in earnings expectations since it seems more natural to elicit earnings expectations than beliefs about the job arrival probability (e.g. previous work has shown that college students have fairly well-formed expectations about their future earnings, and that these earnings expectations (elicited in college) are predictive of future earnings at age 30 (Wiswall and Zafar, 2019; Arcidiacono et al., forthcoming).

Intuitively, higher levels of risk aversion for women lead them to have lower reservation wages, to start searching for jobs earlier, and to accept jobs earlier. On the other hand, higher levels of optimism on the part of men increase their reservation wages, lead them to accept jobs later, and make the gender gap in accepted earnings smaller over time as they learn.[4]

We examine both the model's assumptions and predictions using our survey measures of risk aversion and overconfidence. Risk preferences are measured as the average of responses to two survey questions on the willingness to take risks regarding financial matters or in daily activities. Overoptimism, at the aggregate level, is obtained from comparing students' ex ante earnings expectations distribution with their own (or previous cohorts') ex-post earnings realizations. We show that male students, on average, are significantly more risk tolerant than their female counterparts,[5] and have upward biased beliefs about future earnings. Females also tend to have upward biased beliefs, but the extent of their bias is smaller. Using data on beliefs collected at two points in time during the search process, we also show that male students' beliefs take longer to converge to the "truth" relative to females' beliefs.

Consistent with the model predictions, the data show that, on average, more risk-tolerant students tend to accept jobs later, and there is a strong positive relationship between risk tolerance and accepted offer wages. Gender differences in risk preferences account for a non-trivial proportion (approximately 19%) of the residual gender gap in accepted earnings[6] and, at the individual level, the degree of overoptimism (crudely measured as the percent gap between ex ante expected earnings and ex post realized earnings) is strongly positively associated with month of job acceptance.[7] More risk averse individuals start searching for jobs earlier, and we find a systematic positive relationship between reported reservation wages and both risk tolerance and overoptimism. In analyzing these reduced form relationships, we also consider other potential explanations for the empirical patterns

[4]Throughout the text, we use the terms "overconfidence" and "overoptimism" interchangeably, acknowledging that these are not the same concepts. In the model, this manifests itself as students having upward biased beliefs about the mean of the offer distribution that they face.

[5]As discussed in a recent review paper by Shurchkov and Eckel (2018), the most common finding in the literature that spans different environments and methods is that women tend to be slightly more risk averse than men. However, the magnitude of the gender difference appears to depend on the elicitation method, context, and framing. In particular, the Holt and Laury (2002) multiple price list elicitation method where subjects are asked to make ten binary choices between a less-risky and a more-risky lottery tends to find smaller (sometimes zero) gender differences relative to elicitation methods that use a simpler set of decisions involving 50/50 gambles (e.g. Eckel and Grossman, 2002; Eckel and Grossman, 2018; Charness and Gneezy, 2012). Several researchers suggest that more complex elicitation methods may mask gender differences (e.g. Charness et al., 2013). Studies that use survey questions as an alternative to incentivized choices over lotteries tend to find larger gender differences. Crosetto and Filippin (2016) find that these survey measures of risk tend to correlate strongly with the Eckel and Grossman (2002; 2008b) measure and weakly with the Holt and Laury (2002) measure.

[6]The residual gender earnings gap is adjusted for gender differences in standard demographics (e.g. cohort, race, US-born, and parents' education), concentration, and undergraduate GPA. Inclusion of further (endogenous) controls such as city fixed effects, industry fixed effects, and hours worked do not change the results substantively.

[7]One should be cautious in interpreting this gap measure at the individual level. Since most students receive only one draw from the offer distribution (that is, one offer), one cannot categorically conclude that a positive value of this gap measure signals overoptimism at the *individual level*. However, at the aggregate level, the fact that expectations are clearly biased upwards relative to realizations suggests that individuals, on average, are overoptimistic.

such as gender differences in patience, procrastination, and rejection aversion. While we are unable to fully rule out these alternative explanations, we show that most of these explanations are not consistent with the full set of empirical patterns observed in the data.

We next calibrate the model's parameters via Simulated Methods of Moments (SMM), choosing the parameters to minimize the distance between specific model-generated moments and data-generated moments, such as many of the ones discussed above. In terms of the moments that we target, data on the evolution of earnings expectations is used to inform the learning rule and overconfidence, while information on the time path of mean accepted offers by gender and the share of students who have accepted offers over time is used to inform the preference and search parameters. The calibrated model is able to broadly match the key empirical patterns observed in the data. For example, we capture the decline in the gender gap in accepted earnings and the fact that women begin searching for, and accept jobs earlier than men.

Apart from providing us with testable implications that we can take to the data, our calibrated model allows us to conduct various counterfactual exercises of interest, which we undertake in the final part of the paper. First, to assess the importance of biased beliefs in generating the observed gender earnings gap over the course of the job search period, we conduct a counterfactual simulation in which both males and females have perfect information. We find that gender differences in overconfidence explain about 25% of the mean gender gap in earnings. Moreover, we show that while overconfidence, on average, results in a larger gender earnings gap in favor of men, this rise in earnings comes at a cost. The welfare gain of perfect information is more than twice as large for men relative to women. This result is supported by evidence from the survey that men are less likely to be satisfied with the job search process and report more search regrets than women. Second, we simulate a policy counterfactual that relaxes the deadline for deciding on a job offer – something that arguably could be mandated by universities – and thus serve to mitigate the effects of risk aversion as well as overconfidence. The model simulations indicate that such a policy reduces the gender gap by about 40%.

Our work is related to three main strands of literature. First, it contributes to the growing literature on the role of psychological attributes and behavioral biases in job-finding behavior. Most of these studies focus on search behavior among unemployed workers. For example, DellaVigna and Paserman (2005) study the relationship between time preferences and job search and show that workers who are more impatient exert lower search effort and exit unemployment more quickly. DellaVigna et al. (2017) show that a job search model with reference-dependent preferences appears to fit the observed patterns of exit from unemployment better than standard job search models. In terms of the relationship between risk preferences and job search, evidence from laboratory and observational data points toward a strong negative correlation between risk aversion and reservation wages (Cox and Oaxaca, 1992; Pannenberg, 2010).[8] In particular, Spinnewijn (2015) finds that

[8]In addition, McGee (2015) and Caliendo et al. (2015) find that job-seekers with higher internal locus of control (i.e., an individual who attributes success to his or her own efforts and abilities rather than luck or fate) search for jobs

unemployed workers are overly optimistic about how quickly they will find work and examines the implications of biased beliefs for the optimal design of unemployment insurance. These studies, however, do not focus on gender differences in psychological attributes and job search behavior.

Second, this paper is also related to a small literature that seeks to explain gender gaps through a search framework. Earlier work by Bowlus (1997) and Bowlus and Grogan (2009) uses an equilibrium search framework to show that gender differences in labor market search resulting from women's greater tendency to exit jobs for non-participation (because of personal reasons) can account for a non-trivial proportion of the gender wage gap in the U.S. and the U.K.[9] More recently, Le Barbanchon et al. (2019) show that women trade-off commuting time against wages in their job search decisions. Other papers use matched employer-employee data and equilibrium search models to examine the role of compensating differentials resulting from gender differences in preferences for job amenities, statistical discrimination, taste discrimination, and labor market attachment in explaining gender pay gaps over the lifecycle (Morchio and Moser, 2020; Xiao, 2020; Flabbi and Moro, 2012; Flabbi, 2010). More closely related to our work, Vesterlund (1997) extends the Diamond-Mortensen-Pissarides model and shows that gender differences in risk aversion could result in women accepting lower quality matches, and lower wages conditional on productivity. Although our paper also uses a search framework, our focus is on early career job search, and in understanding the roles of gender differences in risk aversion, overconfidence, and (lack of) learning. Non-participation and joint relocation due to family constraints do not feature in our setting, as we do not find that they are first-order considerations for our sample of young, recent, graduates searching for their first job after graduation.[10]

Finally, our paper contributes to the recent literature that examines less traditional explanations for the persistence of gender differences in labor market outcomes, including the role of gender differences in behavioral traits and psychological attributes. Recent review articles by Shurchkov and Eckel (2018) and Blau and Kahn (2017) summarize the large and growing experimental evidence from both the lab and the field that typically finds that women, on average, tend to exhibit greater risk aversion, lower levels of competitiveness, and a lower willingness to negotiate relative to men.[11] More recent work has sought to link these gender differences in behavioral traits to observed gender

more intensively and have higher reservation wages. Using a laboratory setting, McGee and McGee (2016) further show that the relationship between locus of control and search behavior is driven by differences in beliefs regarding the returns to search effort. Relatedly, Flinn et al. (2020) examine how education and the Big Five personality traits influence job search behavior and labor market outcomes by developing and estimating a partial equilibrium search model. Using a panel dataset of newly-unemployed individuals in Germany, they find that the gender wage gap can be accounted for by the differential valuation of women's personality traits relative to men, with conscientiousness and agreeableness emerging as the key traits that contribute to the observed gaps.

[9] Albanesi and Sahin (2018) study differences in observed outcomes (specifically, the unemployment rate) and infer from these observed outcomes differences in job search behavior. They do not use direct information on offers and acceptance decisions for men and women, but rather calibrate a search model to match differences in the unemployment rate between men and women.

[10] We do not have data on commuting times. However, it is worth noting that, conditional on speciality, we do not find gender differences in the geographic locations of the first jobs of individuals in our sample.

[11] See also reviews by Bertrand (2011) and Azmat and Petrongolo (2014).

gaps in the labor market. Blau and Kahn (2017) provides a summary of the results of several studies that examine the quantitative importance of psychological attributes or non-cognitive skills on the gender pay gap and find that, overall, these traits account for a small to moderate portion of the gender pay gap (about 16% or less). Our paper extends this literature by showing how gender differences in two behavioral attributes – risk aversion and overconfidence – affects job search behavior, and consequently, early career wage gaps among a group of highly-skilled men and women entering the corporate sector.[12]

While our focus on early career job search abstracts from family considerations that have been emphasized as a key explanation for the widening of gender pay gaps over the lifecycle, there are reasons to expect early-career wage gaps to matter for gaps later in one's career. In the simplest case where earnings grow proportionately with job experience, initial gaps will naturally persist over time.[13] In addition, when switching jobs, employers are likely to use information on previous salaries to benchmark pay (Hansen and McNichols, 2020). There is also a growing literature which documents that initial conditions in the labor market are long-lasting, with young workers entering the labor market during a recession facing lower wages relative to cohorts that entered during better economic times for at least 10 to 15 years (e.g. Oyer, 2006; Kahn, 2010; Oreopoulos et al., 2012; Wee, 2016). Recent work by Rothstein (2019) suggests even more permanent effects of the Great Recession on college graduates, which he argues might be due, in part to the fact that weaker labor market conditions early in one's career could result in a weak bargaining position that persists throughout the lifecycle (Beaudry and DiNardo, 1991). Furthermore, given that workers typically switch jobs several times over the lifecycle, we expect that the same forces that we argue matter for early-career job search (i.e., risk aversion and biased beliefs) will likely matter for subsequent job searches. Thus, we believe that our paper offers a new explanation for the persistent gender wage gap.

The rest of the paper proceeds as follows. In the next section, we describe the survey instruments and sample selection. Section 3 presents the main characteristics of our sample of undergraduate business students, as well as empirical facts on gender differences in job search behavior and labor market outcomes. Section 4 develops a model of job search that can explain the patterns in the

[12]Several other papers examine the dynamics of the gender gap among professionals and the highly-educated later in the lifecycle and emphasize the role of labor supply and other career adjustments around motherhood as a key explanation for the observed divergence in labor market trajectories between similarly skilled men and women (Bertrand et al., 2010; Azmat and Ferrer, 2017; Noonan et al., 2005). These factors, while clearly important in understanding the gender earnings gap, are unlikely to be first-order considerations for our sample of young graduates. We will provide some evidence that supports this view in the sections that follow.

[13]It is worth noting that the raw gender earnings gap in our sample is quite similar to that in the 2014 to 2018 American Community Survey, among individuals who are 23-27 years old and have a Bachelor's degree in a business major. The raw gender gap in the ACS is 12.6% for these individuals and increases to 32.3% for business majors who are 35-54 years old. While some of this increase may reflect compositional differences across cohorts, these patterns suggest that a significant fraction of the earnings gaps appear at the stage of entry into the labor market. Among non-business college graduates, the raw gender gap is larger at 17.7% for those aged 23-27 and 33.5% for those aged 35-54.

data. Section 5 discusses the empirical evidence that provides support for the model assumptions and presents the reduced-form analysis of the model predictions. Section 6 discusses the policy counterfactuals and reports the results from the simulations. Section 7 concludes.

2 Survey Design and Administration

The data are from original surveys administered to undergraduate business majors from Boston University's Questrom School of Business (Questrom). Questrom is a selective, private business school at Boston University that offers both undergraduate and graduate programs. It has a relatively large undergraduate enrollment of about 3,200 students (across four years of study). Our analysis is based on two main survey instruments: (1) a retrospective survey of recent Questrom alumni ("Survey of Graduates"), and (2) a prospective survey of current Questrom students ("Survey of Current Students"). The online surveys were administered using the SurveyMonkey platform.[14] We describe each survey in detail in the subsections that follow.

2.1 Survey of Graduates

Our first data source is from the Survey of Graduates, an online survey administered to the 2013 to 2017 Questrom graduating classes between April 2017 and February 2018. We obtained a list of student emails from the Questrom Alumni Office and invited eligible alumni to participate in the online survey via email. The survey took approximately 20 minutes to complete and individuals were compensated with a $20 Amazon gift card for successfully completing the survey. A total of about 1,000 alumni completed the survey, corresponding to a response rate of about 20%. The survey included questions on demographic and academic background, salary and other job characteristics (for the initial as well as current job), negotiation behavior, perceived ability, salary of peers, and risk attitudes. Central to our analysis, we collected detailed information on the timing of job offers and characteristics not only for the job offer that individuals accepted, but also for offers that individuals ended up rejecting (up to three of such offers) for the initial job search, which starts in college for most students. This allows us to construct a detailed timeline of how the job search process unfolds for each individual in our sample in the months leading up to and after graduation. We supplement this information with data from a similar post-graduation survey of the 2018 and 2019 graduating classes that was conducted in January 2019 and 2020, respectively. This is the third and final component of the "Survey of Current Students" that we describe in greater detail below. Throughout, we will refer to the merged alumni surveys for the 2013-2019 graduating classes as the "Graduate Survey."

This retrospective survey is the main source of empirical facts regarding search behavior. Risk preferences are elicited as the average of responses to the following two questions (both measured

[14] When appropriate, questions have built-in logical checks. Item non-response is rare.

on a scale from 1 "not willing at all" to 7 "very willing"): (1) *How would you rate your willingness to take risks regarding financial matters?* and (2) *How would you rate your willingness to take risks in daily activities?* These survey-based risk measures are similar to those that have been validated against the experimental approach by Dohmen et al. (2011) and Falk et al. (2016).[15] Since very few individuals picked the lowest possible value on the scale for each of the two risk questions, we combine the lowest two values and rescale the responses to be between 1 and 6. For the analysis, we use the simple average of the re-scaled responses to the two risk questions as a measure of an individual's risk preferences (results are qualitatively robust to using either measure).

2.2 Survey of Current Students

Our second source of data is from a prospective survey of students who graduated in 2018 and 2019. Unlike the alumni survey which is retrospective, these students were surveyed twice before graduation and once after graduation, allowing us to elicit earnings expectations and intended job search behavior at different points during the job search process. The prospective nature of the survey also allows us to compare students' earnings expectations at the beginning of the job search process with their actual realized outcomes to explore systematic biases in beliefs.

Students from the 2018 graduating class were first surveyed in the Fall of their senior year (October 2017) while those from the 2019 graduating class were first surveyed either in the Fall or Spring of their junior year (in November 2017 or March 2018, respectively). We refer to this as the "baseline survey" in the text. The first follow-up survey (i.e., mid-search survey) for each cohort was conducted approximately three months before graduation in March of the senior year. The final post-graduation survey was administered eight months after graduation, in the following January.

The baseline survey, which took about 10 minutes to complete, was conducted in-class in two mandatory courses that Questrom undergraduates typically take in their junior and senior years. Course instructors set aside 10 minutes at the end of class and provided students with the link to the online survey, which students could complete using a smartphone or a laptop. Students were compensated with a $10 Amazon gift card for successfully completing the survey. The response rate for the baseline survey was high – approximately 85% of those enrolled in the class completed the survey.[16] We also sent the survey to students in the 2019 cohort who were not enrolled in the mandatory module in October 2018.[17] Overall, approximately 1,055 students completed the baseline survey, representing about 50%(65%) of the 2018 (2019) graduating classes.[18]

[15] Dohmen et al. (2011) also show, using data from the German Socio-economic Panel (SOEP), that self-rated willingness to take risk (in general) is a good predictor of actual risk-taking in various domains such as financial matters, career, health, etc.

[16] Even though the survey was conducted in-class, some students did not show up to class or chose not to complete the survey.

[17] These students may have taken the module prior to or after their junior year.

[18] The higher response rate for the 2019 graduating class is due to the fact that the in-class survey was conducted

The baseline survey collected information on demographic characteristics, earnings expectations, intended job search behavior, and measures of various psychological attributes such as risk preferences, time preferences, and procrastination. The first follow-up survey, administered three months prior to graduation, collected data on earnings expectations and current job search experience for students who had yet to find a job; students who had already accepted a job were asked about their actual labor market outcomes and job search experience. The final post-graduation survey, conducted 8-9 months after graduation, is similar in structure to the graduate survey described above and asked students detailed information about their job search outcomes including the timing and job characteristics of the offers that they received, regardless of whether the offer was accepted or rejected. Nearly half of the 968 students with valid responses for the baseline survey responded to the follow-up survey and about 33% took all three surveys (see Table A.1). In terms of background characteristics, the sample of students who responded to more than one survey is disproportionately female, Hispanic, less likely to concentrate in finance, and less risk tolerant, compared to those who responded only to the baseline survey. They are also slightly more likely to be US-born and less likely to have a father with a bachelor's degree. There appears to be little difference across the samples in terms of ability proxies such as GPA, perceived relative ability, and expected total pay (see Table A.2).

2.3 Selection into the Survey and Sample Selection

The voluntary nature of the survey naturally raises the question of the extent to which the survey samples are representative of the underlying population of BU undergraduate business students. To provide a sense of how respondents compare with non-respondents, we would ideally use administrative student-level information for all the eligible cohorts of students. Unfortunately, we have limited administrative data from the undergraduate student office that only includes some background information (e.g. gender, current GPA, international student, concentration, etc.) on all students enrolled as business majors in a given semester from Spring 2017 to Fall 2018. As such, we examine selection into the baseline (in-class) survey for the Survey of Current Students (i.e., the 2018–2019 cohorts).[19]

Table A.4 shows how our survey sample compares with the eligible cohort of students from the 2018–2019 cohorts. While there are some significant differences between the respondent sample and the eligible cohort (e.g., our sample is disproportionately US-born and has slightly more credit hours), the overall profile of students in our sample appears broadly representative to that of the eligible cohort. More importantly, for our purposes, we do not find much evidence of differential selection into our survey sample on the basis of gender (see last column of Table A.4).

in both semesters of the mandatory course and the survey was also sent to students who were not enrolled in the module. For the 2018 graduating class, we were only able to conduct the survey in one of the semesters that the course was offered. Also, for this cohort, we did not send the survey to students who were not surveyed in-class.

[19]The survey response rates for each admin data cohort are reported in Table A.3.

Before proceeding, we clarify some of the key data choices we make. We drop survey responses that have missing values on key covariates such as cohort and gender, or do not have a valid email address. All earnings variables (reaizations and expectations) are converted to 2017 dollars based on the CPI. Individuals' salaries are also adjusted based on reported work hours to reflect full-time equivalent earnings. To handle outliers, we drop observations where the reported total first year earnings are less than $20,000 and more than $175,000.[20] Finally, we also winsorize the month of job acceptance, job offer, job rejection, and start of job search to be between -15 and 15, where 0 is defined as the month of graduation.

3 Empirical Facts on Gender Differences in Job Search Behavior

In this section, we describe our sample, document some statistics regarding initial labor market outcomes, and then establish two novel facts regarding gender differences in job search behavior. Our focus is on the job search process for undergraduate business majors searching for their first job after graduation. This analysis uses the Survey of Graduates from the 2013-2019 graduating cohorts.

3.1 Sample Description

Table 1 reports the main characteristics of our analysis sample which comprises graduates who have accepted an offer by the time of the survey.[21] The last column of the table reports the p-value of the test of equality of the means across gender. Women make up slightly more than half of the sample. Men and women appear broadly comparable in terms of demographics, family background, and GPA – the differences are typically small and not statistically significant. The biggest gender difference is observed in terms of degree concentration. Men are significantly more likely to report concentrating in finance than women (65% vs. 38%), while women are significantly more likely to concentrate in marketing (37% vs. 14%). Women are also significantly more likely to concentrate in law and organizational behavior, although these are relatively small fields of study.[22] Consistent with the prior literature, women in our sample report significantly lower willingness to

[20]This criterion drops about 7% of our main analysis sample (i.e. those who have accepted an offer). The main results are robust to winsorizing earnings (above 175,000 and below 20,000) instead of dropping the outliers (results available upon request).

[21]Note that the proportion of men and women who accepted an offer to work right after graduation does not vary by gender. Summary statistics for the full sample are reported in Table A.5 and are broadly similar to the summary statistics for the sample conditional on having accepted a job (i.e. the main analysis sample).

[22]Undergraduate business majors in Questrom are required to declare at least one functional concentration. In our sample, slightly more than 50% of the alumni report a second functional concentration. Functional concentrations provide students with a deeper study of a specific functional area in the study and practice of management (see http://questromworld.bu.edu/udc/academics/concentrations/). There are 11 functional concentrations that students can choose from. These include Accounting, Finance, General Management, Innovation and Entrepreneurship, International Management, Law, Management Information Systems, Marketing, Operations & Technology Management, Organizational Behavior, and Strategy.

take risks in financial or daily matters relative to men. The raw gender difference in risk attitudes is approximately one-fifth of the mean or half of a standard deviation.[23] Men are also more than twice as likely to report an average willingness to take risks of five or more (on a six-point scale) as compared to women (23% vs. 9%). Despite having similar GPAs as men on average, women report significantly lower perceived relative ability, consistent with the previous literature documenting that men tend to be more (over)confident than women.

3.2 Initial Labor Market Outcomes

Turning to initial labor market outcomes in Table 2, we find that, conditional on accepting an offer, close to 95% of students in the sample had a first job that was based in the U.S. and are currently working full-time. Moreover, in the full sample, we find that the vast majority of students (close to 85%) accepted an offer to work after graduating from BU. There is little evidence of significant gender differences in these employment outcomes, consistent with the idea that for this sample of high-achieving business students, male and female students are similarly career-oriented at this early-career stage (see Table A.5).[24] Nevertheless, there is a large gender gap in accepted earnings (i.e., total pay in the first job in the first year), with women earning about 10% less than their male counterparts; the gender gap goes up to 13% when looking at current earnings. The magnitude of these earnings gaps are comparable to the gender gap in annual earnings of about 12.6% among young college graduates (between the ages of 23 to 27) in the U.S. with an undergraduate business major as measured using the 2014–2018 American Community Survey (ACS).[25] Not surprisingly, the observed gender difference in concentration translates to similar differences in industry choice with men significantly more likely to work in financial services, while women are more likely to be in advertising/marketing and consumer products/retail.

The summary statistics also reveal some suggestive gender differences in job search behavior. The average student in the sample accepts their first job about half a month before graduation, with women accepting their first job almost one month before men. Close to 92% of women accept jobs within six months of graduation, compared with 86% of men. These patterns form the basis of our first empirical fact in the next section. Despite the significant gender difference in the timing of job acceptance, on average, women and men receive a similar number of offers (about 1.7) and are equally likely to have rejected at least one offer (approx. 40%). While this may appear to be puzzling, the last panel shows that women start searching for jobs earlier than men and search

[23] This gap is somewhat larger than what has been documented in the prior literature. For example, in Dohmen et al. (2011) the size of the gender effect on a similarly survey-based measure of willingness to take risks, in general (elicited on a 0 to 10 scale), is approximately 13% of the mean or about one-quarter of a standard deviation.

[24] In this sample, less than 2% of individuals are currently married, and approximately 47% are in a relationship. Women are slightly more likely to be in a relationship than men, but the difference is small (4.4 pp) and marginally significant at the 10 % level. In Section 3.3, we discuss the role of marriage market considerations in the job search process.

[25] We consider wage-earners in the ACS who are not currently in school and report working full-time, full-year (i.e. 35 or more hours per week and 40 or more weeks per year).

behavior differs for both genders along several dimensions.[26,27] In the model and empirical analysis, we seek to jointly rationalize these gendered patterns of timing of search and job acceptance timing.

3.3 Two Novel Facts

3.3.1 Fact 1: Females Accept Jobs Earlier

The first main empirical fact that we document is a systematic gender difference in the timing of job acceptance among men and women in our sample. Figure 1 shows the proportion of men and women who have accepted a job as a function of months since graduation. As discussed above, the month since graduation on the x-axis has been rescaled so that 0 indicates the month of graduation (i.e. May); therefore, negative numbers along the scale indicate the months prior to graduation and positive numbers indicate the months post-graduation. Job acceptances prior to (and after) 9 months before (and after) graduation are grouped into a single category (-9 or +9, respectively). As observed in the figure, the distribution of job acceptance timing for men is shifted to the right of that for females, indicating that more women have accepted jobs than men at almost every point in the job search process; a formal statistical test developed by Davidson and Duclos (2000) indicates that the male distribution first order stochastically dominates the female distribution ($p < 0.01$). By graduation, 60% of females have accepted a job, compared to 52% of males ($p = 0.004$).

Table 3 shows that the observed gender difference in the timing of job acceptance is robust to the inclusion of controls for background characteristics (e.g. cohort fixed effects, a dummy for US-born, and fixed effects for race and parents' education) and academic background (concentration fixed effects and GPA). Columns (1) to (3) report estimates of the gender difference using a hazard model where the outcome is the probability of accepting a job within six months of graduation, while columns (4) to (6) report estimates from a linear specification using month of job acceptance as the outcome variable. Column (1) indicates that women are 23% more likely to accept a job within six months of graduation relative to men. Column (2) shows that the expected hazard increases to 1.29 with the inclusion of the individual-level covariates. The observed gender difference in job acceptance timing does not appear to be driven by gender differences in industry choice – the hazard

[26] In the subsample of students ($N = 452$) for whom we have data on both the timing of starting search and job acceptance timing, we find that gender differences in starting search can account for slightly more than half of the observed gender gap in job acceptance timing. That is, conditional on starting search earlier, females still accept jobs about half a month earlier than males (the gender gap in job acceptance timing in this subsample is about 1.3 months).

[27] For example, we observe that men spend more hours searching for jobs per week and send out many more applications. They also have a greater tendency to apply for jobs for which they are under-qualified (27% for men vs. 24% for women, $p = 0.12$). They also generate fewer offers per application as compared to women (1.2 for men vs. 1.6 for women per 100 applications, $p = 0.09$). This suggests that men and women may target their search differently, and could be applying to different kinds of jobs. These patterns are broadly consistent with ongoing work by Faberman et al. (2020), who similarly document gender differences in job search and targeting. A full exploration of these patterns are beyond the scope of this paper. Nevertheless, in the conclusion, we discuss how extending the model to incorporate heterogeneity in job types could potentially reconcile some of these patterns.

odds ratio is slightly lower at 1.24 and remains highly statistically significant with the inclusion of industry fixed effects in column (3).[28] The OLS specifications reported in columns (4) to (6) corroborate these findings – on average, women accept jobs about 0.9 months earlier than men. The inclusion of covariates increases the observed gap to 1.1 months, while the inclusion of industry fixed effects results in a gap of about 0.85 months. All the estimates are statistically significant at the 1% level.

3.3.2 Fact 2: Declining Gender Gap Over Job Search Process

The second empirical fact that we observe in the data is that the cumulative gender earnings gap in accepted offers in favor of men declines steadily over the job search period. As observed in Figure 2, over the job search period, the cumulative mean accepted offer declines for both men and women, with men experiencing a larger decline than women. Overall, we observe that the average gender gap (male - female) across all accepted offers starts at around 17% in August of the senior year and declines to about 10% by the following October. This implies that relative to women, men who accept jobs early tend to accept jobs that offer higher pay and over the course of the job search period, men increasingly accept jobs that offer lower pay. Figure A.2 confirms that the observed decline in the cumulative gender earnings gap in accepted offers is robust to the inclusion of controls for background characteristics (i.e. cohort, race, nationality, and parent's education) and academic background (i.e. concentration and GPA). It is also worth pointing out that most the closing of the gender gap in accepted offers happens by the time of graduation, as evidenced in Figure 2.

One may wonder about the extent to which these patterns could be due to gender differences in preferences for non-wage amenities (Wiswall and Zafar, 2017). While such gender differences may explain part of the gender gap in wage levels, they cannot explain the trends over the course of the job search process (within and between gender). In Figure A.3, we show that the observed decline in cumulative gender earnings gap still remains even after controlling for job characteristics such as work flexibility, sick leave, parental leave, expected earnings growth, and perceived layoff risk. This suggests that the observed patterns are not driven by gender-specific changes in the non-wage attributes of accepted jobs over the job search period. These job characteristics are obviously all choices, and so this analysis should be interpreted only as suggestive. In addition, our data show that the prevalence of non-wage amenities tends to be higher in jobs that are accepted by females: the mean number of non-wage amenities at their jobs is 7.40 versus 6.84 for males ($p < 0.01$). However, within gender, the correlation between accepted earnings and the number of non-wage amenities at the job is positive, implying that the observed gender earnings gaps are unlikely to be driven by compensating differentials.[29]

[28] It is not clear that one should control for industry since the choice of industry to work in is endogenous.

[29] The positive correlation between earnings and non-wage amenities is observed unconditionally as well as conditional on the standard set of controls for demographic characteristics and academic background, as well as industry

3.3.3 Making Sense of the Patterns

In the next section, we develop a formal model of job search to account for these key facts in the data. We show how a standard model of job search that incorporates gender differences in risk aversion and overconfidence can generate (1) gender differences in job acceptance timing, and (2) a decline in the gender gap in accepted offers over the course of the job search period. The model will also be able to reconcile some of the other observed patterns in the data such as the relative times at which males and females begin their job search, the patterns in the value of offers received over time, and the patterns in the probability of receiving an offer over time.

However, before we move to the model section, we specifically examine whether the observed gender difference in the timing of job acceptance is driven by factors such as gender differences in the outside option, expected duration at the job, and family/marriage market considerations. In what follows, we consider each of these potential explanations in turn, and rule them out as possible factors.

Gender differences in the outside option. First, it is worth noting that the fact that the gender gap in job acceptance timing is largely unaffected by the inclusion of controls for family background (as proxied for by father's and mother's education) implies that gender differences in liquidity constraints are unlikely to be the reason why women systematically accept jobs earlier than men. Indeed, as observed in Table 1, parental education is very similar across gender. Further, for a subsample of students for whom we have information on student debt, we also find limited gender differences in the likelihood of having any student debt or the amount of debt. Both genders also report similar importance of having a job by graduation – on the question, "On a 5-point scale, how is it to you that you have a job lined up before the end of your senior year (that is, before you graduate)?" the vast majority (more than 80%) indicate the top two values on the scale. The mean difference in the response by gender is small and only marginally significant at the 10% level (4.38 vs. 4.24, $p = 0.08$) (see Figure A.1).

Expected duration at the job. Another possible explanation for the gendered patterns of job search that we observe is that perhaps women expect to stay at their initial job for a shorter duration than men and, hence have lower reservation wages and accept jobs earlier. Two pieces of evidence suggest that this is unlikely to be driving the observed empirical patterns. First, for the older cohorts that have been in the labor market for 1 to 4 years, we find little evidence of differential transition rates to subsequent jobs by gender. Second, for the 2019 cohort, we collect data on how long individuals plan to stay at the first job. There is little systematic difference by gender; if anything, females expect to stay slightly longer at the first job than their male counterparts (2.16 years versus 1.92 years; difference not statistically significant at conventional levels).

fixed effects.

Family/marriage market considerations. It is possible that women's differential job search behavior could be influenced by marriage market considerations and expectations about their future labor supply if married. To investigate this possibility, we examine whether women's self-reported probabilities of working full-time or part-time at age 30 are correlated with the timing of job acceptance and find little evidence of a systematic relationship.[30]

Another aspect related to family/marriage market considerations is the possibility that women may choose to accept jobs earlier as they have stronger geographic preferences or face more geographic constraints in their job search. Indeed, previous work by Le Barbanchon et al. (2019) shows that, on average, women have a lower willingness to commute relative to men. Nevertheless, we argue that for our sample of young graduates searching for their first job after graduation, such constraints are less likely to matter differentially by gender. For one, unlike later in the life-cycle, gender differences in employment outcomes at graduation are small (see Tables 2 and A.5). Furthermore, we find little evidence that women are choosing to accept jobs that are closer to their state of birth relative to men, suggesting that women do not appear to be placing a higher weight on proximity to family in their job search decisions.[31] Finally, for a subsample of students who graduated in 2019, we specifically asked students whether factors such as proximity to family and partner location played a role in their job search. Interestingly, we find that while close to half of men and women in the sample indicated that their job search decisions were affected by such considerations, women were, if anything, *less* likely to indicate that family proximity and partner location played a role in their job search (51% for men vs. 43% for women, p-value of the difference = 0.224).[32] Taken together, these results provide suggestive evidence that locational preferences due to family considerations or marriage market considerations are unlikely to be key drivers of the observed gender differences in job search behavior that we document above.

4 Model of Job Search

We now propose a model in which risk averse males and females search for their first post-graduation job while they are still in school. The model makes a number of key assumptions that we validate empirically using our survey data in Section 5. For the time being, we abstract from gender when we lay out the model, and later introduce parameter heterogeneity by gender when we estimate the model.

[30] We also find that women's expectations about future labor supply are uncorrelated with their risk aversion, and although marginally correlated with earnings, do not explain the role of risk aversion in explaining the gender earnings gap. These results are available upon request.

[31] These results are available upon request.

[32] This question was only fielded in the post-graduation survey for the 2019 cohort ($N = 242$). The specific question asked was: *"We are interested in whether any of the following factors played a role in your job search."* Respondents were asked to select any of the following options that applied: *"I wanted to stay close to family, and preferred jobs that were close to them"; "Because of my partner's location, I preferred jobs that were in certain locations"; "I had a preference for certain locations, and that affected the jobs that I considered"; "I had no preferences for job location".*

Time t is discrete and individuals have preferences over consumption given by $u(c) = \frac{c^{1-\iota}-1}{1-\iota}$; agents are risk averse. We denote by $\bar{T} > 1$ the date at which graduation occurs; after $\bar{T}$, we assume that agents are infinitely lived.[33] We assume that from dates $\{1, ..., \bar{T}\}$, students with and without a job earn their value of leisure, b, but that starting from date $t \geq \bar{T}$, individuals with a job earn the agreed upon wage w, while students without a job continue to earn b. Since all students earn b before graduation regardless of whether they have accepted a job, the risk of not having a job by graduation is foregone wages.

Job Offers. Students who have yet to secure a job choose whether or not to search for a job each period, taking into account the i.i.d. cost of search, $c \sim H(c)$. If a student decides to search, they receive an offer with probability λ which is a random draw from $F(log(w)) \sim N(\mu, \sigma)$. For simplicity, we assume there is no search on the job – that is, once the student has secured a job they cannot search further.

Beliefs. To model biases in beliefs, we assume students have an initial ($t = 1$) belief about the mean log offers they will receive, denoted by μ_1. If the true mean log offer is μ^*, then optimistic individuals have beliefs μ_t at date t such that $\mu_t > \mu^*$. To allow for learning and corrections in the bias about the mean log offer, we model a simple learning rule in which beliefs converge to the true value as time progresses. That is, we assume that beliefs at each date t take the following form:

$$\mu_t = \mu_1 e^{-\gamma(t-1)} + \mu^* \left(1 - e^{-\gamma(t-1)}\right) \quad \text{for} \quad \forall t, \tag{1}$$

where γ controls the speed at which learning occurs. This implies that individuals enter with beliefs about the mean log offer given by μ_t which falls to the true μ^* as t increases. As γ goes to ∞, beliefs converge more quickly.

Importantly, while we assume that beliefs change over time, we maintain the assumption that students are myopic. That is, when making their decisions, they assume their beliefs are fixed and will not change over time. As such, behavioral choices (reservation wages and search effort) will be chosen under a fixed belief μ; beliefs are only updated ex-post.

4.1 Values of Employment and Unemployment at date $t > \bar{T}$

Starting at date $\bar{T}$ and for any given belief μ, we assume that agents are infinitely lived and therefore the model is stationary. The value of employment at wage w can be solved for explicitly:[34]

$$W(w, \mu) = \frac{u(w)}{1 - \beta}.$$

[33] As will become clear, this implies that for a given set of beliefs, the model is stationary after $\bar{T}$.

[34] The value of employment will be independent of beliefs since we do not allow for search on-the-job or job separations. We index the value of employment by μ_t for completeness.

The value of unemployment for $t \geq \bar{T}$ is:

$$U(\mu) = \int_c \Big(\max_{s\in\{0,1\}} -cs + u\left(b\right) + \beta s\lambda \int \max\{W(w,\mu_t), U(\mu)\} dF(w;\mu_t,\sigma) \\ + \beta\left(1-\lambda s\right) U(\mu) \Big) dH(c). \tag{2}$$

The value of unemployment depends on beliefs, since the expectation is taken over the subjective offer distribution. Given some draw for search costs c, students must decide whether or not to search. If they choose not to search ($s = 0$), they receive no offers, whereas if they search ($s = 1$), they receive offers with probability λ. Plugging in $s = 1$ above and comparing the value to the case when $s = 0$, the student with belief μ will search if they draw a cost $c \leq c^*\left(\mu\right)$ where $c^*\left(\mu\right)$ is defined as:

$$c^*(\mu) = \beta\lambda \int \max\{W(w,\mu) - U(\mu), 0\} dF(w;\mu,\sigma).$$

Finally, we define the reservation wage $\hat{w}(\mu)$ as the wage which satisfies:

$$W\left(\hat{w}\left(\mu\right), \mu\right) - U\left(\mu\right) = 0.$$

4.2 Values of Employment and Unemployment at date $t \leq \bar{T}$

Before graduation, the model is not stationary since students' decisions will depend on the time until graduation. Let $U_t\left(\mu\right)$ denote the value of being a student with some beliefs μ who has not secured a job before graduation (i.e., in period $t \leq \bar{T}$). This value can be written as:

$$\begin{aligned} U_t\left(\mu\right) = & \int_c \Big(\max_{s\in\{0,1\}} -cs + u(b) \\ & + \beta\lambda s \int_w \max\left\{W_{t+1}(w,\mu), U_{t+1}\left(\mu\right)\right\} dF\left(w;\mu,\sigma\right) \\ & + \beta\left(1-\lambda s\right) U_{t+1}\left(\mu\right) \Big\} \Big) dH(c). \end{aligned} \tag{3}$$

The value is similar to the value of unemployment after graduation, but values are time-dependent. Again, plugging in $s = 1$ and comparing the value to $s = 0$, the student with beliefs μ will search at date t if they draw a cost $c \leq c_t^*(\mu)$ where $c_t^*(\mu)$ is defined as:

$$c_t^*(\mu) = \beta\lambda \int \max\{W_{t+1}(w,\mu) - U_{t+1}(\mu), 0\} dF(w;\mu,\sigma).$$

The value of being employed at some wage w and time $t \leq \bar{T}$ wiht belief μ is:

$$W_t(w,\mu) = u\big(b\big) + \beta W_{t+1}(w,\mu). \tag{4}$$

Finally, we define the reservation wage $\hat{w}_t(\mu)$ as the wage which satisfies:

$$W_t(\hat{w}_t(\mu), \mu) - U_t(\mu) = 0.$$

4.3 Numerical Solution

To solve the model, we create a grid of wages $w \in \{w_1, ..., w_{N_w}\}$ and a grid of beliefs about $\mu \in \{\mu_1, ..., \mu_{N_\mu}\}$. For each possible μ and w, we solve the model backwards in time. Once we have solved for the value functions for every wage and possible belief, the "final" realized values of unemployment at each point in time are dictated by equations (2) and (3) so that:

$$\bar{U}_t = U_t(\mu_t) \quad \text{for} \quad t = \{1, 2, .., \bar{T}\}. \tag{5}$$

4.4 Comparative Statics

In this section, we examine how risk preferences and biases in beliefs affect search behavior in our model. Figure 3 shows how reservation wages and the and the probability of receiving an offer change with risk aversion ι and initial biases μ_1. Panel (a) shows that, for a given level of risk aversion, the reservation wage declines rapidly as one approaches the graduation date since students want to avoid ending up without a job by graduation. As agents become more risk averse (moving from blue to black line), reservation wages drop. Higher degrees of risk aversion imply that agents fear the looming graduation date and its corresponding drop in consumption relatively more; therefore, they lower their reservation wages to avoid ending up with no job by graduation. For the same reason, Panel C shows that students raise the cutoff search cost below which they search as risk aversion rises, leading to higher probabilities of searching for a job.

Changes in the bias of beliefs about the mean log offer have different impacts on search behavior. Panels (b) and (d) in Figure 3 show how reservation wages and the likelihood of searching change as the initial bias in beliefs μ_1 varies. First, as shown in Panel (b), as the bias rises (going from blue to black), the overall option value of search rises, as agents believe they face a more favorable offer distribution. Therefore, reservation wages rise since the option value of search rises. Similarly, while the effect on search effort is smaller, it goes in the same direction; as the return to search rises, the probability that students search also rises (Panel (d)).

5 Empirical Evidence for Model Assumptions and Predictions

Before estimating the model, we provide empirical evidence in support of the model's assumptions and predictions using the survey data.

5.1 Empirical Basis for Model Assumptions

When estimating the model, we will allow the risk aversion parameter ι, the learning rate γ, the true mean of log offers μ^*, and initial beliefs μ_1 to differ by gender. Otherwise, we will tie our hands and assume that all remaining parameters are the same for both genders. We next provide empirical support for these assumptions.

(No) Gender Differences in Outside Options and On-the-Job Search. The model assumes that the value of leisure, b, does not differ by gender. We believe this is borne out by the data: as discussed in Section 3.3.3, family background characteristics and student debt levels do not differ by gender. Moreover, both genders report similar importance of having a job by graduation.

The model also assumes no on-the-job search or job separation. While this is a simplification, this could be a problematic assumption if genders differed in how long they stayed (or expected to stay) at the first job. However, as discussed in Section 3.3.3, we do not find evidence of this either.

Gender Differences in Risk Preferences. When we estimate the model, we allow men and women to have different degrees of risk aversion. This is motivated by the evidence in previous studies and in Table 1 of a significant gender difference in self-reported willingness to take risks.

Biases in Beliefs. We use two approaches to illustrate the empirical basis for biased beliefs (in the form of overconfidence). First, we compare the ex ante earnings expectations distribution of the 2018 (2019) cohort with the earnings realizations of the previous cohort – i.e. 2017(2018) graduating cohort (obtained from the graduate survey). Earnings expectations were elicited using the following question: "*We would next like to ask you about the kind of job that you expect to work at when you first start working after graduation. We would like to know how much you expect to make at this job in the first year.*" This question was asked in the baseline survey for the 2018-2019 cohorts. The distributions of earnings expectations for the 2018-2019 cohorts and the corresponding realizations for the previous cohorts (2017-2018) are shown in Figure 4 separately by gender. For both men and women, the earnings expectations distribution is generally to the right of the distribution of earnings realizations, suggesting that both genders have earnings expectations that tend to be higher than previous years' realizations. However, the rightward shift is much more pronounced for males: 30% of males expect to make less than the previous cohort median, compared to 37% of females.

One might be concerned that the rightward shift of the expectations distribution relative to the realizations distribution of the previous cohort may not necessarily imply an over-optimism bias if students believe that the earnings distributions are non-stationary and are shifting up over time. However, in order to fully explain the different patterns that we observe by gender in Figure 4, student beliefs' about the non-stationarity of the earnings distributions would have to vary systematically by gender. To provide additional evidence that beliefs are indeed biased, we use data from the 2018-2019 graduating cohorts and compare the ex-ante expectations of students with their *own* ex-post realizations. Note that this comparison is possible only for a relatively small subset of students who answered both the baseline and final surveys. Figure 5 plots the two distributions. Consistent with the cross-cohort comparison, on average, both men and women overestimate their earnings, with men exhibiting a somewhat greater degree of optimism regarding their future earnings outcomes.[35]

An alternative interpretation of the observed gap between earnings expectations and realizations is that this reflects misinformation (that is perhaps more prevalent for men relative to women) rather than a psychological attribute such as an optimistic bias. We can rule out this possibility as we also elicit beliefs about population earnings.[36] Collectively, the evidence we present here strongly indicates that students' beliefs - in particular, those of male students – are systematically biased upwards.

Learning Another aspect of biased beliefs that is important for job search is the extent to which learning occurs over the job search period. Although the gender differences in belief bias at the mean is relatively modest, men and women appear to update their beliefs at different speeds. Using data on earnings expectations from two time points, once at the beginning of job search and another mid-search, we are able to observe how earnings expectations evolve. Table 4 reports the earnings expectations and eventual realizations for the full sample (Panel A), as well as the consistent sample of men and women who answered both the baseline and mid-search surveys (Panel B). The data for both samples paint a similar picture – both men and women revise their earnings expectations downward over time. However, looking at the consistent sample, we see that men are slower to update. By the mid-search survey, both the mean and median women's earnings expectations have largely converged to the observed realizations. By contrast, men's earnings expectations remain, on average, about 10% higher than eventual realizations (i.e. overly optimistic).

5.2 Reduced-Form Evidence for the Model Predictions

Next, we provide some reduced-form evidence in support of the key predictions of the model. It is important to bear in mind that the proxies for risk preferences and optimism bias that we use are based on individual self-reports and are likely to be prone to measurement error. In addition to the

[35]To be sure, a search model without any bias in beliefs can have differences in expectations and realizations, but they should be zero on average.

[36]Specifically, the survey asks, "*Consider those [male/female] Questrom graduates from the last five years and who started working full-time immediately after graduation. What do you think their starting total annual salary (in dollars) was, on average?*" To assess whether the observed patterns are driven by misinformation, we compare the distributions of population earnings beliefs, own-earnings expectations of the 2018-2019 cohort, and the distribution of realized earnings of the 2017-2018 cohort. As observed in Figure A.4, both genders appear to underestimate population earnings. This indicates that the bias in own-earnings expectations is more consistent with overoptimism rather than with misinformed beliefs about population earnings.

underlying psychological attributes that they are meant to capture, these survey measures of risk and belief biases could also be correlated with other individual-level characteristics; as such, we view these empirical tests as useful in providing suggestive evidence of the main model mechanisms, and refrain from attaching a strong causal interpretation to the observed correlations. Similarly, given measurement error concerns, we are also cautious about attaching too much weight to the precise magnitude of the observed relationships. For these reasons, when we formally estimate the model, the survey measures of risk and overconfidence do not feature directly in the model, and both risk preferences and the extent of bias in beliefs (and learning) are among the key parameters that will be estimated from the data.

First, we examine the relationship between risk preferences, accepted earnings, and job acceptance timing. As outlined in Section 4.4, the model predicts that higher levels of risk aversion leads to lower reservation wages and lower accepted wages at any given point in time. Moreover, the lower reservation wages translate to a higher likelihood of job acceptance at any point in time. As such, we would expect to see more risk-tolerant individuals accepting jobs later, as well as a positive relationship between risk tolerance and accepted earnings. The model also predicts that part of the relationship between risk preferences and timing of job acceptance is due to more risk averse individuals starting search earlier.

The left panel of Figure 6 presents a binned scatterplot of the relationship between the survey measure of risk tolerance (on the x-axis) and the month of job offer acceptance (on the y-axis) while the right panel of Figure 6 presents a similar plot, with the share accepting a job six or more months after graduation on the y-axis instead. Both figures support the model prediction that risk preferences are positively related with the timing of job acceptance. Likewise, consistent with the model, the left panel of Figure 7 shows a negative relationship between risk tolerance and the likelihood of starting the job search process before graduation.[37] Turning next to the relationship between risk preferences and accepted earnings, as depicted in the right panel of Figure 7, there is a strong positive association between individuals' willingness to take risks and accepted earnings in the first job. The economic magnitude is quite large: a one-point increase in risk tolerance is associated with a nearly $2,000 higher starting salary.

A natural question is how much of the gender earnings gap can our survey measure of risk preferences explain? Table 5 addresses this question. Column (1) indicates that, on average, females earn $6,719 less than their male counterparts. This difference is statistically significant at the 1% level. Adjusting for individual-level differences in background characteristics (i.e., cohort, race, country of birth, and parents' education) and academic background (i.e., GPA and concentration) reduces the gender gap by close to 30% to $4,542 (see Column (2)).[38] This is largely due to

[37] Qualitatively, we find similar patterns within gender, though the relationships are not always precisely estimated. Results available upon request.

[38] Using the 2014–2018 ACS, we find that the inclusion of similar background controls (e.g. dummies for age and year, a dummy for US-born) and fixed effects for detailed major categories within business (13 categories) accounts for 29.7% of the observed gender earnings gap among college graduates who majored in business in the U.S. These

the fact that men tend to choose high-paying concentrations such as finance, while women choose lower-paying concentrations such as marketing. Nevertheless, the residual gender gap in accepted earnings is still highly statistically significant and reasonably large (approximately 7.4% of mean earnings). In Column (3), we add our survey measure of risk preferences. The coefficient on the female dummy declines further to \$3,687 ($p < 0.01$). This implies that gender differences in risk preferences, as measured in our survey, explain approximately 19% of the residual gender earnings gap in accepted offers. The results are similar when we replace the continuous risk measure with a dummy variable for "high" risk tolerance (defined as an average response of 5 or above on the continuous risk measure) (see Column (4)). As shown in the remaining three columns, the results remain qualitatively similar even if we include controls for job characteristics such as industry fixed effects, log hours of work, and city fixed effects (these controls are all choices, and hence endogenous). In this specification, we find that gender differences in risk preferences can explain approximately 25% of the residual gender earnings gap (net of job characteristics) in accepted offers. The results are similar if we use a log specification for earnings instead of levels (see Table A.6).

The model also predicts that a systematic upward bias in beliefs (overoptimism) would lead to higher reservation wages at a given point in time, and hence a lower likelihood of job acceptance at any point.[39] Therefore, we should observe such individuals accepting offers later. To empirically examine the relationship between overoptimism and timing of job acceptance, we turn to data from the subset of individuals for whom we have data on *both* ex-ante earnings expectations and realizations. We construct the individual-level proxy of over-optimism as the percent deviation between the earnings expectations and realizations (with positive values indicating that the individuals' earnings expectations exceed their eventual realizations).[40]As mentioned earlier, caution is warranted in interpreting this measure at the individual level. A positive value of this measure may not necessarily imply overoptimism at the individual level. However, at the aggregate level, expectations are clearly biased upwards (Figures 4 and 5). This measure is positive for 54% of the individuals. Figure 8 shows a clear positive and statistically significant relationship between our proxy of overoptimism and month of acceptance. Consistent with the model's prediction, individuals who are more overoptimistic, as measured by the gap between their expected and realized earnings, are also those who tend to accept jobs later. Unlike risk preferences, the aggregate impact of overoptimism on accepted earnings is ambiguous; while overoptimism will lead to jobs being accepted later at lower reservation wages, for jobs that are accepted early, wages will be higher as a

results are available upon request.

[39]Empirically, in the subsample of individuals for whom we have data on risk preferences and overconfidence ($N = 393$), we find that risk tolerance and overconfidence are virtually uncorrelated ($r = -0.06, p = 0.201$).

[40]As shown in Figure A.5, expectations are indeed predictive of future earnings, though the slope is far from one. This is in line with findings by Conlon et al. (2018) and Wiswall and Zafar (2019) who find that ex-ante earnings expectations of workers and college students, respectively, tend to be predictive of ex-post earnings realizations.

result of higher reservation wages.[41]

In the model, a key mechanism through which risk preferences and overoptimism affect the timing of job acceptance and accepted earnings is through reservation wages. We test this prediction using data on ex-ante reservation earnings from the baseline survey of current students. To increase statistical power, at least for risk preferences, we pool responses from two additional cohorts of students that took the same in-class survey in their junior year. That is, we use data from cohorts of students who are expected to graduate between 2018 and 2021. Reservation earnings were elicited using the following survey question: "*What would the lowest annual total compensation (including base pay, signing bonus, and bonus pay) have to be for you to accept a job offer?*"[42]

The left panel of Figure 9 shows a strong positive association between our survey measure of risk tolerance and students' reports of their ex-ante reservation earnings. Turning to the relationship between reservation earnings and overconfidence, we plot a similar figure in the right panel, for the subset of students for whom we have data on earnings expectations and realizations (i.e., the 2018-2019 cohorts) and meet the sample restrictions as discussed above. Even for this small sample of students, there is evidence of a significant relationship between higher reservation earnings and greater optimism in earnings expectations. Table A.7 further shows that there is a clear gender difference in reservation earnings. Women, on average, report reservation earnings that are about $3,000 less than men. This difference is reduced to about $2,000 controlling for the standard set of individual-level background controls. More importantly, the inclusion of the survey measure of risk preferences and overconfidence reduces the raw (residual) gender gap by 32% (46%), indicating that both attributes can account for a sizable portion of the observed gender difference in reservation earnings. Taken together, these findings lend further support to the model mechanisms.

5.3 Other Potential Explanations

In Appendix A, we consider alternative explanations that may account for the observed empirical patterns. In particular, we consider the extent to which gender differences in other psychological attributes such as procrastination, patience, and rejection aversion, might generate similar patterns in job acceptance timing and earnings. We show that these alternative explanations might be able to explain isolated patterns in the data, but not all of them.

[41] Naively regressing accepted earnings on our proxy of overoptimism gives a negative estimate, which is largely mechanical since overoptimism is defined as (expectations - accepted earnings).

[42] This data was collected for a different project that utilizes the same survey instruments. We do not use the data from the additional cohorts for the other analyses as these students have not completed the follow-up surveys.

We winsorize the top and bottom 2.5% of reservation earnings and further restrict the sample to students with reservations earnings above $10,000, those whose reported reservation earnings are lower than their expected earnings, and indicate that they plan to work immediately after graduation. The results are similar, albeit somewhat weaker, if we do not impose the additional restrictions. These restrictions ensure that the self-reported reservation earnings are less susceptible to outliers and measurement error.

6 Estimation

In this section, we estimate the model using our data on job search. As mentioned earlier, the risk aversion parameter ι, the learning rate γ, the true mean of log offers μ^* and initial beliefs μ_1 are allowed to differ by gender, and we will denote gender-specific parameters with a superscript (one of $\{m, f\}$). All remaining parameters are the same for both genders.

As shown in section 5.1, for parameters that we can directly observe, the assumptions we make are largely supported by the data; returns to search are equivalent across genders, as is the variance of log offers. For parameters with no direct counterparts in the data, the above assumption imposes that search is not differentially costly by gender at this early stage of the job search process (except through endogenous choices of whether or not to search), and that both genders have the same dollar value of leisure, but that it is valued differently only because of risk preferences.

We set the discount rate to $\beta = 0.996$ for both genders to match a five percent annual interest rate in our monthly estimation. The graduation date is set to $\bar{T} = 10$, nine months from when our model begins. Since the variance of log offers in our data is similar across genders, we exogenously set σ to equal the observed variance of log wage offers in our data, pooled across gender. For the average log offer for each gender ($\mu^{*,m}$,$\mu^{*,f}$), we use our data on offers and set them equal to the mean log offer received by each gender. Finally, we make the parametric assumption that search costs c are distributed according to an exponential distribution with parameter ϕ, and estimate the parameter ϕ as part of the procedure below. To pin down the probability of receiving an offer λ conditional on searching, we use the average probability of receiving an offer for those who report searching.

We choose the remaining parameters via Simulated Methods of Moments (SMM), minimizing the distance between specific model-generated moments and data-generated moments. Specifically, we search for the set of eight parameters $\theta = \{b, \phi, \mu_1^m, \iota^m, \gamma^m, \iota^f, \mu_1^f, \gamma^f\}$ that solve the following problem:

$$\hat{\theta} = \text{argmin}_\theta \Big(\frac{\hat{M}(\theta) - M}{M}\Big)' \Big(\frac{\hat{M}(\theta) - M}{M}\Big)$$
$$\text{subject to} \quad \gamma^f \geq \gamma^m \quad \text{and} \quad \iota^f \geq \iota^m$$

where $\hat{M}$ denotes the vector of model-generated moments and M denotes the vector of empirical moments. To find the global solution to this minimization problem, we use the Tik-Tak algorithm (Arnoud et al., 2019), and solve the model on a Sobol set of 100,000 points. We then proceed to look for local minima as described in (Arnoud et al., 2019).

For the empirical moments contained in M, we use data on the evolution of earnings expectations (for which we have information at two points in time, $\bar{T} - 8$ and $\bar{T} - 2$) to inform the learning rule and overconfidence, and information on the time path of cumulative mean accepted offers by gender and the share of students who have accepted offers over time to inform the preference and search parameters.[43] Throughout, and consistent with the evidence outlined above, we impose the restrictions that (i) risk aversion for women is larger than for men, and (ii) $\gamma^f > \gamma^m$, in line with the reduced-form evidence.

While we do not offer a formal proof of identification, we think heuristically of the expectations data at different moments in time as identifying bias and learning, the offer arrival rates as identifying the search cost parameters, mean offers as identifying the offer distribution parameters, and the full cumulative mean accepted offer curve as identifying b, ι^f and ι^m. The discussion in Section 4.4 provides some intuition on how the risk parameter, learning rate, and overconfidence impact the moments that we target.

The estimated parameters are summarized in Table 6. The top panel reports the gender-neutral parameters, while the bottom panel reports the gender-specific parameters. The risk aversion parameter for men is $\iota^m = 1.9$ with a larger value for women of $\iota^f = 2.0$.[44] The value of leisure (net of search costs) before graduation is 5% of offered wages, while the average cost of search is roughly $0.3\% - 0.5\%$ of offered wages for women and men, respectively. The mean annual salary offer is $\$66,068$ for men and $\$59,848$ for women. Men have more optimistic beliefs about the mean offer that they will receive relative to women; the implied bias in wages at graduation is 22% for men and 8% for women. Moreover, the learning rate of women is about 40% higher than that of men.

As can be seen in Table A.9, the model is able to broadly match the key empirical patterns observed in the data. For example, we capture the decline in the gender gap in accepted earnings and the fact that women accept jobs earlier than men. Figure 10 plots the implied gender gap in cumulative mean accepted offers in our estimated model. The model is able to capture the decline in the gender gap as graduation nears, though it slightly underpredicts the level at earlier dates. Figure 11 plots the cumulative share of men and women who have accepted jobs over the job search period, in both the model and the data. The model captures the fact that females accept jobs earlier than males, driven by the fact that they are more likely to search earlier (see Table A.9). Finally, while women are always less likely to reject an offer, the composition of job acceptance dates implies that, overall, men and women are likely to reject at least one offer at similar rates; this is consistent with the raw data as well, where we see similar likelihood of rejecting any offer by gender (see Table 2).

[43] Specifically, for the former we use the value for each gender at $t = 1$, and then the slope parameter from a linear fit of the model-generated data; for the latter, we use the cumulative share that have accepted jobs at $t = 1$ and $t = \bar{T}$ for each gender.

[44] While at face value the difference may appear small, what matters is how these differences translate into differential behavior in the model. Figure 3 shows that reservation wages move significantly for this quantitative move in risk aversion.

7 Policy Counterfactuals

In this section, we use the model to conduct two policy-relevant counterfactuals. First, we simulate an information intervention and investigate the earnings and welfare impacts of eliminating the bias in beliefs about the offer distribution. Second, given the gender differences in risk preferences (both in the data and the model), we investigate the impact of instituting a policy where individuals can hold on to previous offers for a longer duration. These counterfactuals abstract away from general equilibrium considerations. In addition, it is worth noting that we take the gender-specific offer distributions as given. To the extent that those differences might arise due to gender differences in risk preferences/overconfidence, our counterfactuals arguably yield a lower bound of the impacts on the gender gap.

7.1 Costs of Overconfidence: Earnings and Welfare Implications

Overconfidence can have important impacts on welfare and earnings. If students perceive that they face a more favorable offer distribution than they actually do, they will raise their reservation wages or search too hard, and may end up rejecting jobs that they would otherwise have accepted had they known the truth, or pay too much in search costs. For some "lucky" individuals, this can ultimately lead to higher earnings, but for others, once expectations have been revised and reservation wages lowered, earnings might fall. Therefore, the welfare gains from knowing the truth can be heterogeneous.

Evidence from our survey provides some indication that overconfidence might be more costly for men. In particular, women are more likely to be satisfied with the job search process than men (5.94 vs. 5.50 on a 10-point scale) and report significantly fewer search regrets (41% vs. 52%).[45] Men are also significantly more likely to have rejected an offer that is higher than the one they end up accepting relative to women (21% vs. 13.7%). The last fact could also be consistent with compensating differentials; however, given that the literature typically finds that non-wage amenities are valued more by women, we would have expected the gender gap in these statistics to be flipped if that were the case.[46]

We can use the model to study the implications of overconfidence on earnings and welfare. To do so, we conduct the following exercise. We assume that both genders have perfect knowledge about the mean offer, and thus do not need to learn. We then study what happens to earnings and welfare in this counterfactual, perfect information world.

Figure 12 plots the implied gender gap in cumulative mean accepted offers under perfect in-

[45] The survey instrument also included a question regarding regret for accepting a job too early. We find no gender difference in response to this question: roughly 18% of both genders report regret for accepting a job too early.

[46] We also added a module to the nationally representative NY Fed Survey of Consumer Expectations about job search behavior. In response to the question, *"Have you ever regretted rejecting a job offer?"*, 18.9% of males answered "yes" compared to 14.4% of females. That is, the gender gap in ex post regret that we find in our sample also seems to be present in more representative samples.

formation. The solid black line reproduces the model-generated gender gap, previously plotted in Figure 10, along with the empirical gender gap (black dashed line). The red curve plots the implied cumulative gender gap in accepted offers under perfect information. By the time of graduation, the gender gap falls by 18% relative to the model with imperfect information. Overall, as shown in Table 7, the gender gap under perfect information is 10.1% versus 13.5% under imperfect information, or about 75% of the gap.

While overconfidence, on average, results in a larger gender gap in favor of men, the rise in earnings comes at a cost. To get a sense of the welfare implications of imposing perfect information, we solve for the additional constant flow income in the imperfect information, baseline model that would deliver the same change in date $t = 1$ present discount value (PDV) welfare as the change from going from imperfect information to perfect information. For men, the mean (median) welfare gain of perfect information is equivalent to a \$216 (\$108) annual increase in flow income in the baseline imperfect information model. For men to achieve the welfare gain (from the perspective of $t = 1$) that women experience, flow income in the baseline model would only need to increase by \$86 (\$36) annually. Therefore, consistent with the survey data, the expected PDV welfare gains of perfect information are twice as large for men.

7.2 Limiting Exploding Offers

Next, we consider a policy that could arguably minimize the role of risk preferences (and overconfidence) – allowing student to hold onto offers that they receive for an additional month (i.e., slowing down exploding offers). Such a policy removes part of the risk associated with rejecting an offer, as an additional month allows for another possible offer draw. On the other hand, such a policy also makes mistakes due to overconfidence less costly, which may benefit males. Thus, the impact on the gender gap is not ex ante clear. In principle, universities could mandate employers to allow students a longer time to contemplate over offers, and so such a counterfactual is feasible.[47]

To conduct this counterfactual exercise, we extend our baseline model to allow for these "non-exploding" offers. In this environment, all students begin the job search process without an offer in hand. As before, after date $\bar{T}$ the model is stationary:

$$W(w, \mu) = \frac{u(w)}{1 - \beta}.$$

[47] Our goal here is to quantify how such a policy may impact the gender gap. The general equilibrium consequences of such a policy (especially for employers themselves) are not clear at all. In addition, such a policy is only possible if all schools coordinate on it.

The value of unemployment without an offer for $t \geq \bar{T}$ and some belief μ is:

$$
\begin{aligned}
U(\mu) = \int_c \Big(& \max_{s \in \{0,1\}} -cs + u(b(1-\zeta)) \\
& + \beta\lambda s \int \max\{W(y,\mu), U^{offer}(\mu, y), U(\mu_t)\} dF(y;\mu,\sigma)\Big) dH\left(c\right) + \beta(1-\lambda s)U(\mu),
\end{aligned}
$$

while the value with an offer w in hand with belief μ is:

$$
\begin{aligned}
U^{offer}(w,\mu) = \int_c \Big(& \max_{s \in \{0,1\}} -cs + u(b(1-\zeta)) + \beta\lambda s \int \max\{W(w,\mu), W(y,\mu), U^{offer}(y,\mu)\} dF(y;\mu_t,\sigma) \\
& + \beta\left(1 - s\lambda\right) \max\{U(\mu), W(w,\mu)\Big) dH(c).
\end{aligned}
$$

For $t < \bar{T}$, the perceived value of being a student at date t with no job in hand and no offer in hand beliefs μ is:

$$
\begin{aligned}
U_t(\mu) = \int_c \Big(& \max_{s \in \{0,1\}} -cs + u(b) \\
& + \beta\lambda s \int \max\{W_{t+1}(y,\mu), U^{offer}_{t+1}(y,\mu), U_{t+1}(\mu)\} dF(y;\mu,\sigma) \\
& + \beta\left(1 - \lambda s\right) U_{t+1}(\mu)\Big) dH\left(c\right),
\end{aligned}
$$

where the only change from the earlier formulation is that if an offer comes, the student can either accept the offer or hold on to the offer, which gives them the perceived value of having no job, but an offer y in hand, $U^{\text{offer}}_{t+1}(\mu, y)$. For some current offer w, this value is given by:

$$
\begin{aligned}
U^{offer}_t(w,\mu) = \int_c \Big(& \max_{s \in \{0,1\}} -cs + u(b) \\
& + \beta\lambda s \int \max\{W_{t+1}(w,\mu), W_{t+1}(y,\mu), U^{offer}_{t+1}(y,\mu)\} dF(y;\mu,\sigma) + \\
& \beta\left(1 - s\lambda\right) \max\{U_{t+1}(\mu), W_{t+1}(w,\mu)\}\Big) dH(c).
\end{aligned}
$$

In this case, if the student receives another offer y, she has three choices: accept the offer that was held on to w, accept the new offer y, or take the offer y into the next period and reject the offer w. If no offer is received in the current period, the student can either accept the offer they held on to, or reject the offer and continue searching without an offer in hand. The value of employment for each job j remains as in equation (4).

For those who have an offer w in hand, we can re-write the value as:

$$\begin{aligned}U_t^{offer}(w,\mu) = \int_c \Big(& \max_{s\in\{0,1\}} -cs + u(b) \\ & + \beta\lambda s \int_w \max\{W_{t+1}(y,\mu), U_{t+1}^{offer}(y,\mu)\} dF(y;\mu,\sigma) \\ & + \beta\lambda s \int^w \max\{W_{t+1}(w,\mu), U_{t+1}^{offer}(y,\mu)\} dF(y;\mu,\sigma) \\ & \beta\left(1-s\lambda\right)\max\{U_{t+1}(\mu), W_{t+1}(w,\mu)\}\Big) dH(c).\end{aligned}$$

That is, for any offer $y > w$, we know that accepting y will dominate accepting w, and so the choice is between accepting y or holding on to the offer y. For any wage offer $y < w$, accepting the old offer dominates accepting the new offer, so the relevant choice is between accepting the old offer or holding on to the new offer. Therefore, there are two cutoff wages to define. The first defines the wage offers the student will accept for all offers that she receives that are above the current offer w:

$$W_t\left(\mu, y_1^*\left(\mu\right)\right) = U_t\left(\mu, y_1^*\right),$$

and the second is the offers the student will hold on to, for all offers which are below w:

$$W_t\left(\mu, w\right) = U_t\left(\mu, y_2^*\left(\mu, w\right)\right).$$

Therefore, if a student with an offer w in hand and beliefs μ receives an offer, the decision to accept, reject, or hold on to the new offer y is given by $\delta(\mu, w, y)$:

$$\delta(w,y) = \begin{cases} \text{hold } y\text{, reject } w, & \text{for } w \leq y \leq y_1^*\left(\mu\right) \\ \text{accept } y\text{, reject } w, & \text{for } w \leq y_1^*\left(\mu\right) < y \\ \text{hold } y\text{, reject } w, & \text{for } y_2^*\left(\mu, w\right) \leq y \leq w \\ \text{accept } w\text{, reject } y, & \text{for } y \leq y_2^*\left(\mu, w\right) \leq w \end{cases}$$

We solve this model in the same way as discussed in 4.3 and then calculate the implied gender gap in the case where students have two months rather than one month to accept or reject an offer. Note that because the learning rule we adopt is exogenous, there is no change in learning in response to the policy which limits exploding offers. It is not clear how learning would be impacted in reality in such a regime.

The red line in Panel (b) of Figure 12 shows the gender gap in the counterfactual environment in which students can hold on to offers for longer. The gender gap in cumulative accepted offers falls significantly at all points in time. The last row in Table 7 shows that the average gender gap in this case would be about 8%, which is about 40% smaller than the gap in the case with exploding offers. Thus, given our model estimate, such a policy favors females and helps to reduce the gender gap in accepted wages.

8 Conclusion

Despite the central importance of labor market search for understanding job-finding behavior and outcomes, and the large theoretical and empirical literature on this topic, surprisingly little is known about gender differences in job search behavior. In this paper, we collect rich survey data on the job search process and labor market realizations of undergraduate business majors from Boston University and document novel facts about the job search behavior of male and female college graduates in the entry labor market. In particular, we find that women accept jobs close to a month earlier than comparable men and the cumulative gender gap in accepted offers declines over the job search period. Using survey data on risk preferences and beliefs about offer wages (and their subsequent realizations), we provide empirical evidence that men's greater degree of risk tolerance and overconfidence (along with a slower rate of learning) relative to women play a role in explaining the observed gender differences in job acceptance timing and the resulting gender earnings gap.

We show that a job search model that incorporates gender differences in risk aversion, overconfidence (and learning) can match the key patterns in the data. Moreover, by allowing for endogenous search effort, the model is also able to generate other empirical observations such as the fact that women start searching (and receive their first offers) earlier. Policy counterfactuals using the model suggest that gender differences in overconfidence can explain about 25% of the gender gap in accepted earnings at the mean. Although men gain, on average, from having overconfident beliefs, this behavior is costly. Survey evidence shows that females are more likely to be satisfied with the job search process and report significantly fewer search regrets. Using the model to simulate the counterfactual with correct beliefs, we find that the welfare effects of overconfidence are sizable, with men experiencing larger gains from moving to perfect information. We also show that a simple policy of allowing students to hold on to previous offers for just one additional month can reduce the gender gap by 40%.

Our paper highlights that gender differences in psychological attributes such as risk aversion and overconfidence, by affecting how men and women search for jobs, play a non-trivial role in generating early career earnings gaps among the highly-skilled. We thus offer a novel explanation for gender gaps among the highly-skilled. While we focus on the point of entry in the labor market, understanding disparities in the initial conditions is important since they tend to have long-lasting effects on workers (Rothstein, 2019).

Our findings suggest that policies aimed at reducing biased beliefs, especially that of men, can lead to overall welfare gains. Policies could also be adopted to mitigate the effects of risk preferences such as allowing students to hold onto job offers for longer. Other policies could include providing students with more information and guidance during the job search process about the expected timing and distribution of offers. By correcting biased beliefs and helping to resolve uncertainty, these policies could help both men and women make better decisions during the job search process and potentially mitigate the gender earnings gap.

It is worth noting that in the model, we take the gender-specific offer distributions as given and stationary, which essentially treats employers as passive. By allowing the offer distribution to vary by gender, this implicitly allows unobserved factors such as discrimination on the part of employers (e.g., Neumark et al., 1996) or gender differences in preferences for job attributes to affect job search behavior through offered wages. If, however, gendered offer distributions arise, in part, due to gender differences in risk preferences and overconfidence, what we capture in our analysis is a lower bound on the importance of these traits in the job search process. Future work that sheds light on what causes men and women to apply to different jobs would be fruitful. Doing so would require richer data not only on employer-employee matches, but also on application behavior, which is challenging. In principle, one could endogenously generate gender differences in offer distributions and non-stationarity by allowing for heterogeneity in job types. Extending our single-job model to a two-job model could capture additional features of the observed gender differences in search behavior, but identification of such a model is less clear. We do not pursue that for these reasons.

Finally, we have shown that males, relative to their female counterparts, tend to be more overoptimistic and slower to learn. We take these beliefs as given. Our learning rule, while directly informed by the data, also lacks micro-foundations. Survey evidence suggests that this could partially be because men and women gather information differently (e.g., Table 2 shows that men are more likely to rely on referrals, and women find the career center more useful). Future work that tries to understand the origins and persistence of such biases would be valuable. However, the data needs for doing so are quite demanding; we believe a more stylized laboratory setting may be more amenable to answering these questions.

References

Acemoglu, Daron and Robert Shimer, "Efficient Unemployment Insurance," *Journal of Political Economy*, 1999, *107* (5), 893–928.

Albanesi, Stefania and Aysegul Sahin, "The Gender Unemployment Gap," *Review of Economic Dynamics*, October 2018, *30*, 47–67.

Arcidiacono, Peter, Joseph Hotz, Arnaud Maurel, and Theresa Romano, "Ex Ante Returns and Occupational Choice," *Journal of Political Economy*, forthcoming.

Arnoud, Antoine, Fatih Guvenen, and Tatjana Kleineberg, "Benchmarking Global Optimizers," NBER Working Papers 26340, National Bureau of Economic Research, Inc October 2019.

Avilova, Tatyana and Claudia Goldin, "What can UWE Do for Economics?," NBER Working Papers 24189, National Bureau of Economic Research January 2018.

Azmat, Ghazala and Barbara Petrongolo, "Gender and the Labor Market: What Have We Learned from Field and Lab Experiments," *Labour Economics*, 2014, *30*, 32–40.

_ **and Rosa Ferrer**, "Gender Gaps in Performance: Evidence from Young Lawyers," *Journal of Political Economy*, 2017, *125*, 1306–1355.

Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet, "Gender Differences in Job Search: Trading off Commute Against Wage," Working Paper 2019.

Barber, Brad M. and Terrance Odean, "Boys Will be Boys: Gender, Overconfidence, and Common Stock Investment," *Quarterly Journal of Economics*, 2001, *116*, 261–292.

Beaudry, Paul and John DiNardo, "The Effect of Implicit Contracts on the Movement of Wages over the Business Cycle: Evidence from Micro Data," *Journal of Political Economy*, 1991, *99* (4), 665–688.

Bertrand, Marianne, "New Perspectives on Gender," in Orley C. Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 4b, Amsterdam: Elsevier, Ltd., 2011, pp. 1545–1592.

_ **, Claudia Goldin, and Lawrence F. Katz**, "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors," *American Economic Journal: Applied Economics*, 2010, *2*, 228–255.

Blau, Francine D. and Lawrence Kahn, "The Gender Wage Gap: Extent, Trends, and Explanations," *Journal of Economic Literature*, 2017, *55* (3), 789–865.

Bowlus, Audra J., "A Search Interpretation of Male?Female Wage Differentials," *Journal of Labor Economics*, 1997, *15* (4), 625–657.

_ **and Louise Grogan**, "Gender Wage Differentials, Job Search, and Part-Time Employment in the UK," *Oxford Economic Papers*, 2009, *61*, 275–303.

Buser, Thomas and Huaiping Yuan, "Do Women Give up Competing More Easily? Evidence from the Lab and the Dutch Math Olympiad," *American Economic Journal: Applied Economics*, 2019, *11* (3), 225–252.

_ **, Muriel Niederle, and Hessel Oosterbeek**, "Gender, Competitiveness, and Career Choices," *Quarterly Journal of Economics*, 2014, *129* (3), 1409–1447.

Caliendo, Marco, Deborah Cobb-Clark, and Arne Uhlendorff, "Locus of Control and Job Search Strategies," *Review of Economics and Statistics*, 2015, *97* (1), 88–103.

Charness, Gary and Uri Gneezy, "Strong Evidence for Gender Differences in Risk Taking," *Journal of Economic Behavior & Organization*, 2012, *83* (1), 50–58.

_ **,** _ **, and Alex Imas**, "Experimental Methods: Eliciting Risk Preferences," *Journal of Economic Behavior & Organization*, 2013, *87*, 43–51.

Conlon, John J., Laura Pilossoph, Matthew Wiswall, and Basit Zafar, "Labor Market Search with Imperfect Information and Learning," Working Paper 2018.

Cox, James C. and Ronald L. Oaxaca, "Direct Tests of the Reservation Wage Property," *Economic Journal*, 1992, *102*, 1423–1432.

Crosetto, Paolo and Antonio Filippin, "A Theoretical and Experimental Appraisal of Four Risk Elicitation Methods," *Experimental Economics*, 2016, *19* (3), 613–641.

Croson, Rachel and Uri Gneezy, "Gender Differences in Preferences," *Journal of Economic Literature*, 2009, *47* (2), 1–27.

Davidson, Russell and Jean-Yves Duclos, "Statistical Inference for Stochastic Dominance and for the Measurement of Poverty and Inequality," *Econometrica*, 2000, *68* (6), 1435–1464.

DellaVigna, Stefano and M. Daniele Paserman, "Job Search and Impatience," *Journal of Labor Economics*, 2005, *23* (3), 527–88.

_ **, Attila Lindner, Balazs Reizer, and Johannes F. Schmeider**, "Reference-Dependent Job Search: Evidence from Hungary," *Quarterly Journal of Economics*, 2017, *132* (4), 1969–2018.

Dittrich, Marcus and Kristina Leipold, "Gender Differences in Time Preferences," *Economics Letters*, 2014, *122* (3), 413–415.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner, "Risk Aversion, Risk, and the Duration of Unemployment," *Journal of the European Economic Association*, 2011, *9* (3), 522–550.

Eckel, Catherine C. and Philip J. Grossman, "Sex Differences and Statistical Stereotyping in Attitudes Toward Financial Risk," *Evolution and Human Behavior*, 2002, *23* (4), 281–295.

_ **and** _ , "Sex and Risk: Experimental Evidence," in Charles Plott and Vernon Smith, eds., *Handbook of Experimental Economics Results*, Vol. 1, Elsevier, New York, 2008a.

— **and** — , "Forecasting Risk Attitudes: An Experimental Study Using Actual and Forecast Gamble Choices," *Journal of Economic Behavior & Organization*, 2018, *68* (1), 1–17.

Faberman, Jason, Andreas I. Mueller, Ayşegül Şahin, and Giorgio Topa, "Job Search Behavior among the Employed and Non-Employed," Working Paper 23731, National Bureau of Economic Research August 2017.

— **, Andreas Mueller, and Aysegul Sahin**, "Job Search and the Gender Wage Gap," Working Paper June 2020.

Falk, Armin, Anke Becke, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde, "Global Evidence on Economic Preferences," *Quarterly Journal of Economics*, 2018, *133* (4), 1645–1692.

— **, Anke Becker, Thomas Dohmen, David B. Huffman, and Uwe Sunde**, "The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences," IZA DP No. 9674 2016.

Feinberg, Robert M., "Risk Aversion, Risk, and the Duration of Unemployment," *The Review of Economics and Statistics*, 1977, *59* (3), 264–271.

Flabbi, Luca, "Gender Discrimination Estimation in a Search Model with Matching and Bargaining," *International Economic Review*, 2010, *51* (3), 745–783.

— **and Andrea Moro**, "The Effect of Job Flexibility on Female Labor Market Outcomes: Estimates from a Search and Bargaining Model," *Journal of Econometrics*, 2012, *168* (1), 81–95.

Flinn, Christopher, Petra Todd, and Weilong Zhang, "Personality Traits, Job Search and the Gender Wage Gap," HCEO Working Paper Series 2020-010 2020.

Hansen, Benjamin and Drew McNichols, "Information and the Persistence of the Gender Wage Gap; Early Evidence from California?s Salary History Ban," NBER Working Papers 27054, National Bureau of Economic Research 2020.

Holt, Charles A. and Susan K. Laury, "Risk Aversion and Incentive Effects," *American Economic Review*, 2002, *92* (5), 1644–1655.

Kahn, Lisa, "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," *Labour Economics*, 2010, *17* (2), 303–316.

Krueger, Alan B. and Andreas Mueller, "Job Search and Job Finding in a Period of Mass Unemployment: Evidence from High-Frequency Longitudinal Data," Working Paper, Princeton University, Department of Economics, Center for Economic Policy Studies 2011.

McGee, Andrew D., "How the Perception of Control Influences Unemployed Job Search," *Industrial and Labor Relations Review*, 2015, *68* (1), 184–211.

— **and Peter McGee**, "Search, Effort, and Locus of Control," *Journal of Economic Behavior & Organization*, 2016, *126* (Part A), 89–101.

Morchio, Iacopo and Christian Moser, "The Gender Pay Gap: Micro Sources and Macro Consequences," Working Paper April 2020.

Neumark, David, Roy J. Bank, and Kyle D. Van Nort, "Sex Discrimination in Restaurant Hiring: An Audit Study*," *The Quarterly Journal of Economics*, 08 1996, *111* (3), 915–941.

Niederle, Muriel and Lise Vesterlund, "Do Women Shy Away From Competition? Do Men Compete Too Much?," *Quarterly Journal of Economics*, 2007, *122* (3), 1067–1101.

Noonan, Mary C., Mary E. Corcoran, and Paul Courant, "Pay Differences among the Highly Trained: Cohort Differences in the Sex Gap in Lawyers? Earnings," *Social Forces*, 2005, *84*, 853–72.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, "The Short- and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 2012, *4* (1), 1–29.

Oyer, Paul, "Initial Labor Market Conditions and Long-Term Outcomes for Economists," *Journal of Economic Perspectives*, 2006, *20* (3), 143–160.

Pannenberg, Markus, "Risk Attitudes and Reservation Wages of Unemployed Workers: Evidence from Panel Data," *Economics Letters*, 2010, *106*, 223–226.

Pissarides, Christopher A., "Risk, Job Search, and Income Distribution," *Journal of Political Economy*, 1974, *82* (6), 1255–67.

Reuben, Ernesto, Matthew Wiswall, and Basit Zafar, "Preferences and Biases in Educational Choices and Labor Market Expectations: Shrinking the Black Box of Gender," *Economic Journal*, 2017, *127*, 2153–2186.

Rothstein, Jesse, "The Lost Generation? Scarring after the Great Recession," Working Paper 2019.

Shurchkov, Olga and Catherine C. Eckel, "Gender Differences in Behavioral Traits and Labor Market Outcomes," in Susan L. Averett, Laura M. Argys, and Saul D. Hoffman, eds., *The Oxford Handbook of Women and the Economy*, Oxford University Press, 2018, pp. 481–512.

Spinnewijn, Johannes, "Unemployed but Optimistic: Optimal Insurance Design with Biased Beliefs," *Journal of the European Economic Association*, 2015, *13* (1), 130–167.

Steel, Piers, "Arousal, Avoidant and Decisional Procrastinators: Do They Exist?," *Personality and Individual Differences*, 2010, *48* (8).

Vesterlund, Lise, "The Effects of Risk Aversion on Job Matching: Can Differences in Risk Aversion Explain the Wage Gap?," Working Paper 1997.

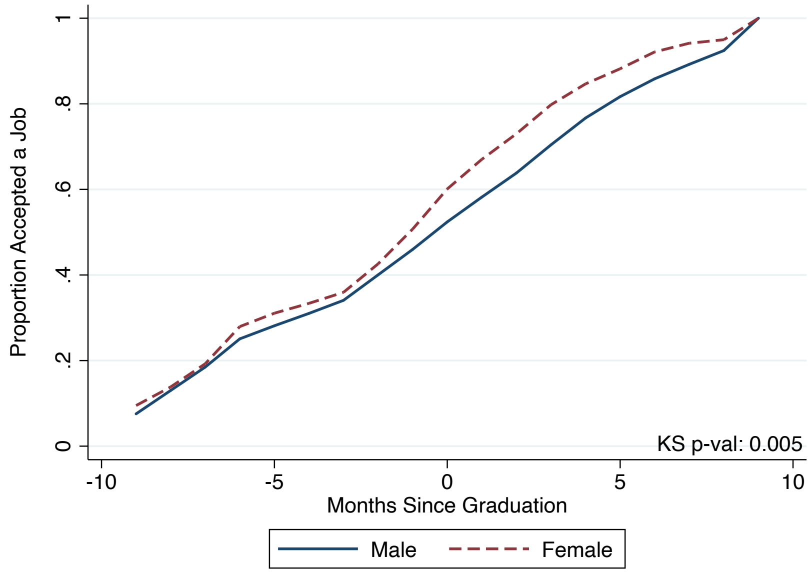
Wee, Shu Lin, "Delayed learning and human capital accumulation: The cost of entering the job market during a recession," 2016. Unpublished manuscript.

Wiswall, Matthew and Basit Zafar, "Preference for the Workplace, Investment in Human Capital, and Gender*," *The Quarterly Journal of Economics*, 2017, *133* (1), 457–507.

_ **and** _ , "Human Capital Investments and Expectations about Career and Family," *Working Paper*, 2019.

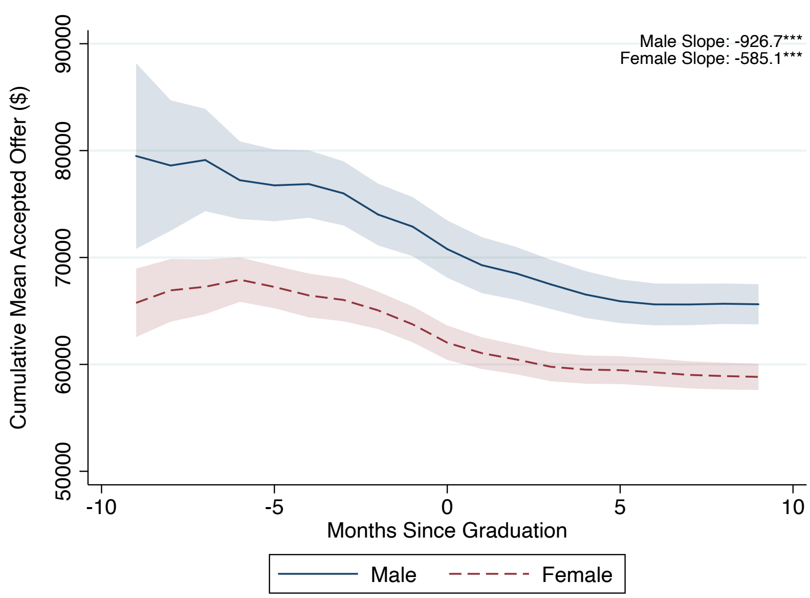
Xiao, Pengpeng, "Wage and Employment Discrimination by Gender in Labor Market Equilibrium," Working Paper 2020.

Figure 1: CDF of Job Acceptance Timing, By Gender



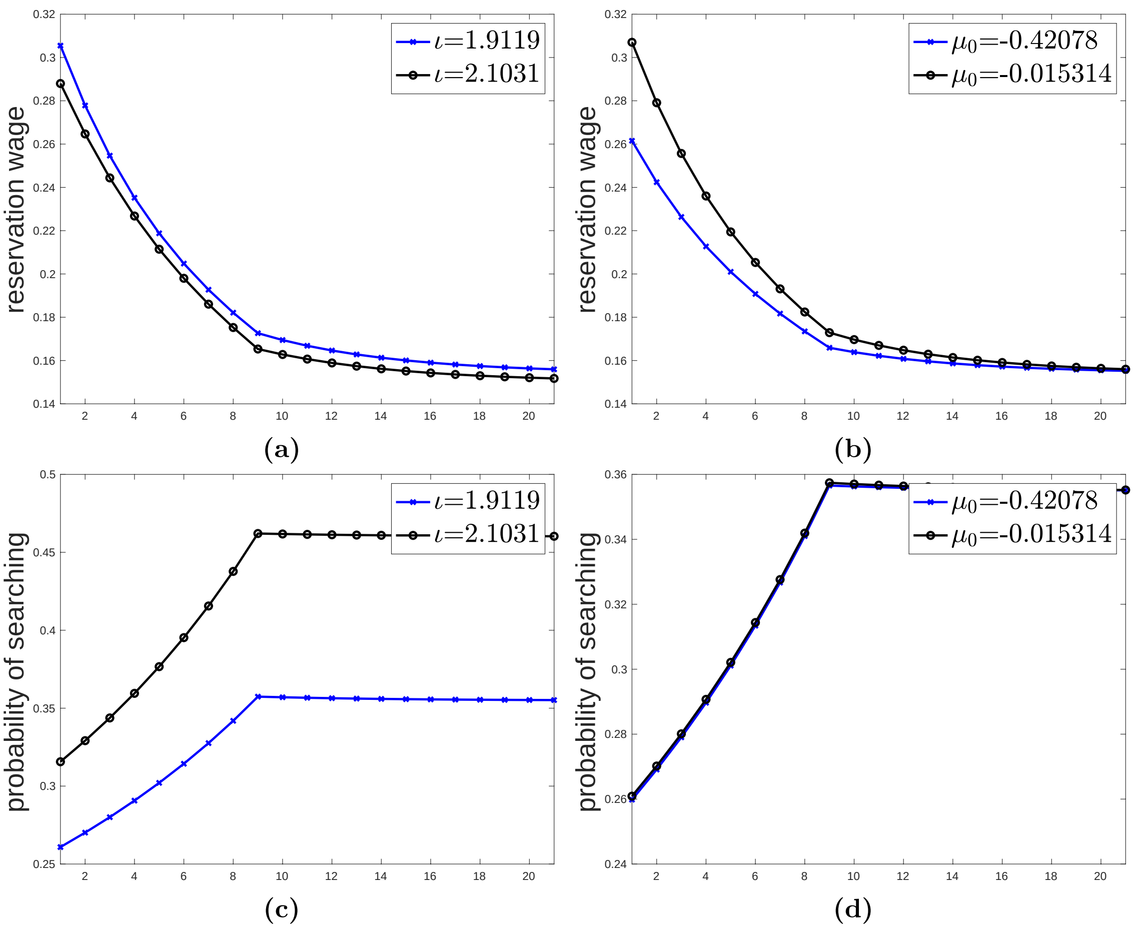
Note: The figure plots the proportion of males and females who accepted a job in each month relative to the month of graduation (indicated as 0). Months since graduation = 9 and -9 includes individuals who accepted a job 10 or more months after or before graduation, respectively.

Figure 2: Cumulative Mean Accepted Offer by Months Since Graduation and Gender



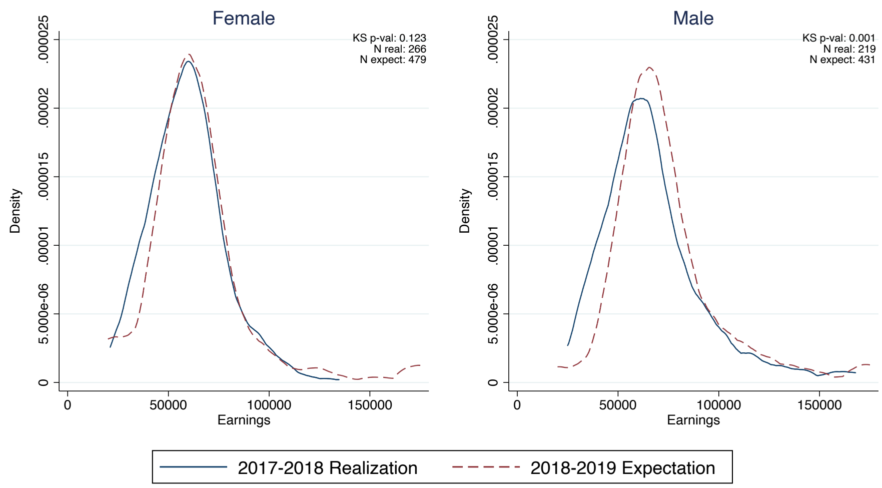
Note: The figure plots the cumulative mean accepted offer as a function of months since graduation separately for males (solid blue line) and females (dashed red line). Months since graduation is defined relative to the month of graduation (indicated as 0). The 95% confidence interval bands are based on bootstrapped standard errors.

Figure 3: Comparative Statics in Risk Aversion and Biases in Beliefs



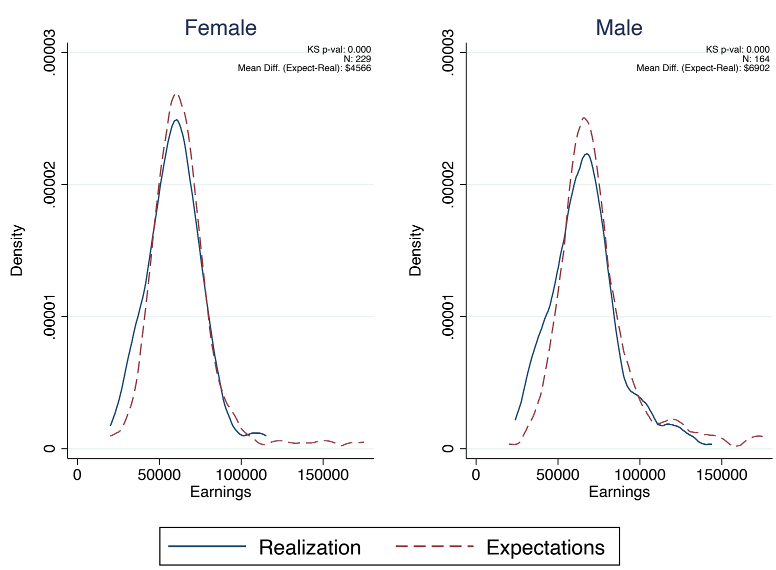
Note: This figure shows how reservation wages (Panels a and b) and the probability of searching (Panels c and d) change as risk aversion varies (left two panels) and biases vary (right two panels). For these numerical exercises, we use the estimated parameter values for males; ι and μ_1 vary around their respective estimated male values as depicted above.

Figure 4: Gender Difference in Beliefs Bias – Cross-Cohort Comparison



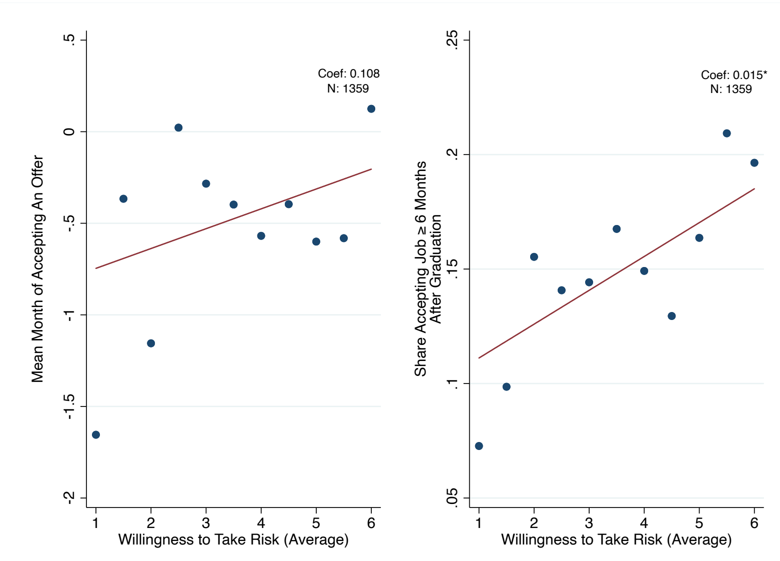
Note: The distribution of expected earnings is constructed based on the earnings expectations (in 2017 dollars) reported by students from the 2018-2019 graduating cohorts. Earnings expectations were elicited during the in-class survey that was conducted in the senior or junior year. The distribution of realized (actual) earnings is based on the first year earnings of the accepted offer of the previous cohorts of graduating students (i.e. 2017-2018 cohorts).

Figure 5: Gender Difference in Beliefs Bias – Within Individual Comparison



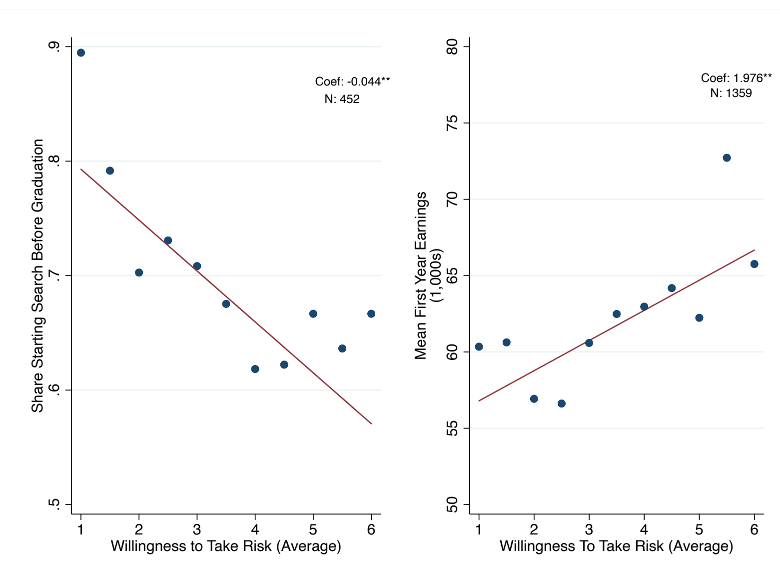
Note: The sample is restricted to individuals for whom we have data on both earnings expectations and realizations. The figure plots the distribution of the difference between ex-ante earnings expectations and ex-post earnings expectations separately by gender. Earnings expectations and realizations are in 2017 dollars.

Figure 6: Relationship Between Timing of Job Acceptance and Risk Preferences



Note: Each graph is a binned scatter plot of a measure of the timing of job acceptance on the survey measure of risk preferences. The y-axis for the left panel plots the mean month of accepting an offer (defined relative to the month of graduation) while the y-axis for the right panel plots the share accepting a job within six months of graduation. The willingness to take risks is the average of two survey questions that ask respondents to rate their willingness to take on financial risks and daily risks. Both risk questions are measured on a 1 to 6 scale.

Figure 7: Accepted Earnings, Timing of Search, and Risk Preferences

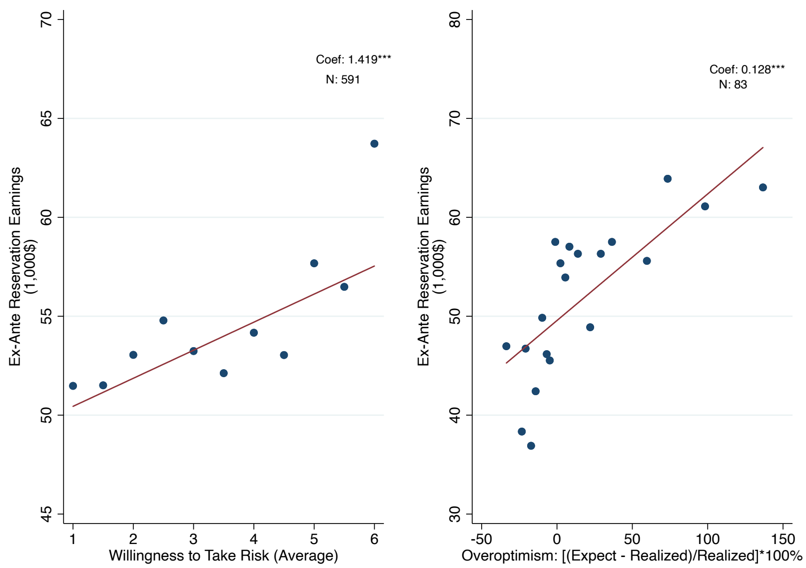


Note: This figure shows binned scatter plots of share of students starting search before graduation (left panel) and total accepted earnings in the first year (right panel) on the survey measure of risk preferences. The willingness to take risks is the average of two survey questions that ask respondents to rate their willingness to take on financial risks and daily risks. Both risk questions are measured on a 1 to 6 scale.

Figure 8: Relationship Between Timing of Job Acceptance and Biased Beliefs

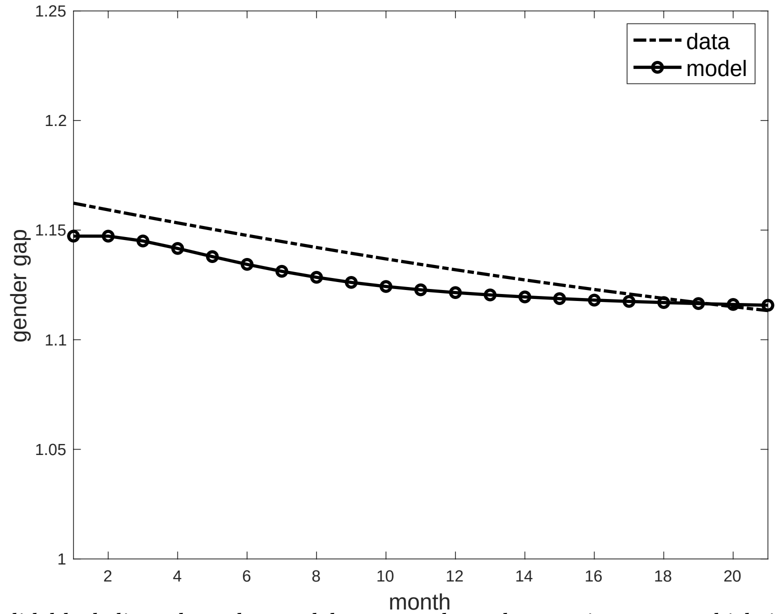
Note: This figure is a binned scatter plot of the month of job offer acceptance (defined relative to the month of graduation) on the individual-level measure of the extent of biased beliefs. This measure of overoptimism is defined as the difference between expected and realized earnings as a percentage of realized earnings. We can only construct this for the 2018 and 2019 graduating cohorts for whom we have data on both earnings expectations and realizations. To account for outliers, we winsorize the top and bottom 2.5% of the overconfidence measure.

Figure 9: Ex-Ante Reservation Earnings, Risk Preferences, and Overoptimism



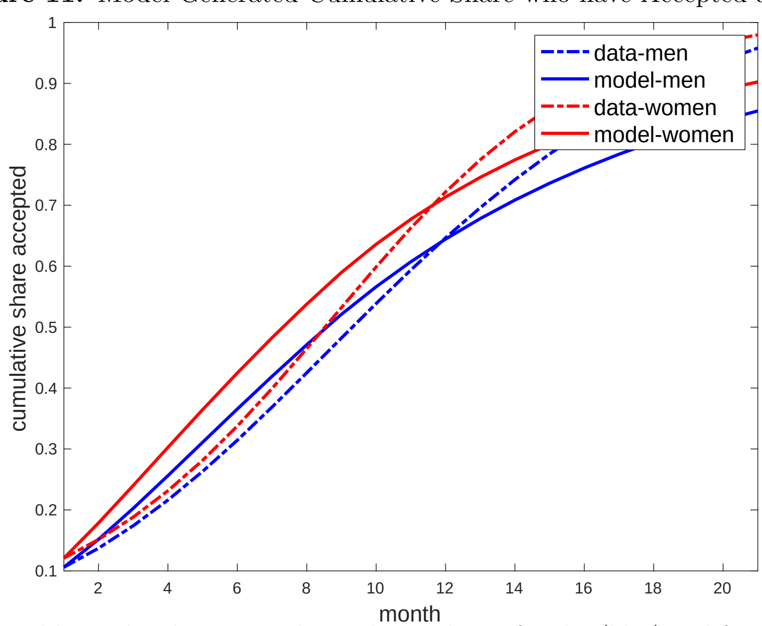
Note: This figure is a binned scatter plot of reported ex-ante reservation earnings (expressed in 2017 dollars) from the in-class survey on risk preferences (left panel) and overconfidence (right panel). For risk preferences, we use all available data from students who completed the in-class survey and answered the reservation earnings question. These students are expected to graduate between 2018 and 2021. For overconfidence, we are limited to students for whom we have data on earnings expectations and realizations. To account for outliers, we winsorize the top and bottom 2.5% of reservation earnings and the overconfidence measure. We also restrict the sample to students with reservations earnings above $10,000 and whose reported reservation earnings are lower than their expected earnings.

Figure 10: Model-Generated Gender Earnings Gap



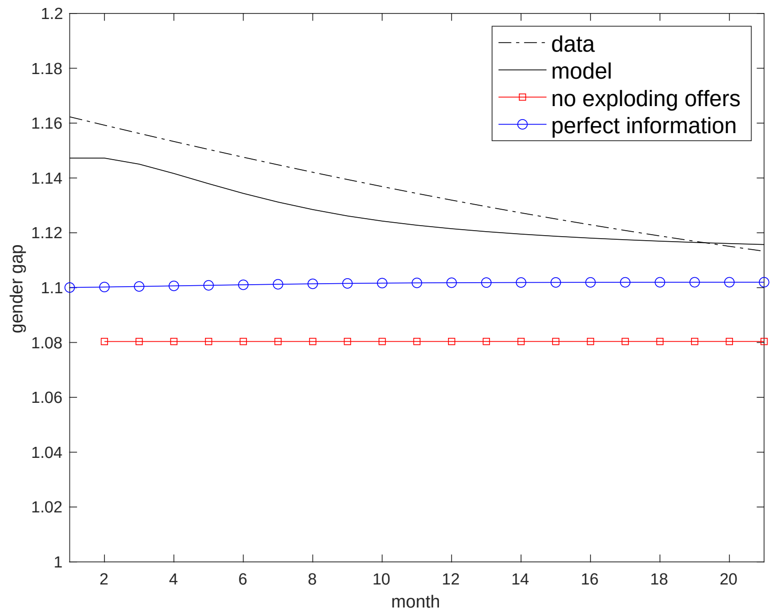
Note: The solid black line plots the model-generated gender earnings gap, which is the ratio of the cumulative accepted male compensation to the cumulative accepted female compensation. The dotted black line plots its empirical counterpart.

Figure 11: Model-Generated Cumulative Share who have Accepted a Job



Note: The dotted lines plot the empirical cumulative share of males (blue) and females (red) who have secured a job, while the solid lines plot the model-generated share of males (blue) and females (red) who have secured a job by some date.

Figure 12: Counterfactual Gender Gaps



Note: The solid black line plots the model-generated gender earnings gap, which is the ratio of the cumulative accepted male compensation to the cumulative accepted female compensation. The black dotted line plots its empirical counterpart. The red dashed line plots the counterfactual gender gap assuming students have perfect information about the offers they will receive. The blue line plots then counterfactual gender earnings gap from eliminating exploding offers. Note that, because the optimal strategy in this model is never to accept an offer within the first period, there is no gender gap depicted for $t = 1$.

Table 1: Sample Characteristics of Graduates

	All	Men	Women	p-value
Observations	1359	622	737	
Age	22.58	22.78	22.42	0.001
	(2.00)	(2.04)	(1.95)	
White/Caucasian	50.9%	53.6%	48.6%	0.071
Black/ African American	4.3%	3.2%	5.2%	0.078
American Indian	0.4%	0.6%	0.1%	0.124
Hispanic/ Latino	11.1%	10.6%	11.6%	0.526
Asian/ Pacific Islander	33.3%	32.0%	34.4%	0.352
Born in U.S.	75.3%	76.4%	74.4%	0.392
Father BA+	78.0%	80.2%	76.1%	0.281
Mother BA+	74.4%	74.3%	74.5%	0.950
GPA	3.32	3.31	3.33	0.199
	(0.34)	(0.35)	(0.33)	
Concentration:				
Accounting	17.1%	18.8%	15.6%	0.118
Entrepreneurship	3.8%	4.7%	3.0%	0.105
Finance	50.4%	65.4%	37.7%	0.000
General Management	2.7%	2.7%	2.7%	0.983
International Management	5.9%	2.1%	9.1%	0.000
Law	9.3%	7.2%	11.0%	0.017
Management Info. Systems	19.1%	20.4%	17.9%	0.241
Marketing	26.2%	13.8%	36.6%	0.000
Operations & Tech. Mgmt.	10.9%	9.8%	11.8%	0.239
Organizational Behavior	3.9%	1.9%	5.6%	0.001
Cohort:				
2013	11.0%	11.3%	10.7%	0.753
2014	10.6%	11.4%	9.9%	0.368
2015	10.4%	10.1%	10.7%	0.723
2016	14.9%	17.2%	13.0%	0.031
2017	14.5%	14.0%	14.9%	0.625
2018	21.2%	21.2%	21.2%	0.980
2019	17.4%	14.8%	19.5%	0.021
Perceived Relative Ability (1-5)	3.90	4.01	3.80	0.000
	(0.81)	(0.84)	(0.76)	
Risk Tolerance (1-6)	3.49	3.83	3.19	0.000
	(1.22)	(1.20)	(1.16)	
Percent High Risk (≥ 5)	15.4%	22.8%	9.1%	0.000

Table 2: Summary Statistics: Initial Job Characteristics and Search Behavior

	All	Men	Women	p-value
Observations	1359	622	737	
First Job in U.S.	95.1%	93.5%	96.6%	0.038
Currently Employed Full-Time	94.4%	94.2%	94.6%	0.774
Industry:				
Accounting	9.3%	7.4%	11.0%	0.023
Advertising/Marketing	8.9%	5.3%	11.9%	0.000
Consulting Services	12.7%	13.3%	12.1%	0.484
Cons. Products/Retail	9.3%	5.6%	12.5%	0.000
Entertainment Media	1.9%	1.8%	2.0%	0.721
Financial Services	24.3%	30.7%	18.9%	0.000
Government/Education	2.4%	2.7%	2.2%	0.503
Health	3.2%	2.7%	3.7%	0.335
Other	27.8%	30.3%	25.7%	0.060
First Year Total Pay	$61,708	$65,352	$58,633	0.000
	(20,832)	(23,567)	(17,647)	
Current Job Total Pay	$66,954	$72,186	$62,680	0.000
	(27,879)	(33,201)	(21,736)	
Interned for First Job	28.6%	29.3%	28.1%	0.613
Referral Helped	25.0%	31.0%	20.5%	0.007
Month Accept Offer	-0.48	0.02	-0.89	0.005
	(6.00)	(6.26)	(5.73)	
Accept Before Grad	56.6%	52.4%	60.1%	0.004
Accept Job within 6 mo. of Grad	89.3%	85.9%	92.1%	0.000
Time Given to Consider (wks.)	2.37	2.44	2.32	0.352
	(2.27)	(2.20)	(2.33)	
Number of Offers	1.70	1.71	1.69	0.636
	(0.95)	(0.95)	(0.95)	
Rejected Any Offer	42.6%	43.4%	41.9%	0.582
Search Behavior (2018/2019 cohorts only)				
Observations	524	224	300	
Month Start Active Job Search	-3.96	-3.26	-4.49	0.082
	(7.42)	(7.54)	(7.30)	
Total Number of Applications	75.22	94.67	60.72	0.002
	(118.28)	(147.32)	(88.37)	
Offers Per 100 Applications	13.86	11.67	15.50	0.088
	(23.48)	(22.71)	(23.95)	
Hours Spent Searching Per Week	9.61	10.30	9.10	0.120
	(8.05)	(7.97)	(8.09)	
Proportion of Jobs Underqualified	25.43	26.97	24.28	0.124
	(18.40)	(18.17)	(18.52)	
Usefulness of Career Center in Search (1-5)	2.41	2.19	2.57	0.002
	(1.26)	(1.23)	(1.26)	

Table 3: Gender Differences in the Timing of Job Acceptance

	Hazard Model			OLS		
	Accept Offer within 6 mo. of Grad.			Month Accept Offer		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	1.227***	1.288***	1.241***	-0.912***	-1.130***	-0.847***
	(0.067)	(0.079)	(0.079)	(0.328)	(0.331)	(0.328)
Basic Controls		X	X		X	X
Industry FE			X			X
Mean	0.893	0.893	0.893	-0.477	-0.477	-0.477
R^2				0.006	0.157	0.202
N	1359	1359	1359	1359	1359	1359

Note: Basic controls include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education. Industry controls include fixed effects for 19 industry groups. Robust standard errors reported in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table 4: Learning Process

		Baseline Expectations	Mid-Search Expectations	Realizations
A. Full Sample				
Men	Mean	73,938	68,079	66,918
	Median	67,098	62,305	65,389
	N	431	97	203
Women	Mean	64,746	55,374	59,917
	Median	61,395	54,174	59,430
	N	479	122	267
B. Consistent Sample				
Men	Mean	73,876.79	64,912.58	58,609.51
	Median	66,619.18	62,305.44	54,122.28
	N	93	93	52
Women	Mean	60,228.09	54,781.33	54,357.87
	Median	58,518.78	53,685.78	53,295.34
	N	116	116	77

Note: Both samples include individuals from the 2018 and 2019 graduating cohorts. Baseline only includes those without jobs at the baseline survey. Final realizations only include those who had a job by the post-graduation survey. The full sample include all individuals who responded to the survey indicated. The consistent sample includes only individuals who answered both the baseline and mid-search surveys, had not accepted a job by the mid-search survey, and revised their expectations by less than 100 percent.

Table 5: Gender Gap in Accepted Earnings

	Dependent Variable: Accepted Earnings in the First Job						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-6719***	-4542***	-3687***	-4106***	-2826**	-2095	-2579*
	(1147)	(1146)	(1148)	(1157)	(1326)	(1344)	(1357)
Risk Tolerance			1505***			1422***	
			(453)			(541)	
Risk Tol. ≥ 5				3609**			2220
				(1621)			(2092)
Controls		X	X	X	X	X	X
Add. controls					X	X	X
Mean	61708	61708	61708	61708	61708	61708	61708
R^2	0.026	0.170	0.178	0.174	0.578	0.582	0.579
N	1359	1359	1359	1359	1359	1359	1359

Note: The dependent variable is total accepted earnings in the first year in 2017 dollars. Basic controls include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education. Additional controls include fixed effects for industry (19 groups), city, and weekly hours of work. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table 6: Model Parameters

Parameter	Description	Men	Women
β	discount rate	0.996	
σ^*	variance log offer	0.307	
ϕ	mean cost of search (utils)	435.643	
b	value of leisure	0.018	
λ	returns to search	0.269	
		Men	Women
μ^*	mean log offer	-1.114	-1.213
μ	expected log offer	-0.030	-0.369
	$\Longrightarrow$implied bias in wages (% dev.) at grad	22.403	8.392
ι	risk aversion	1.912	2.009
γ	learning rate	0.187	0.261

Note: In the upper panel the single Value column spans both Men and Women (header: "Value").

Table 7: Counterfactual Gender Gap

	Mean Gender Gap (%)	$T_g - 8$	T_g
Data	14.787	15.925	13.686
Gender gap predicted by:			
Model	13.512	14.725	12.428
perfect information	10.098	10.023	10.166
2-month offers	8.036	8.036	8.037

Note: The gender earnings gap is defined as the difference in male and female earnings as a percentage of female earnings (i.e. $(\frac{w_m}{w_f} - 1) * 100\%$). The table reports the mean gender gap as well as the gender gap 8 months before graduation ($T_g - 8$) and at graduation (T_g) in the data, under the baseline model, and based on two different counterfactual simulations. Under perfect information, individuals are assumed to have perfect information about mean offers (i.e. $\mu_t = \mu^*$). Under 2-month offers, individuals are allowed to hold onto the offer for an additional month.

A Appendix: Other Potential Explanations

A.1 Patience/Time Discounting

The process of searching for a job involves intertemporal trade-offs. In particular, job seekers face substantial immediate costs – e.g. looking for job opportunities, sending our resumes, preparing for interviews – and delayed rewards. Standard job search models with exponential discounting imply that patience (or lower willingness to discount future benefits and costs) should be positively correlated with search effort, reservation wages, and accepted wages (DellaVigna and Paserman, 2005). Some of the observed gender differences in job acceptance timing and accepted earnings may thus be consistent with greater patience on the part of men.

To examine this issue, we included a question in the current student survey to obtain an individual-level measure of patience. We use a similar qualitative measure of patience as Falk et al. (2018), based on the survey question: "*On a scale of 1 to 7, how would you rate your willingness to give up something that is beneficial for you today in order to benefit more from that in the future?*" Similar to the risk measure, since very few individuals picked the lowest possible value on the Likert scale, we combine the lowest two values and rescale the responses to be between 1 and 6. Consistent with Falk et al. (2018), we find that males are slightly more patient than females in our sample (4.37 vs. 4.10, $p = 0.022$).[48] The relationship between patience, job acceptance timing, and earnings is shown in Figure A.6. As observed in the left panel of Figure A.6, we find that individuals who are more patient, if anything, accept jobs earlier rather than later. The estimated relationship, however, is small and not statistically significant.[49] Turning to the right panel of Figure A.6, patience appears to be positively (but insignificantly) related with accepted earnings. Taken together, these findings suggest a limited role for gender differences in patience in explaining the overall empirical patterns.

A.2 Procrastination

Next, we consider the possibility that the observed gender differences in job search behavior are driven by male students' greater tendency to procrastinate. We use three questions from the Irrational Procrastination Scale (Steel, 2010), an instrument developed by psychologists to measure an individual's degree of procrastination. In particular, respondents are asked to indicate the extent to which they feel that each of the following statements applies to them on a 1 (not true of me) to 7 (always true of me) scale: (1) *I often find myself performing tasks that I had intended to do days before;* (2) *I often regret not getting to tasks sooner;* (3) *I work best at the "last minute" when the pressure is really on.* We create an index that aggregates the responses to the three questions by first standardizing the responses to each of the questions to have mean 0 and standard deviation 1. The index is the average of the normalized responses for the three questions, re-standardized to have an overall mean of 0 and standard deviation of 1.

Using this index, men are more likely to procrastinate than women (the gap is 0.2 standard deviations, $p = 0.032$). Among the students in our sample, if anything, those who score higher on

[48]By contrast, using a hypothetical online choice experiment with more than 1,000 participants where subjects chose between hypothetically receiving 100 pounds in one month vs. a difference amount in 13 months, Dittrich and Leipold (2014) find that men are more impatient than women.

[49]If anything, more patient individuals also start searching for jobs earlier, but this association is weak and imprecisely estimated.

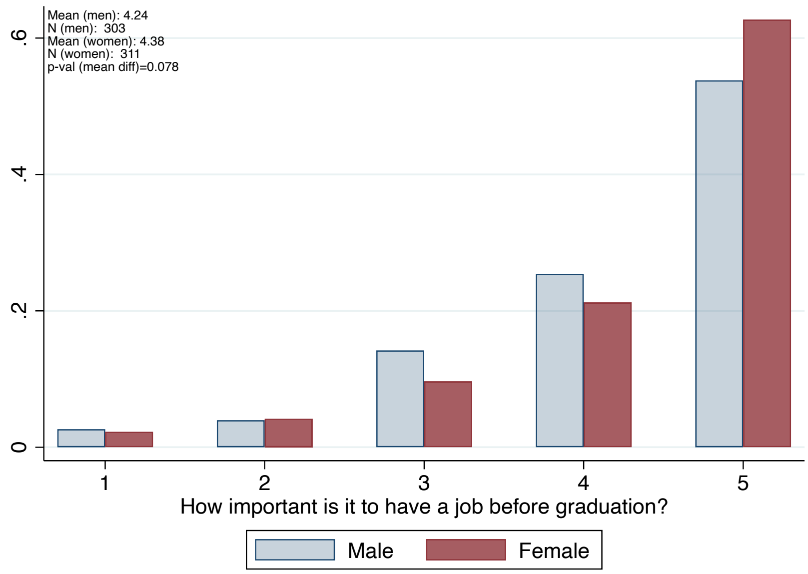
the procrastination index report having accepted their job *earlier*, although the association is not statistically significant. Procrastination is positively (but insignificantly) correlated with accepted earnings (see Figure A.7). Overall, these findings suggest that male students' greater tendency to procrastinate is unlikely to be a key driver of the observed patterns.

A.3 Rejection Aversion

Another alternative explanation is that women may accept jobs earlier than men because they are rejection averse. While we are not aware of any work that systematically documents gender differences in rejection aversion, there is an emerging literature that suggests that women tend to be more averse to negative feedback (e.g. Buser and Yuan, 2019; Avilova and Goldin, 2018). While we cannot fully dispel this alternative mechanism, we provide some suggestive evidence that rejection aversion is unlikely to be a first-order explanation. First, we find that a large share of males and females in our sample reject jobs, and the gender difference in the likelihood of rejecting a job is small (43.4% of men vs. 41.9% of women rejected at least one offer, $p = 0.582$). Therefore, it is not the case that women are simply accepting *any* job. If women are more rejection averse than men, we might expect women to be more likely to apply to jobs for which they (think they) are overqualified; however, in the data, we observe that both genders apply at fairly similar rates to jobs for which they are overqualified. Furthermore, we find that over time, job search behavior does not appear to change differentially by gender. Women who accept earlier are not more likely to be over-qualified for the job relative to women who accept later (see Table A.8). Therefore, there appears to be no evidence, at least in our data, that women are more rejection averse than men in job search.

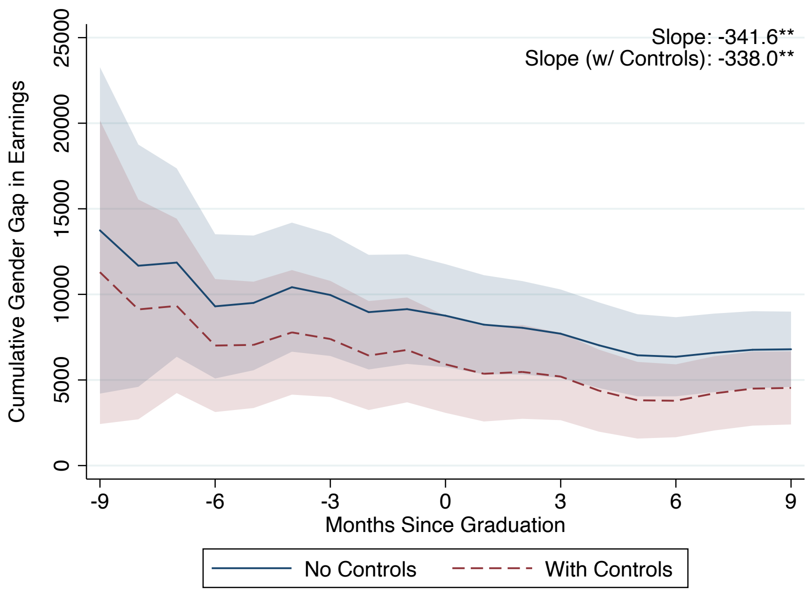
B Appendix: Figures and Tables

Figure A.1: Importance of Having a Job by Graduation



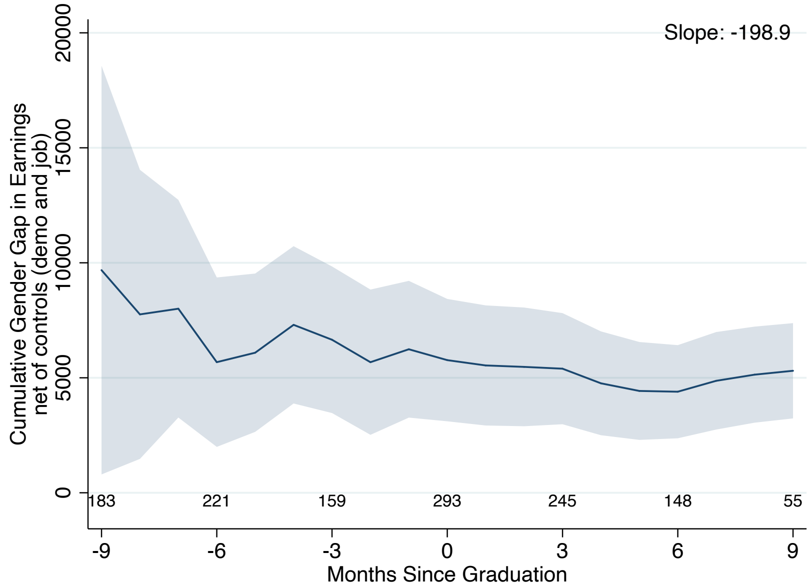
Note: The figure plots the distribution of male and female responses to the following question that was asked to students as part of the in-class survey: *"On a 5-point scale, how important is it to you that you have a job lined up before the end of your senior year (that is, before you graduate)?"*

Figure A.2: Cumulative Gender Gap in Mean Accepted Offer by Months Since Graduation



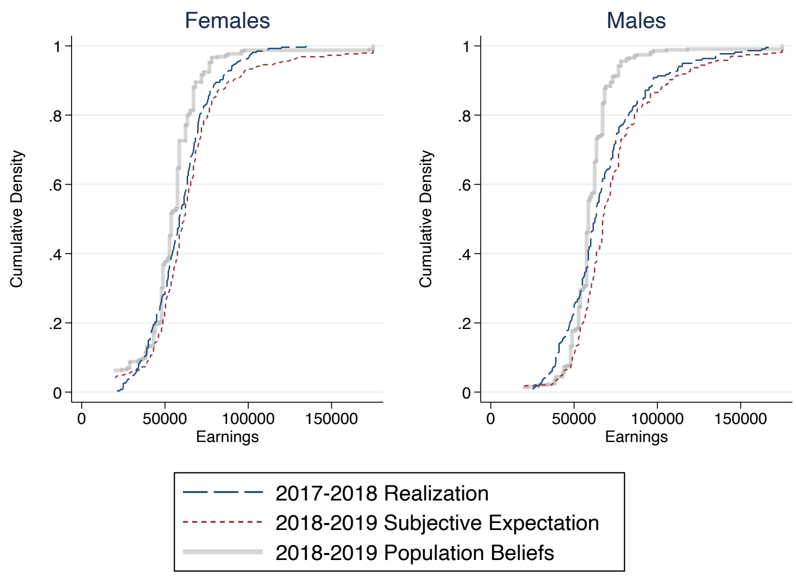
Note: The figure plots the cumulative gender gap in mean accepted earnings as a function of months since graduation. Controls include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education. Months since graduation is defined relative to the month of graduation (indicated as 0). The 95% confidence interval bands are based on bootstrapped standard errors.

Figure A.3: Cumulative Gender Gap in Mean Accepted Offer by Months Since Graduation (Including Job Controls)



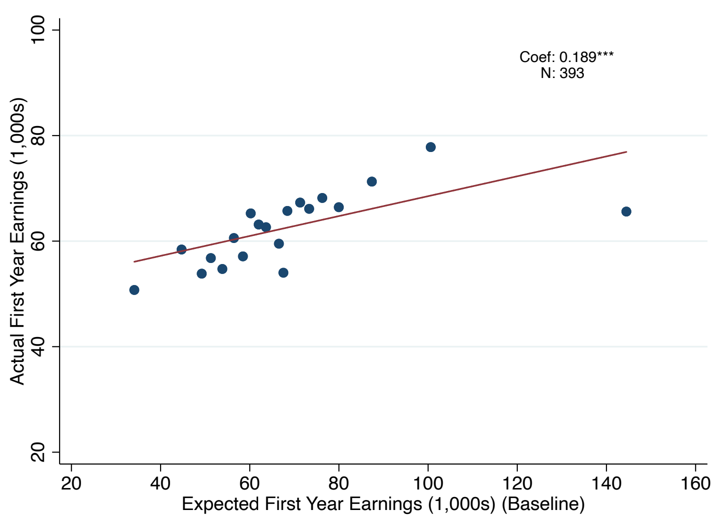
Note: The figure plots the cumulative gender gap in mean accepted earnings as a function of months since graduation net of controls for demographic and job characteristics. In addition to the demographic controls listed in Figure A.2, additional controls include job industry fixed effects, dummies for job amenities such as flexible work hours, sick leave, childcare benefits, maternity/paternity leave, and expected earnings growth over the next 12 months in the job. Months since graduation is defined relative to the month of graduation (indicated as 0). The 95% confidence interval bands are based on bootstrapped standard errors.

Figure A.4: Gender Difference in Beliefs Bias – Cross-Cohort Comparison



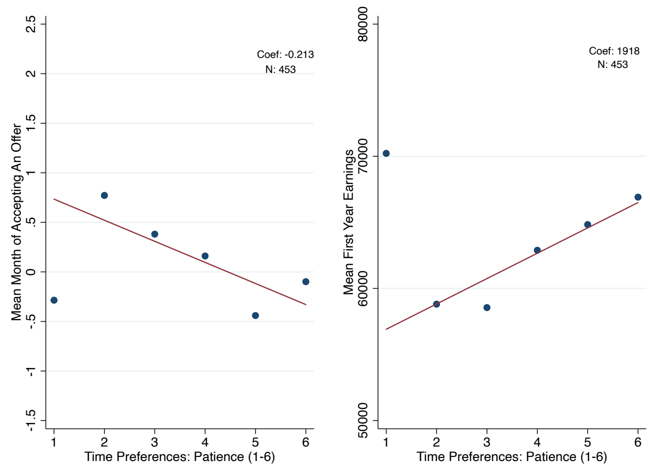
Note: The distribution of expected earnings is constructed based on the earnings expectations (in 2017 dollars) reported by students from the 2018-2019 graduating cohorts. Earnings expectations were elicited during the in-class survey that was conducted in the senior or junior year. The distribution of realized (actual) earnings is based on the first year earnings of the accepted offer of the previous cohorts of graduating students (i.e. 2017-2018 cohorts). Population beliefs for the 2018-2019 graduating cohorts are elicited using the following question: "Consider those [males/females] who started working full-time immediately after graduation. What do you think their starting total annual salary (in dollars) was, on average?"

Figure A.5: Relationship between Ex-Ante Earnings Expectations and Realizations



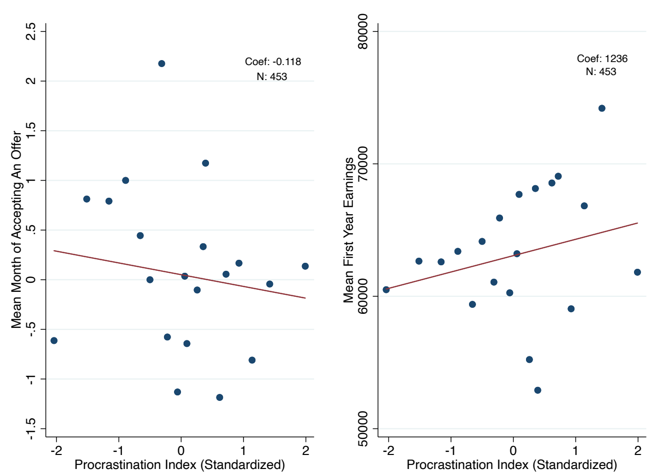
Note: This figure is a binned scatter plot of accepted earnings in the first year on students' ex-ante earnings expectations elicited in the baseline "Survey of Current Students." Both measures are in 2017 dollars.

Figure A.6: Job Acceptance Timing, Earnings, and Patience



Note: The sample includes individuals from the 2018-2019 graduating cohorts. This figure graphs the binned scatter plot of the month of job offer acceptance (defined relative to the month of graduation) (left panel) and accepted earnings (right panel) on the survey measure of patience. Patience is measured using the following question "On a scale from 1 (not willing at all) to 7 (very willing), how would you rate your willingness to give up something that is beneficial for you today in order to benefit more from that in the future?" Due to the small number of responses for the bottom two options, we combine them into a single category and re-scale the responses to the question to be between 1 and 6. The patience question was fielded to a subset of the "current student" sample.

Figure A.7: Job Acceptance Timing, Earnings, and Procrastination



Note: The sample includes individuals from the 2018-2019 graduating cohorts. This figure graphs the binned scatter plot of the month of job offer acceptance (defined relative to the month of graduation) (left panel) and accepted earnings (right panel) on the procrastination index. The procrastination index is constructed using three questions from the Irrational Procrastination Scale (Steele, 2010) and is standardized to have mean 0 and standard deviation 1. See text for details in the construction of the index. The procrastination questions were fielded to a subset of the "current student" sample.

Table A.1: Sample Sizes for Survey of "Current" Students

	Number of Observations
Took All Three Surveys	319
Took All Three Surveys, 2018 Cohort	152
Took Base and Post-Grad	466
Took Base and Mid-Search	454
Took Mid-Search and Post-Grad	323
Took Base and NOT Post-Grad	502
Took Post-Grad and NOT Base	87
Have Data on Baseline Expectations and Realizations	393
Have Data on Baseline Expectations	910
Have Data on Realizations	515
2018 Cohort	492
2019 Cohort	563

Table A.2: Responses Across Waves

		Baseline	Baseline + Mid	Baseline + Final	All Three
		(1)	(2)	(3)	(4)
Observations		968	454	466	319
Female		0.530	0.588**	0.577*	0.596**
Age		20.75	20.73	20.74	20.74
		(0.87)	(0.76)	(0.76)	(0.78)
GPA		3.25	3.27	3.27	3.28
		(0.34)	(0.35)	(0.33)	(0.34)
Cohort	2018	0.418	0.463	0.459	0.476*
	2019	0.582	0.537	0.541	0.524*
Race	White	0.413	0.392	0.399	0.395
	Black	0.034	0.046	0.039	0.047
	American Indian	0.003	0.002	0.004	0.003
	Hispanic	0.116	0.152*	0.146	0.160**
	Asian	0.404	0.385	0.391	0.379
Born in U.S.		0.598	0.630	0.650*	0.655*
Father BA+		0.738	0.701	0.677**	0.685*
Mother BA+		0.730	0.693	0.695	0.690
Concentration	Accounting	0.150	0.154	0.148	0.166
	Entrepreneurship	0.036	0.020*	0.032	0.019
	Finance	0.537	0.487*	0.485*	0.455**
	General Management	0.020	0.009	0.013	0.000**
	Intl Management	0.052	0.070	0.069	0.075
	Law	0.070	0.079	0.071	0.066
	Mgmt Info. Systems	0.219	0.247	0.247	0.266*
	Marketing	0.251	0.280	0.273	0.285
	Ops. & Tech Mgmt	0.089	0.104	0.092	0.113
	Org Behavior	0.028	0.035	0.030	0.041
Risk Tolerance		3.53	3.35***	3.44	3.27***
		(1.14)	(1.15)	(1.13)	(1.13)
Perceived Rel. Ability (1-5)		3.77	3.9	3.80	3.80
		(0.79)	(0.78)	(0.77)	(0.77)
Expected Total Pay ($)		69,099	68,372	68,357	67,945
		(27506.73)	(26675.54)	(24796.33)	(24233.23)

Note: The table reports the means and standard deviations of the background characteristics of the students from the 2018-2019 graduating cohorts who responded to various components of the "Survey of Current Students" as indicated in the columns. The stars indicate the p-value of the difference in means for the respective sample relative to the mean for students who responded to baseline survey (i.e. Column (1)). ***significant at the 1% level, **5% level, *10% level.

Table A.3: Response Rates Based on Administrative Data

Cohort:	2017	2018	2019
Cohort Size (based on admin data)	852	802	736
Share Post Graduate Survey	0.27	0.31	0.31
Share Baseline Survey (in-class)		0.49	0.65
Post Grad Survey | Baseline		0.50	0.48
Mid | Baseline		0.52	0.47
All three		0.17	0.23
Baseline | Post Grad Survey		0.78	1.00

Note: The administrative data covers all students enrolled in the BU undergraduate business program in the Spring before graduation for the 2017 and 2018 graduating class and the Fall before graduation for the 2019 graduating class. A "cohort" in the administrative data is defined as students who are projected to graduate in the Spring, Summer, or Fall of the given year.

Table A.4: Who Responded to the Surveys?

	Questrom Population (2018–2019)			Sample			
	Male	Female	Difference	Male	Female	Difference	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(6) - (3)
Female		0.500			0.529		0.165
Foreign Student	0.31	0.35	-0.04	0.29	0.26	0.03	0.83
GPA	3.16	3.25	-0.09***	3.16	3.26	-0.10***	0.80
Credit Hours	16.03	16.12	-0.09	16.40	16.43	-0.03	0.86
Finance	0.42	0.67	-0.25***	0.38	0.67	-0.28***	0.40
Marketing	0.34	0.13	-0.21***	0.36	0.13	-0.23***	0.39
No. Observations		1538			865		

Note: The table reports the mean characteristics between the 2018–2019 cohort of Questrom students and the sample of survey respondents separately by gender. Columns (3) and (6) report the male-female difference for the population and sample, respectively. Column (7) reports the p-value of the difference in the male-female gap between the population and the sample. ***significant at the 1% level, **5% level, *10% level.

Table A.5: Summary Statistics of All Respondents vs. Analysis Sample, By Gender

		Full sample		Accepted		
		Men	Women	Men	Women	p-value
Observations		744	869	622	737	
Age		22.56	22.30	22.78	22.42	0.459
		(2.02)	(1.92)	(2.04)	(1.95)	
Race	White/Caucasian	51.2%	46.2%	53.6%	48.6%	0.990
	Black/ African American	3.3%	4.5%	3.2%	5.2%	0.631
	American Indian	0.7%	0.1%	0.6%	0.1%	0.906
	Hispanic/ Latino	10.8%	11.0%	10.6%	11.6%	0.715
	Asian/ Pacific Islander	34.1%	38.2%	32.0%	34.4%	0.640
Born in U.S.		72.3%	69.6%	76.4%	74.4%	0.836
Father BA+		75.0%	72.2%	75.9%	72.5%	0.858
Mother BA+		71.4%	71.0%	71.4%	72.0%	0.756
GPA		3.29	3.32	3.31	3.33	0.766
		(0.35)	(0.33)	(0.35)	(0.33)	
Concentration	Accounting	17.9%	16.3%	18.8%	15.6%	0.548
	Entrepreneurship	5.2%	3.3%	4.7%	3.0%	0.875
	Finance	65.9%	37.9%	65.4%	37.7%	0.936
	General Management	2.4%	2.9%	2.7%	2.7%	0.690
	International Management	2.7%	8.9%	2.1%	9.1%	0.633
	Law	8.2%	10.7%	7.2%	11.0%	0.561
	Management Info. Systems	19.4%	18.5%	20.4%	17.9%	0.562
	Marketing	13.3%	35.9%	13.8%	36.6%	0.946
	Operations & Tech. Mgmt.	9.3%	11.6%	9.8%	11.8%	0.878
	Organizational Behavior	2.0%	5.1%	1.9%	5.6%	0.676
Accepted Job Offer to Work after Grad		83.6%	84.8%			0.507
Cohort	2013	9.8%	9.7%	11.3%	10.7%	0.862
	2014	9.8%	8.6%	11.4%	9.9%	0.881
	2015	9.3%	9.9%	10.1%	10.7%	0.989
	2016	15.9%	12.0%	17.2%	13.0%	0.912
	2017	14.0%	14.8%	14.0%	14.9%	0.978
	2018	21.8%	23.7%	21.2%	21.2%	0.517
	2019	19.5%	21.3%	14.8%	19.5%	0.309
Perceived Relative Ability (1-5)		3.99	3.78	4.01	3.79	0.833
		(0.85)	(0.76)	(0.84)	(0.76)	
Risk Tolerance		3.82	3.20	3.83	3.19	0.713
		(1.20)	(1.15)	(1.20)	(1.16)	
Percent High Risk (≥ 5)		22.8%	9.0%	22.8%	9.1%	0.959

Note: The table compares the mean characteristics between the full sample of respondents and those who accepted a job by gender. The last column reports the p-value of a statistical test of the comparison of the gender difference in means between the two samples (full sample vs. accepted sample).

Table A.6: Gender Gap in Log Earnings

	Dependent Variable: Log Accepted Earnings in the First Job						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.097***	-0.058***	-0.046**	-0.050***	-0.039*	-0.029	-0.035
	(0.018)	(0.018)	(0.018)	(0.018)	(0.021)	(0.022)	(0.022)
Risk Tolerance			0.021***			0.020**	
			(0.007)			(0.008)	
Risk Tol. ≥ 5				0.059**			0.038
				(0.024)			(0.030)
Controls		X	X	X	X	X	X
Add. controls					X	X	X
Mean	10.98	10.98	10.98	10.98	10.98	10.98	10.98
R^2	0.021	0.179	0.184	0.182	0.604	0.607	0.605
N	1359	1359	1359	1359	1359	1359	1359

Note: The dependent variable is the natural log of total accepted earnings in the first year (in 2017 dollars). Basic controls include cohort fixed effects, major fixed effects, GPA, a dummy for US-born, and fixed effects for race, father's education, and mother's education. Additional controls include fixed effects for industry (19 groups), city, and weekly hours of work. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table A.7: Gender Gap in Reservation Earnings

	Dependent Variable: Reservation Earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-3232***	-2579**	-2872***	-2182**	-1873*	-1363	-1528	-1017
	(1077)	(1080)	(1068)	(1066)	(1138)	(1132)	(1118)	(1111)
Risk Tolerance		1133**		1188**		1141**		1165**
		(525)		(518)		(542)		(533)
Overconfidence (%)			124***	126***			142***	143***
			(36)	(37)			(32)	(33)
Controls					X	X	X	X
Mean	54071	54071	54071	54071	54071	54071	54071	54071
R^2	0.014	0.023	0.039	0.048	0.136	0.143	0.162	0.170
N	591	591	591	591	591	591	591	591

Note: The dependent variable is ex-ante reservation earnings in 2017 dollars. Basic controls include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table A.8: Qualification By Acceptance Month

			Accept Offer Before Grad	Accept Offer After Grad	p-value
All [452]	Prop. Apps.	Over Qualified	18.4	20.1	0.280
		Qualified	58.3	52.4	0.005
		Under Qualified	23.2	27.5	0.014
Men [193]	Prop. Apps.	Over Qualified	18.5	19.3	0.724
		Qualified	58.2	50.7	0.021
		Under Qualified	23.3	29.9	0.011
Women [259]	Prop. Apps.	Over Qualified	18.4	20.8	0.266
		Qualified	58.4	53.8	0.098
		Under Qualified	23.2	25.4	0.335

Note: This table reports the average proportion of jobs that individuals applied to for which they felt that they were over-qualified for, had the right qualifications for, and were under-qualified among those who accepted a job before graduation (first column) and after graduation (second column). These means were reported for the full sample, and separately by gender (as indicated in the rows). The last column reports the p-value of the difference in means across individuals who accepted a job before and after graduation.

Table A.9: Model Fit

	Men		Women	
Moment	Data	Model	Data	Model
cumulative mean accepted offer				
$t = 1$	0.412	0.410	0.354	0.357
slope	-0.005	-0.004	-0.003	-0.003
expected salary				
$t = 2$	0.385	0.361	0.337	0.321
$t = 8$	0.338	0.348	0.307	0.314
cumulative share accepted				
$t = 1$	0.106	0.106	0.121	0.121
$t = 10$	0.539	0.566	0.599	0.636
probability of searching				
$t = 1$	0.159	0.261	0.161	0.297
$t = 10$	0.386	0.357	0.394	0.424