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

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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 are largely driven 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 and estimate a job search model that incorporates these gender differences in risk aversion and (over)optimism about perspective offers. Our counterfactual exercises show that gender differences along these two dimensions have similar quantitative importance in explaining the observed gender gap in accepted earnings. Simple policies such as allowing students to hold onto offers for an additional month (that is, slowing down exploding offers) or providing them with accurate information about the labor market cuts the gender gap by two-thirds and one half, respectively.

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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 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) 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 ask graduates from the 2013-2019 graduating classes details about the job search process that led

[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.

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, 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 six 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, opposed 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 controls discussed above.

In the second part of the paper, we develop a formal model to account for these key facts in the data. We show how a model of non-stationary 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]

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 male reservation wages, lead men to accept jobs later, and make the gender gap in accepted earnings smaller over time as they learn.[4]

[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).

[4]Throughout the text, we use the terms "overconfidence" and "overoptimism" interchangeably, acknowledging

Before formally estimating the model, 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.

Consistent with the model predictions, 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 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 estimate the model via Simulated Methods of Moments (SMM), choosing the parame-

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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 parent's 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.

ters to minimize the distance between the model-generated moments and data-generated moments. In particular, we use data on the evolution of earnings expectations to pin down the learning rule and overconfidence, and estimate the remaining preference parameters of the model using information on the characteristics of accepted offers for each gender. The estimated 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, the fact that women accept jobs earlier than men, and various other patterns regarding the nature of offers over time by gender.

Apart from providing us with testable implications that we can take to the data, our structural model allows us to conduct various counterfactual exercises of interest, which we undertake in the final part of the paper. First, to assess the quantitative importance of risk preferences and biased beliefs in generating the observed dynamics of the gender earnings gap over the course of the job search period, we conduct a counterfactual in which both males and females have perfect information. We find that gender differences in overconfidence explain about 50% of the mean gender gap in earnings. Likewise, differences in risk attitudes explain a similar amount of the mean gender gap. We use the same counterfactual to assess the welfare costs of imperfect information, and find that although men achieve a higher starting salary relative to women (on average) from having overconfident beliefs, this behavior is costly; the welfare gain of perfect information is six times larger for males. 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. Finally, we simulate a policy counterfactual that relaxes the deadline for deciding on a job offer, something that arguably could be mandated by universities. Given the large gender differences in risk preferences and their important role in explaining the observed behavior, we show that such a policy would close the gender gap by two-thirds.[8]

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 appear 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 point toward a strong negative correlation between risk aversion and reservation wages (Cox and Oaxaca, 1992; Pannenberg, 2010).[9] In particular, Spinnewijn (2015) finds that

[8]As we later discuss, there are no inefficiencies in the model that such a policy alleviates.

[9]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 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. Another set of recent work highlights the importance of biased beliefs in understanding

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.[10] 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, and labor market attachment in explaining gender pay gaps over the lifecycle (Morchio and Moser, 2020; Xiao, 2020). 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.[11] Furthermore, we provide a quantitative assessment of these channels in determining the gender gap in earnings at graduation that is disciplined by the data we collected.

Finally, our paper also 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.[12] More recent work has sought to link these gender differences in behavioral traits to observed gender 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

the search behavior of unemployed workers.

[10] 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.

[11] 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.

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

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.[13]

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.[14] 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 markets 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 surveys and provide a description of the sample. Section 3 presents the empirical facts on gender differences in job search behavior and labor market outcomes for our sample of undergraduate business students. Section 4 develops a model of job search that can explain the patterns in the data. Section 5 discusses the empirical evidence that provide support for the model assumptions and presents the reduced-form analysis of the model predictions. Section 6 outlines the estimation of the model and presents the model estimates. Section 7 discusses the policy counterfactuals and reports the results from the simulations. Section 8 concludes.

[13] Several other papers examine the dynamics of the gender gap among professionals and the highly-educated later in the life-cycle 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.

[14] It is worth noting that the raw earnings gender gap in our sample is quite similar to that in the 2014-2018 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.

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).[15] 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 surveys are computer-based and were administered online using the SurveyMonkey platform.[16] We describe each survey in detail in the sections that follow.

2.1 Survey of Graduates

Our first data source is from the "Survey of Graduates," an online survey of the 2013 to 2017 Questrom graduating classes conducted between April 2017 and February 2018. We obtained a list of student emails from the Questrom Alumni Office and invited eligible students to participate in the online survey via email. The survey took approximately 20 minutes to complete and students 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, for most students, happens in college). 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 combine this data 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 will be described 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 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

[15]The full-time MBA enrolment at BU is a lot smaller with about 150 students per cohort.

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

against the experimental approach by Dohmen et al. (2011) and Falk et al. (2016).[17] 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, for this survey, 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 year. Course instructors set aside 10 minutes at the end of class and provided students with the link to the online survey, which they 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.[18] We also sent the survey to students in the 2019 cohort who were not enrolled in the mandatory module in October 2018.[19] Overall, approximately 1,055 students completed the baseline survey, representing about 50(65)% of the 2018 (2019) graduating classes.[20]

The baseline survey collected information on demographic characteristics, earnings expecta-

[17] 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.

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

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

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

tions, 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 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.2). 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.3).

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, ideally, we would use administrative student-level information for all the eligible cohorts of students. Unfortunately, we only have limited administrative data from the undergraduate student office that 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.

To examine selection into the baseline (in-class) survey for current students, we use data from the 2018-2019 cohorts.[21] We estimate pooled regressions of each student characteristic on a dummy for responding to either survey (alumni or baseline) and cohort fixed effects. As shown in Table A.5, there are significant differences between respondents and non-respondents for both surveys. Respondents to the graduate survey are disproportionately female and US citizens, and are positively selected on GPA. They are also more likely to concentrate in marketing and information systems, and less likely to concentrate in finance, as compared to non-respondents. Similarly, for the current students, females and native students are more likely to respond to the baseline survey. The GPA of respondents and non-respondents are broadly similar; however, respondents have more course credit hours and are more likely to concentrate in marketing and less likely to concentrate in finance or accounting relative to non-respondents. These differences should be kept in context for the empirical analysis.

[21] The survey response rates for each admin data cohort are reported in Table A.4.

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 (realizations and expectations) are converted to 2017 dollars based on the CPI. For individuals who report earnings for jobs or offers for less than 42 hours per week, their salaries are adjusted assuming they work full-time (i.e. 42 hours per week). To handle outliers, we drop observations where the reported total first year earnings are less than $20,000 and more than $175,000.[22] We also winsorize expected total compensation and offered compensation to be between $20,000 and $175,000. 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 marker outcomes, and then establish two novel facts regarding gender differences in the 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. 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 background characteristics 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.[23] Consistent with the prior literature, women in our sample report significantly lower willingness to take risks in financial or daily matters relative to men. The raw gender difference in risk attitudes is approximately one-

[22]This criterion drops about 7% of our main analysis sample (i.e. those who have accepted an offer).

[23]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.

fifth of the mean or half of a standard deviation.[24] 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, on average, similar GPAs as men, women report significantly lower perceived relative ability, consistent with the previous literature that finds that men tend to be more 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.1).[25] 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).[26] Not surprisingly, the observed gender difference in concentration translate 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 similar number of offers (about 1.7) and are similarly likely to have rejected at

[24]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.

[25]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 percent level. It is possible, however, that women's job search process is influenced by marriage market considerations and expectations about their future labor supply if married. In calculations not shown here, but available upon request, we find that women's self-reported probabilities of working full-time and of working part time at age 30 are uncorrelated with their risk aversion, the timing of the job acceptance, and although marginally correlated with earnings, do not explain the role of risk aversion in explaining the gender gap.

[26]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).

least one offer (approx. 40%). While this may appear to be puzzling, the last panel shows that the search behavior differs for the two genders along several dimensions. First, females start the job search process earlier. Second, males and females exhibit vastly different search behaviors. Males 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, $p = 0.12$).[27] 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 males and females are targeting their search differently, and may be applying to different kinds of jobs.[28] We incorporate these patterns in the model, that is described later in section 4. It is also interesting that males are more likely to rely on referrals, while females rate the Career Center guidance much more useful.

3.3 Two Novel Facts

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 of 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.[29] 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

[27] The survey asked: "*Of the jobs that you applied for, what proportion of jobs did you feel: You were over-qualified for; You had the right qualifications for; You were under-qualified for*", with the responses required to sum to 100. Given that male students tend to be more overconfident, this is likely a lower bound on the extent to which males overreach in their application behavior, relative to females.

[28] These patterns are broadly consistent with ongoing work by Faberman et al. (2020), who similarly document gender differences in job search and targeting. Another recent working paper by Fluchtmann et al. (2020) finds gender differences in job applications among UI recipients from Denmark and attributes them to women systematically applying more to jobs that are part-time, have shorter commutes, and are at family-friendly firms. As mentioned earlier, the early-career job search behavior of highly-skilled individuals are less likely to be influenced by these family factors.

[29] A formal statistical test developed by Davidson and Duclos (2000) indicates that the male distribution first order stochastically dominates the female distribution ($p < 0.01$).

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 odds ratio is slightly lower at 1.24 and remains highly statistically significant with the inclusion of industry fixed effects in column (3).[30] 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.

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.1 confirms that the observed decline in the cumulative gender earnings gap in accepted offers is robust to the inclusion of controls for background characteristics (cohort, race, nationality, and parent's education) and academic background (concentration and GPA). It is also worth pointing out that most the closing of the gender gap in accepted offers in Figure 2 happens by the time of graduation.

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.2, 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

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

driven by compensating differentials.[31]

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.

4 Model of Job Search

We consider 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 justify and validate empirically using our survey data in Section 5.

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 $T_g > 1$ the date at which graduation occurs and $T > T_g$ the retirement date from the labor market. We assume that from dates $\{1, ..., T_g\}$, students with and without a job earn their value of leisure, b, but that starting from date $t \geq T_g$, individuals with a job earn the agreed upon wage w, and those without a job earn $b \cdot (1 - \zeta)$, $\zeta \in (0, 1)$. Since all students earn b before graduation, ζ represents a psychic cost (measured in dollars) of not having a job by graduation in addition to foregone wages, as consumption will drop at date T_g if no job is secured by then.

There are two types of jobs j that students can apply to each period. Each job will make random offers from some distribution $F_j\left(log(w)\right) \sim N\left(\mu_j, \sigma_j\right)$ for $j = \{1, 2\}$. In the first, the mean offered wage is lower, but conditional on some choice of search effort s, the probability of receiving an offer $\lambda_j \cdot s$ is higher. Therefore, students face a tradeoff between the probability of securing a job and the value of the offer, and search behavior responds to this tradeoff. We assume that search is costly, and individuals face a cost of searching ϕs^{ρ} with $\rho > 1$. The cost function satisfies the standard conditions: it is increasing, convex, and continuously differentiable in search effort.[32]

To model bias in beliefs, we assume students have an initial ($t = 1$) belief about the mean log offers they will receive from the better (higher mean log wage) job conditional on search, μ_2, denoted by $\hat{\mu}_{2,1}$. If the true mean log offer from the higher mean log wage job is μ_2, then optimistic individuals have beliefs $\hat{\mu}_{2,t}$ at date t such that $\hat{\mu}_{2,t} > \mu_2$. To allow for learning and corrections in bias, we model a simple learning rule in which beliefs converge to the true value as time progresses.

[31] 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 fixed effects.

[32] For models of job search with endogenous search effort, see Lentz (2010), Faberman and Kudlyak (2019), and Faberman et al. (2017).

That is, we assume that beliefs at each date t take the following form:

$$\hat{\mu}_{2,t} = \hat{\mu}_{2,1} e^{-\gamma(t-1)} + \mu_2 \Big(1 - e^{-\gamma(t-1)}\Big) \quad \text{for} \quad t = 1, 2, ..., T \tag{1}$$

where γ controls the speed at which learning occurs. This implies that individuals enter with beliefs about the mean log offer in the higher mean log offer job given by $\hat{\mu}_{2,1}$ which falls to the true μ_2 as t increases. As γ goes to ∞, beliefs converge more quickly. Beliefs about the mean of the offer distribution of jobs of type $j = 1$ are assumed to be unbiased.

Let $U_t(\hat{\mu})$ denote the value of being a student with beliefs $\hat{\mu} = [\hat{\mu}_1 \;\; \hat{\mu}_2]$ who has no job secured at date t.[33] This value can be written as:

$$\begin{aligned} U_t(\hat{\mu}) = \;& u\left(b\left(1 - \mathbf{I}_{t>T_g}\zeta\right)\right) + \\ & \max_{j\in(1,2)} \Bigg\{ \max_{s_j \in \left(0, \bar{s}_j\right)} -\phi s^{\rho} + \beta\lambda_j s_j \int_w \max\Big(W_{t+1}(w), U_{t+1}(\hat{\mu})\Big) dF\left(w; \hat{\mu}_j, \sigma\right) \\ & + \beta\left(1 - \lambda_j s_j\right) U_{t+1}(\hat{\mu}) + \varepsilon_j \Bigg\} \end{aligned} \tag{2}$$

where $\varepsilon_j \sim T1EV\,(0, 1)$ is an idiosyncratic shock which affects the probability of choosing one job over another.[34] $W_t(w)$ is the value of being a student at date t who has secured a job at wage w, which is given by:

$$W_t(w) = u\left(b\mathbf{I}_{t<T_g} + w\mathbf{I}_{t\geq T_g}\right) + \beta W_{t+1}(w) \tag{3}$$

The value of employment does not depend on beliefs since we do not allow for job separations or search on-the-job. Optimal search effort conditional on applying to job j must satisfy:

$$s_j^* = \min\left\{ \left\{ \frac{\lambda_j}{\phi\rho}\beta \int_w \max\Big(W_{t+1}(w) - U_{t+1}(\hat{\mu}), 0\Big) dF\left(w; \hat{\mu}_j, \sigma\right) \right\}^{\frac{1}{\rho-1}}, \frac{1}{\lambda_j} \right\}$$

where the min operator accounts for the fact that the probability of receiving an offer must not exceed 1. Using standard results from extreme value theory (McFadden, 1974), the probability of applying to a job j is then:

$$\pi_j = \frac{\exp\Big(-\phi s_j^{*\rho} + \beta\lambda_j s_j^* \int_w \max\Big(W_{t+1}(w), U_{t+1}(\hat{\mu})\Big) dF\left(w; \hat{\mu}_j, \sigma\right) + \beta\Big(1 - \lambda_j s_j^*\Big) U_{t+1}(\hat{\mu})\Big)}{\sum_k \exp\Big(-\phi s_k^{*\rho} + \beta\lambda_k s_k^* \int_w \max\Big(W_{t+1}(w), U_{t+1}(\hat{\mu})\Big) dF\left(w; \hat{\mu}_k, \sigma\right) + \beta\left(1 - \lambda_k s_k^*\right) U_{t+1}(\hat{\mu})\Big)}$$

[33]This notation is for convenience, since $\hat{\mu}_1 = \mu_1$ by assumption.

[34]We introduce this shock to smooth the decision problem so that shares of individuals choose one job over another rather than there being a discrete jump in behavior.

Finally, we think of agents as being myopic. Therefore, they do not take into account how they will update their beliefs about μ_2 over time when making decisions, and thus $\hat{\mu}$ is fixed in the value functions outlined above. Therefore, acceptance strategies for any belief μ will be given by a reservation wage, $w^*(\hat{\mu})$, defined implicitly as:

$$W_t\left(w^*\left(\hat{\mu}\right)\right) - U_t\left(\hat{\mu}\right) = 0 \tag{4}$$

4.1 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 $\hat{\mu} \in \{\hat{\mu}_1, ..., \hat{\mu}_{N_\mu}\}$.[35] 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 equation (1) so that:

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

4.2 Comparative Statics

In this section, we examine how risk preferences and biases in beliefs affect search behavior. Figure 3 shows how reservation wages and the likelihood of applying to the job with lower mean offers (and a higher probability of receiving an offer) change as risk aversion ι varies and as biases $\hat{\mu}_2$ vary. Panel (a) shows that as agents become more risk averse (moving from the red to the blue), reservation wages drop. Higher degrees of risk aversion imply that agents fear the looming graduation date and its corresponding drop in consumption relatively more; they therefore lower reservation wages to avoid ending up with no job by graduation. This, along with the psychic cost of not having a job by graduation, explains the kink in reservation wages at month 0 (month of graduation). Similarly, as risk aversion rises, search effort in both jobs rises, for exactly the same reasons just described. Finally, since the job with the lower mean offered wage has a higher arrival rate conditional on search effort, agents increasingly apply to job 1 as risk aversion rises (Panel (c)). Moreover, at a certain level of risk aversion, they always apply to job 1.[36]

Changes in the bias of beliefs about the mean log offer in job 2 have different impacts on search behavior. Panels (b) and (d) in Figure 3 show how reservation wages and the likelihood of applying to the job with lower mean offers (and a higher probability of receiving an offer) change as the bias $\hat{\mu}$ varies. First, as shown in Panel (B), as the bias rises (going from blue to red), the overall option value of search rises, as agents believe they face a more favorable offer distribution in job 2. Therefore, reservation wages rise since the option value of search rises. Search effort in job 1

[35] For convenience, we choose the grid of μ to be equivalent to what the time series of beliefs will be as implied by Equation (1).

[36] To foreshadow the estimation, this implies that risk aversion can never be too high if the model aims to match changes in mean offers over time.

falls, while search effort in job 2 rises as the bias rises.[37] Finally, the trade-off between the two jobs becomes more stark as the bias increases, and job 2 becomes relatively more desirable. As such, agents are less and less likely to apply to job 1 as the bias in beliefs rises (see Panel (D)).

5 Empirical Evidence for Model Assumptions and Predictions

Before formally estimating the model, in this section, we provide empirical evidence in support for the model assumptions and predictions using the survey data.

5.1 Empirical Basis for Model Assumptions

Psychic Cost of Not Having a Job by Graduation Empirical evidence supporting the assumption that students want a job before graduation can be seen in Figure 4 which shows the distribution of answers to the following question that was asked to students (either juniors or seniors) in the baseline 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)?"* As observed from the figure, more than 50% of males and females respond that it is "extremely important," and the vast majority (more than 80 percent) indicate the top two values on the scale. Women are somewhat more likely to indicate a stronger importance of having a job lined up before graduation relative to men (4.38 vs. 4.24, $p = 0.08$), but the magnitude of the difference is fairly small. We interpret the evidence as suggesting that students, regardless of gender, place a high importance on finding a job before graduation. The cost ζ is meant to capture this fact, as they perceive some cost of not having found employment by the time of graduation in the form of foregone consumption.[38]

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*

[37] Regarding the latter, since the perceived returns to search in terms of the mean expected wage rises, searching in job 2 becomes more attractive, so search effort there rises. However, in job 1, the only thing that changes is the outside option of searching next period; therefore, the returns to search in job 1 fall, and search effort falls too.

[38] With $\zeta = 1$, there would still be the cost of forgone wages from not having a job, so ζ represents an additional cost.

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 5 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 5, 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 6 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.[39]

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.[40]

Collectively, the evidence we present here strongly indicates that students' beliefs - in particular, 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

[39]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.

[40]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.3, 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.

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 survey (Panel B). The data for both samples paint a similar picture – both men and women revise their earnings expectations downward over time. Men, however, 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% too optimistic.

Two Jobs An important component of our model is that there are two job types. While we cannot observe the types of jobs that students apply to directly, we argue that the two-job feature of the model is necessary to be consistent with the empirical evidence on both the decline in mean offers over time as well as the rise in the probability of receiving an offer over time (as depicted in Figure A.4). The presence of two job types which trade off mean offers and the probability of receiving offers is able to capture this pattern. As graduation nears, student become more likely to apply to the job with lower mean offered wages and higher returns to search. A model with dynamic selection in types cannot easily generate these trends jointly. This is because with only dynamic selection on unobservables, those who find jobs first would be those with higher mean offers and higher probabilities of receiving offers. So while mean offers would fall, the arrival rate of offers would also fall.[41] The fact that we allow for endogenous search effort is simply to capture, quantitatively, the rise in the probability of receiving an offer over time, which cannot be captured fully through changes in the types of jobs students search for. A two-job model also allows us to indirectly capture gender differences in search behavior that we documented in the lower panel of Table 2, albeit in a reduced-form way.

5.2 Reduced-Form Evidence for the Model Predictions

Before formally estimating the model, we also 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. Also, in addition to the underlying psychological attributes that they are meant to capture, these survey measures of risk and belief biases could 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

[41] While at the individual level the model does indeed predict that search effort rises over time as graduation nears, with heterogeneous types the increase in search effort at the individual level is not enough to counteract the overall decline in search effort coming from the dynamic selection in types.

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 4.2, 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 more risk averse individuals start searching earlier.

The left panel of Figure 7 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 7 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 8 shows a negative relationship between risk tolerance and the likelihood of starting the job search process before graduation.[42]

Turning next to the relationship between risk preferences and accepted earnings, as depicted in the right panel of Figure 8, 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 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 percent level. Adjusting for individual-level differences in background characteristics (cohort, race, country of birth, and parent's education) and academic background (GPA and concentration) reduces the gender gap by close to 30 percent to \$4,542 (see Column (2)).[43] This is largely due to 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, explains approximately 19% of the residual gender

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

[43]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 results are available upon request.

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 24% to 35% 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. 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 expectations and realizations (with positive values indicating that the individuals' earnings expectations exceed their eventual realizations).[44]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 5 and 6). This measure is positive for 54% of the individuals. Figure 9 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 result of higher reservation wages.[45]

In the model, a key mechanism through which risk preferences and overoptimism affects 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 expect to graduate between 2018 and 2021. Reservation earnings were elicited using the following survey question: "*What would the lowest annual total compensa-*

[44]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.

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

tion (including base pay, signing bonus, and bonus pay) have to be for you to accept a job offer?"[46] The left panel of Figure 10 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. Overall, these findings lend further support to the model mechanisms.[47]

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.

6 Model Estimation and Results

We estimate the model using Simulated Method of Moments (SMM).[48] The parameters that need to be estimated for each gender are the discount rate, β, the parameters governing the true offer distribution (μ_j and σ_j for $j \in \{1, 2\}$), the parameters governing the arrival probability conditional on no search (λ_j for $j \in \{1, 2\}$), the parameters governing the cost of searching, ϕ and ρ, the value of leisure without a job secured, b, the cost of not having a job by graduation, ζ, the two parameters governing overconfidence and learning, $\hat{\mu}_{2,1}$ and γ, and the risk aversion parameter ι.

[46]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.

[47]One possibility that could explain some of the gendered patterns of job search that we observe is that perhaps women expect to stay at their initial job for a shorter duration and, hence, have lower reservation wages. However, this explanation is hard to reconcile with the systematic relationships that we observe between risk preferences, biased beliefs, and reservation wages/accepted earnings that we find. In addition, 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. Finally, 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).

[48]In particular, we use the TikTak algorithm outlined in Arnoud et al. (2019). We solve the model 250,000 times on a Sobolset for each parameter and then do a local search at the minimum value found on the Sobol grid.

With the exception of the risk aversion parameter, the learning rate, and beliefs ($\hat{\mu}_{2,1}$), we tie our hands and assume all remaining parameters are the same for both genders. This assumption implies that men and women do not place different valuations on the costs of not finding a job by graduation, which is consistent with the survey evidence we have presented, and that search is not differentially costly by gender at this early stage of the job search process. Importantly, this assumption also implies that there are no differences in outcomes due to - for example - gender discrimination in offers, but only through differential search behavior that is a result of differences in risk aversion and beliefs. If we allow for differences in the offer distribution between men and women, we cannot identify differences in risk aversion in the data, which relies on the slopes of accepted offers and the probability of finding a job. Since our data clearly suggest differences in risk aversion, we chose to abstract from discrimination in offers by assuming the job offers are the same.

Calibrated Parameters To begin, we set the discount rate to $\beta = 0.996$ for both genders to match a five percent annual interest rate in our monthly calibration. Empirically, as described earlier, we find that mean log offers decline with time. However, the variance of log offers is constant over time for both genders. In our 2-job model, this is only possible if the variance of log offers is the same in both jobs. We therefore exogenously set the parameters governing the variances of log wage offers for both jobs (σ_j^*, $j \in \{1, 2\}$) to equal the observed variance of log wage offers in our data, pooled across gender.

Targeted Moments To estimate the remaining parameters, we target the cumulative mean accepted wage at dates $t = \{-9, -8, -7, ..., 0, 1, ..., 19\}$ for each gender, the mean expected salary at dates $t = -2$ and $t = -8$, the cumulative share of individuals with offers at dates $t \in \{-9, 0, 10\}$ for each gender, the average probability of receiving an offer at dates $t \in \{-9, 0, 10\}$ for each gender, the mean log offer at dates $t \in \{-9, 0, 10\}$ for each gender, and the probability of rejecting an offer at dates $t \in \{-9, 0, 10\}$ for each gender.

Identification 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,[49] the offer arrival rates as identifying the search cost parameters, the mean offers as identifying the offer distribution parameters, and the full cumulative mean accepted offer curve as identifying b, ζ, and ι. Throughout, and consistent with the evidence outlined above, we impose the restrictions (i) that

[49] Recall that expected earnings are elicited as follows: "*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 is not the belief of the wage offer distribution that the individual thinks he/she faces. Instead, this is the belief regarding expected earnings, which conditions on offers being above the individual's reservation wage. While this moment is key to identifying beliefs, it is therefore also affected by other parameters in the model which govern the reservation wage.

risk aversion for women is larger than for men, in line with our reduced form evidence, and (ii) that mean log offers in job 2 must be higher than job 1, $\mu_2 > \mu_1$, while the returns to search are higher in job 1 than job 2, $\lambda_1 > \lambda_2$.

The discussion in section 4.2 provides some intuition on how the risk parameter, learning rate, overconfidence, and the cost of not having a job by graduation impact the moments that we target. We are also currently performing two additional exercises which we believe support our identification arguments. First, we calculate the moments described in Honore et al. (2020), which builds on work by Andrews et al. (2017). Specifically, we group all of our moments into six types: (i) those related to realized compensation, (ii) those related to expectations, (iii) those related to the share that have found a job, (iv) those related to the probability of receiving offers, (v) those related to the value of offers received, and finally (vi) those related to the probability of rejecting offers. The idea is to show how the precision of our estimates respond to removing each of these types of moments, with a larger movement implying that the moment is important for identifying that particular parameter. Second, we simulate data from our model at the estimated parameters, and then re-run our estimation algorithm to see if it is able to recover the parameters.

Estimates The estimated parameters along with their asymptotic standard errors are reported in Table 6, while the model-generate moments and their empirical counterparts are reported in Table A.8. The top panel of Table 6 depicts the gender neutral parameters, while the bottom panel depicts the gender-specific parameters. The model estimates a risk aversion parameter for men of $\iota_m = 1.49$ and a larger value for women of $\iota_f = 1.74$. The value of leisure (net of search costs) before graduation is between $20 - 30\%$ of offered wages (depending on the job considered), and falls to about $3 - 5\%$ of offered wages after graduation. The mean annual salary offer in job $j = 1$ (job $j = 2$) is $\$57,031.00$ ($\$81,069.00$). At the beginning of job search, men believe the mean offer in job 2 is $\$99,997.00$ while women believe it is $\$86,590.00$. The learning rate of women is about five times that of men.

Model Fit Figure 11 plots the implied gender gap in our estimated model. The model is able to capture the decline in the gender gap as graduation nears, only slightly under-predicting its magnitude at earlier dates. Nonetheless, when the model does under-predict, it does so by at most 3 percent. Figure 12 plots the cumulative share accepted for men and women, in both the model and the data. The model captures the fact that females accept jobs earlier than males.

As can be seen in Table A.8, overall the model does a good job of capturing the bias in beliefs and the learning rate for men. The probabilities of receiving offers are increasing over time for both genders, as the graduation date nears and risk aversion kicks in through increased search effort. Finally, as also shown in Table A.8, the model is able to capture the decline in mean offers received as well as the increase in the probability of receiving an offer over time. The former arises because both males and females become more and more likely to search in the high arrival rate job as the graduation. Naturally, however, because men are less risk averse than women, they respond less to the looming graduation date.

7 Policy Counterfactuals

In this section, we use the model to conduct two policy counterfactuals. First, we mimic an information intervention in the model and investigate the (earnings and welfare) impacts of eliminating the bias in beliefs about the offer distribution. Second, given the large 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.

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 apply to the "wrong" jobs, and may end up rejecting jobs that they would have otherwise accepted had they known the truth. 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 costly for men. In particular, females 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%).[50] 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.[51]

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

Figure 13 plots the implied gender gap under perfect information. The solid black line reproduces the model-generated gender gap, previously plotted in Figure 11, along with the empirical gender gap (black dashed line). The blue curve plots the implied cumulative gender gap in accepted

[50] 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.

[51] We 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.

offers under perfect information. By the time of graduation, the gender gap falls by 51% relative to the model with imperfect information. Overall, as shown in Table 7, the gender gap under perfect information is 5.5% versus 11.5% under imperfect information.

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 welfare as the change from going from imperfect information to perfect information.[52] For men, the mean (median) welfare gain of perfect information is equivalent to a \$494 (\$293) annual increase in flow income in the baseline imperfect information model. For men to achieve the welfare gain that women experience, flow income in the baseline model would only need to increase by \$77.29 (\$54.08) annually. Therefore, consistent with the survey data, the welfare gains of perfect information are six time larger for men.

7.2 Controlling Exploding Offers

The red curve in Figure 13 shows that equalizing risk preferences by gender also leads to a large decline in the gender gap. In fact, Table 7 shows that the decline in the average gender gap in such a scenario is as large as moving towards perfect information. While it is not clear what policies could close the gender gap in risk preferences, we instead consider a policy that could arguably minimize the role of risk preferences: what if students could hold onto offers that they receive for one month? Such a policy might have the potential to close the gender gap at graduation, since imposing such a rule removes a bit of the risk associated with rejecting an offer, as an additional month allows for another possible offer draw. Universities could mandate employers to allow students to contemplate over an offer for at least a month, and so such a counterfactual is quite feasible.[53]

To conduct this counterfactual 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. The perceived value of being a student at date t with no job in hand and beliefs $\hat{\mu}$ is now:

$$\begin{aligned} U_t(\hat{\mu}) = \; & u\left(b\right) + \\ & \max_{j \in (1,2)} \Bigg\{ \max_{s_j \in \left(0, \bar{s}_j\right)} -\phi s_j^{\rho} + \beta \lambda_j s_j \int_w \max\Big(W_{t+1}(w), U_{t+1}^{\text{offer}}(\hat{\mu}, w)\Big) dF\left(w; \hat{\mu}_j, \sigma\right) \\ & + \beta\left(1 - \lambda_j s_j\right) U_{t+1}(\hat{\mu}) + \varepsilon_j \Bigg\}, \end{aligned} \tag{6}$$

where the only change from the earlier formulation is that if an offer comes, the student can either

[52] The exercise does not allow agents to adjust their behavior knowing that they will receive this increase. This is therefore a standard consumption equivalent variation exercise.

[53] 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.

accept the offer or hold on to the offer, which gives them the perceived value of having no job, but an offer w in hand, $U^{\text{offer}}_{t+1}(\hat{\mu}, w)$. For some offer w, this value is given by:

$$\begin{aligned} U^{\text{offer}}_t(\hat{\mu}, w) = \; & u\left(b\right) + \\ & \max_{j\in(1,2)} \{ \max_{s_j\in\left(0,\bar{s}_j\right)} -\phi s_j^{\rho} + \beta\lambda_j s_j \int_y \max\left(W_{t+1}(y), U^{\text{offer}}_{t+1}(\hat{\mu}, y), W_{t+1}(w)\right) dF\left(y; \hat{\mu}_j, \sigma_j\right) \\ & + \beta\left(1-\lambda_j s_j\right) \max\{W(w), U_{t+1}(\hat{\mu})\} + \varepsilon_j \Big\}. \end{aligned} \tag{7}$$

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 (3).

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

$$\begin{aligned} U^{\text{offer}}_t(\hat{\mu}, w) = \; & u\left(b\right) + \\ & \max_{j\in(1,2)} \Big\{ \max_{s\in\left(0,\bar{s}_j\right)} -\phi s_j^{\rho} + \beta\lambda_j s_j \int_w^{\infty} \max\left(W_{t+1}(y), U^{\text{offer}}_{t+1}(\hat{\mu}, y)\right) dF\left(y; \hat{\mu}_j, \sigma\right) \\ & + \beta\lambda_j s_j \int_0^{w} \max\left(U^{\text{offer}}_{t+1}(\hat{\mu}, y), W_{t+1}(w)\right) dF\left(y; \hat{\mu}_j, \sigma\right) \\ & + \beta\left(1-\lambda_j s_j\right) \max\{W(w), U_{t+1}(\hat{\mu})\} + \varepsilon_j \Big\}. \end{aligned} \tag{8}$$

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:

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

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

$$W_t\left(w\right) = U_t\left(\hat{\mu}, y_2^*\left(\hat{\mu}, w\right)\right)$$

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

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

We solve this model and then calculate the implied gender gap when instead students have two months rather than one month to accept or reject an offer.

Figure 14 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 moments in time, and is nearly eliminated by the time of graduation. The last row in Table 7 shows that the gender gap in this case would be about 3.5%, which is about a third of the 11.5% gap in the case with exploding offers.

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 non-stationary job search model that incorporates gender differences in risk aversion, overconfidence (and learning), and where individuals incur some cost of not having a job by the time they graduate, 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. Decompositions using the model suggest that risk preferences and overconfidence contribute similarly to the gender earnings gap and together explain about 60% of 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 two-thirds.

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. These 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 mitigate the gender earnings gap.

It should be pointed out that our framework may overstate the importance of risk preferences. In the model, the main reason the two genders apply to different kinds of jobs is risk preferences (with females being more likely to apply to jobs with lower mean but higher arrival rates). If, in the real world, discrimination on part of employers (e.g. Neumark et al., 1996) drives part of the gender gap in job search behavior, that would not be captured in our setting. Doing so would require richer data not only on employer-employee matches, but also on application behavior, which is challenging. Likewise, we do not directly incorporate the role of non-wage benefits in our setting. As mentioned earlier, while that could explain why the two genders apply to different kinds of jobs, it cannot explain trends over time within and between genders.

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 males and females gather information differently (with males more likely to rely on referrals, and females more likely to find the career center useful). 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.

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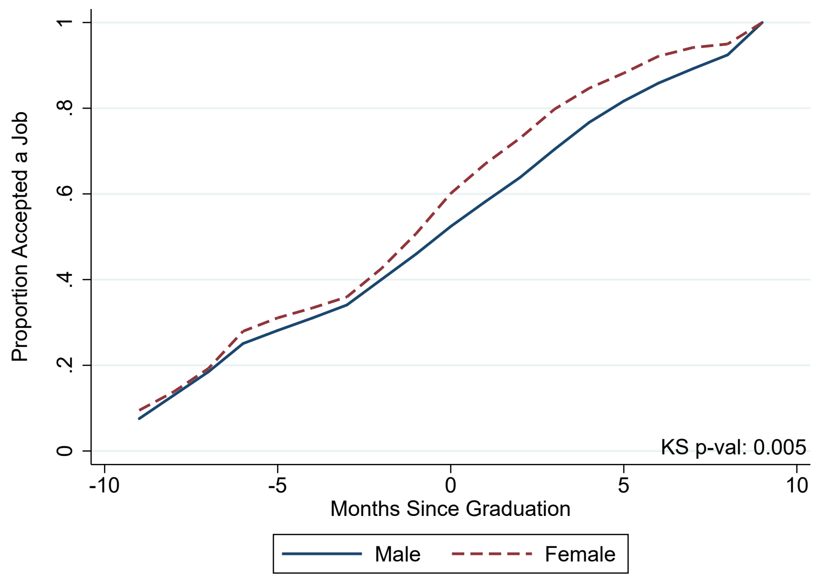
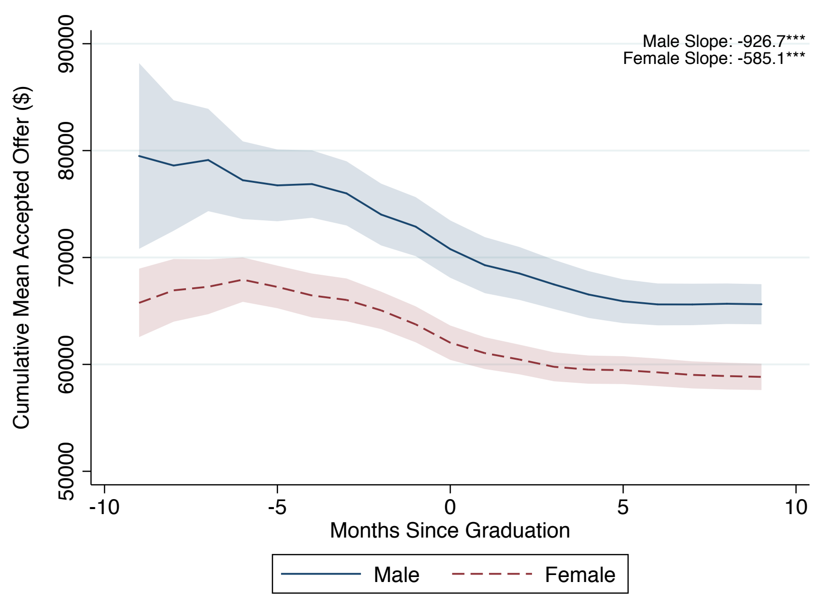
Figure 1: CDF of Job Acceptance Timing, By Gender



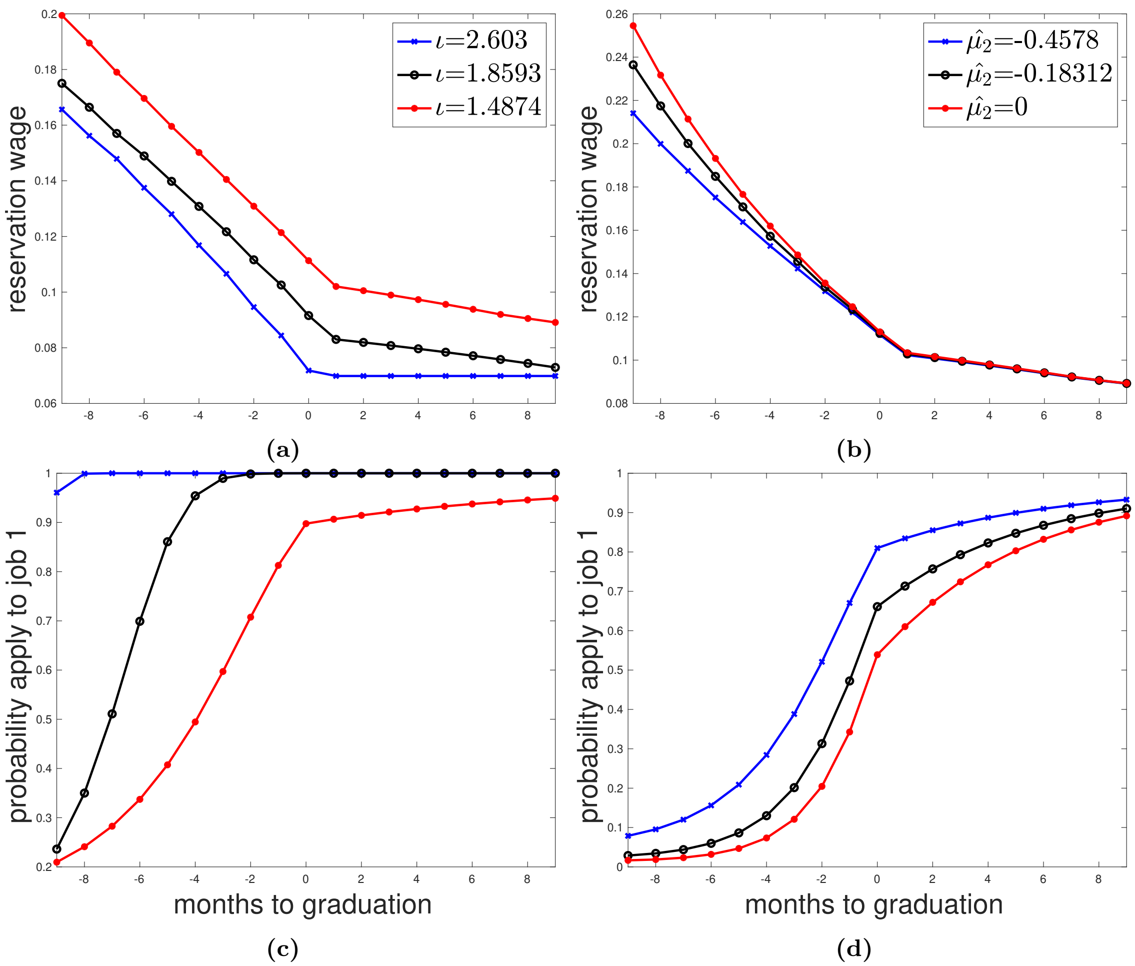
Note: The figure plots the proportion of males and females who accepted a job in each month relative to the month of graduation (indicated as 0). Months since graduation = 9 and -9 includes individuals who accepted a job 10 or more months after or before graduation, respectively.

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



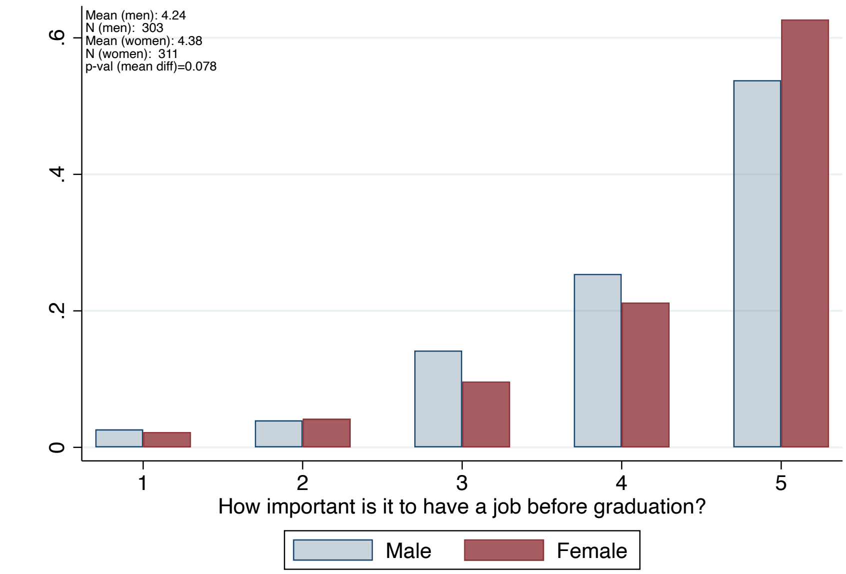
Note: The figure plots the cumulative mean accepted offer as a function of months since graduation separately for males (solid blue line) and females (dashed red line). Months since graduation is defined relative to the month of graduation (indicated as 0). The 95% confidence interval bands are based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

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



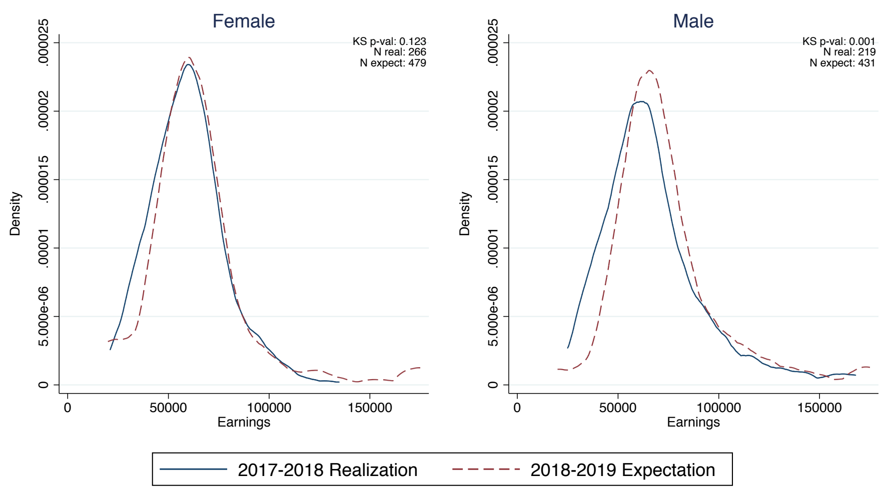
Notes. This figure shows how reservation wages (Panels a and b) and the probability of applying to job 1 (Panels c and d) change as risk aversion varies (left two panels) and biases vary (right two panels). For these numerical exercises, we use the estimated value of all parameter values, with the exception of ι and $\hat{\mu}_2$, which we vary as depicted above.

Figure 4: Importance of Having a Job by Graduation



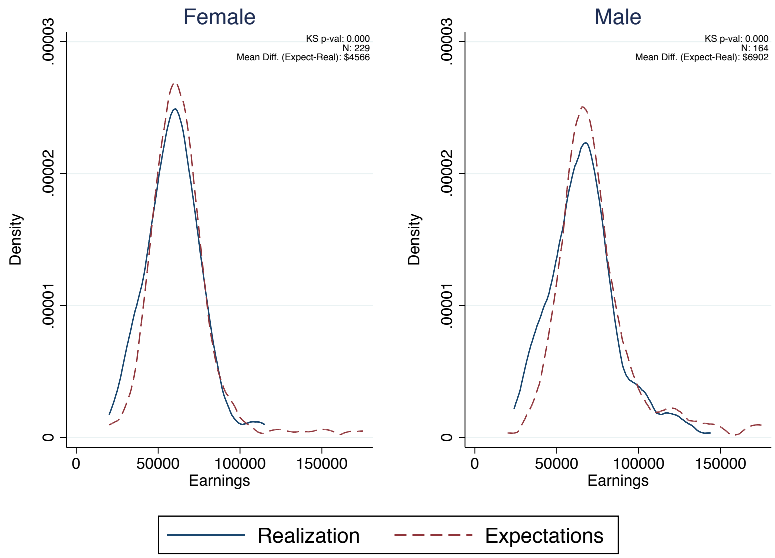
Note: The figure plots the distribution of male and female responses to the following question that was asked to students as part of the in-class survey: *"On a 5-point scale, how important is it to you that you have a job lined up before the end of your senior year (that is, before you graduate)?"*

Figure 5: Gender Difference in Beliefs Bias – Cross-Cohort Comparison



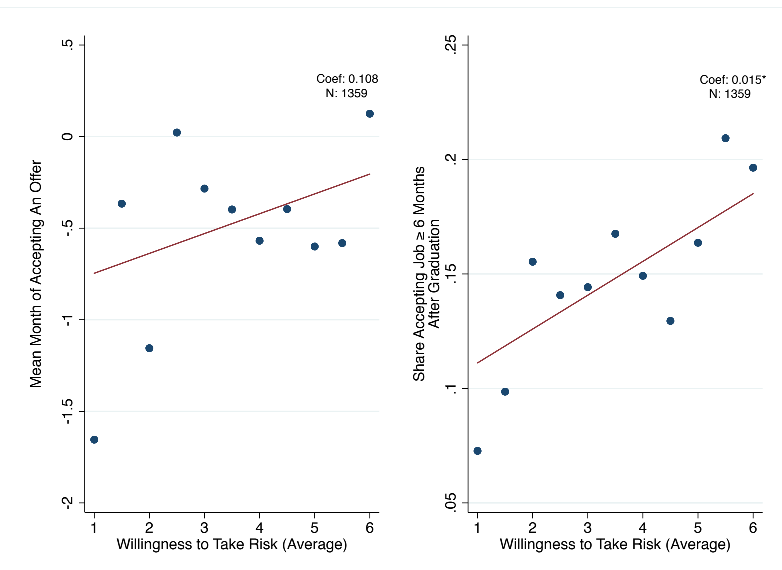
Note: The distribution of expected earnings is constructed based on the earnings expectations (in 2017 dollars) reported by students from the 2018-2019 graduating cohorts. Earnings expectations were elicited during the in-class survey that was conducted in the senior or junior year. The distribution 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 6: Gender Difference in Beliefs Bias – Within Individual Comparison



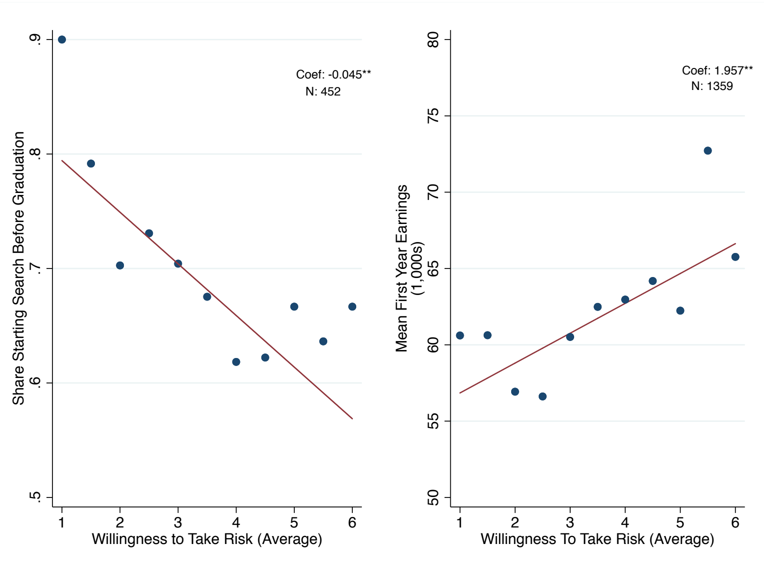
Note: The sample is restricted to individuals for whom we have data on both earnings expectations and realizations. The figure plots the distribution of the difference between ex-ante earnings expectations and ex-post earnings expectations separately by gender. Earnings expectations and realizations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

Figure 7: Relationship Between Timing of Job Acceptance and Risk Preferences



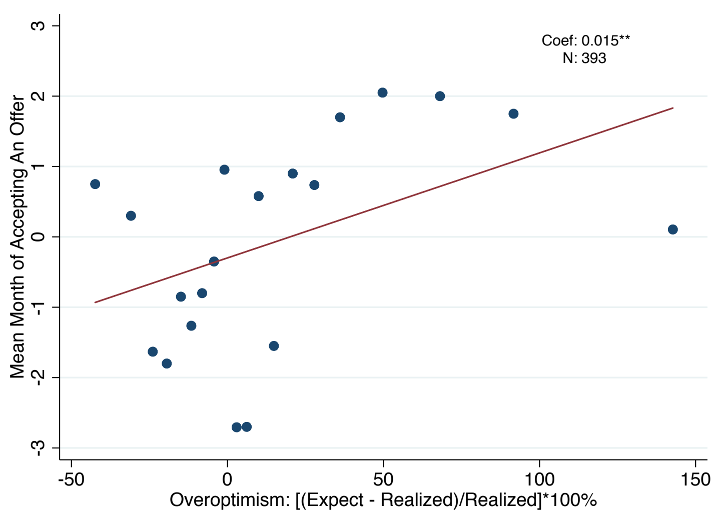
Note: Each graph is a binned scatter plot of a measure of the timing of job acceptance on the survey measure of risk preferences. The y-axis for the left panel plots the mean month of accepting an offer (defined relative to the month of graduation) while the y-axis for the right panel plots the share 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 8: Accepted Earnings, Timing of Search, and Risk Preferences



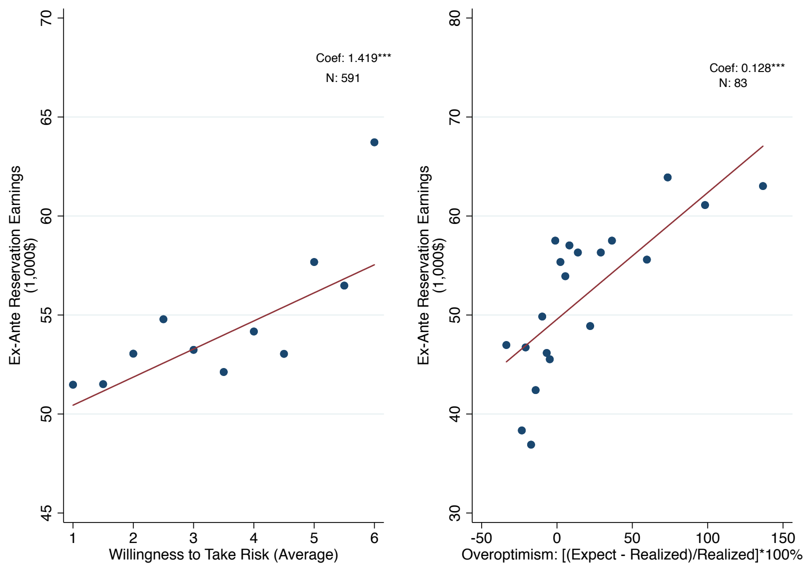
Note: This figure shows binned scatter plots of starting search before graduation (left panel) and total accepted earnings in the first year (right panel) on the survey measure of risk preferences. The willingness to take risks is the average of two survey questions that ask respondents to rate their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

Figure 9: Relationship Between Timing of Job Acceptance and Biased Beliefs



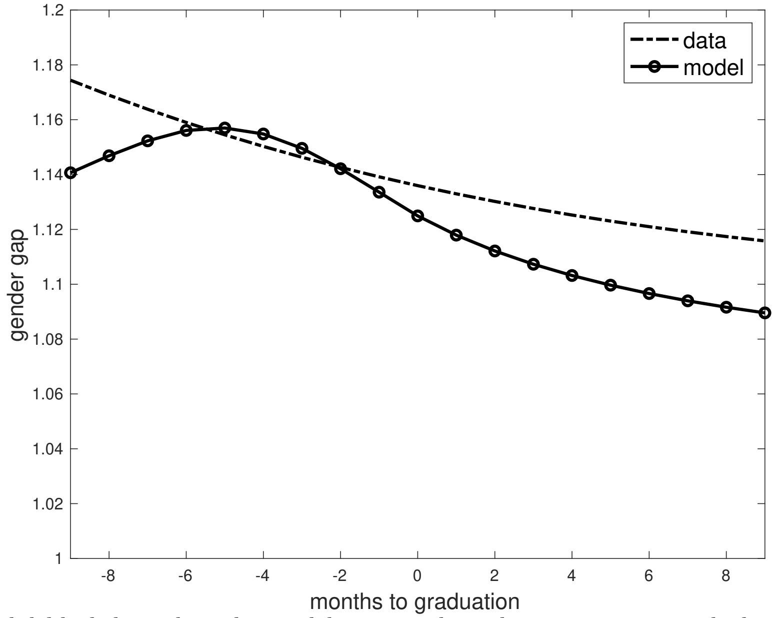
Note: This figure is a binned scatter plot of the month of job offer acceptance (defined relative to the month of graduation) on the individual-level measure of the extent of biased beliefs. This measure of overoptimism is defined as the difference between expected and realized earnings as a percentage 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 10: Ex-Ante Reservation Earnings, Risk Preferences, and Overoptimism



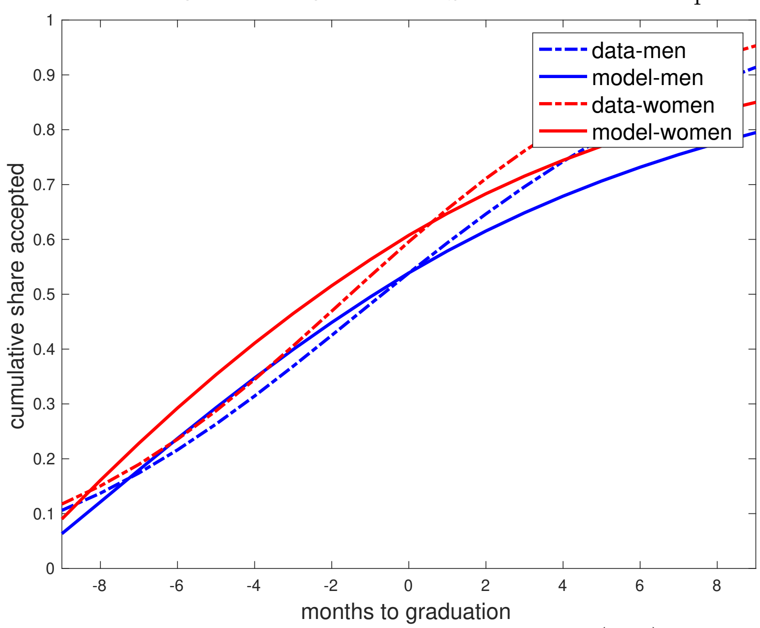
Note: This figure is a binned scatter plot of reported ex-ante reservation earnings (expressed in 2017 dollars) from the in-class survey on risk preferences (left panel) and overconfidence (right panel). For risk preferences, we use all available data from students who completed the in-class survey and answered the reservation earnings question. These students expect 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 11: Model-Generated Gender Earnings Gap



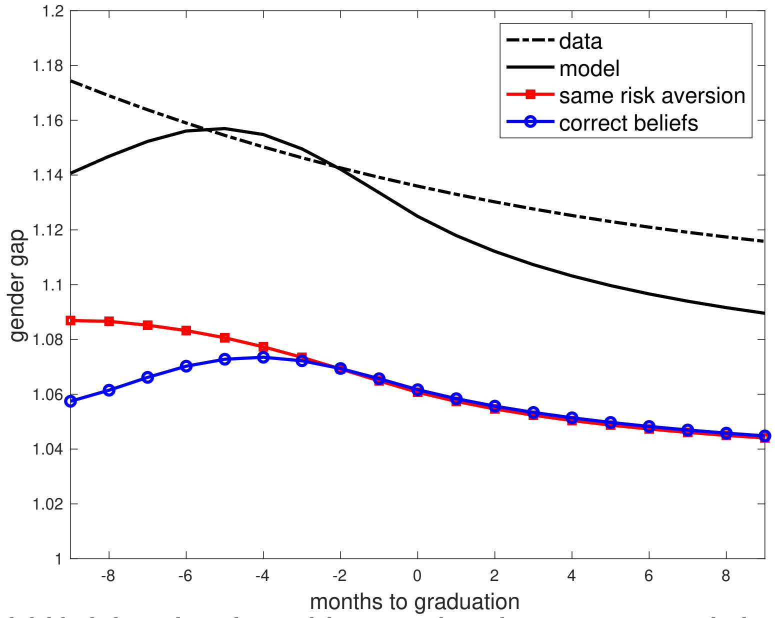
Note: The solid black line plots the model-generated gender earnings gap, which is the ratio of the cumulative accepted male compensation to the cumulative accepted female compensation. The dotted black line plots its empirical counterpart.

Figure 12: Model-Generated Cumulative Share who have Accepted a Job



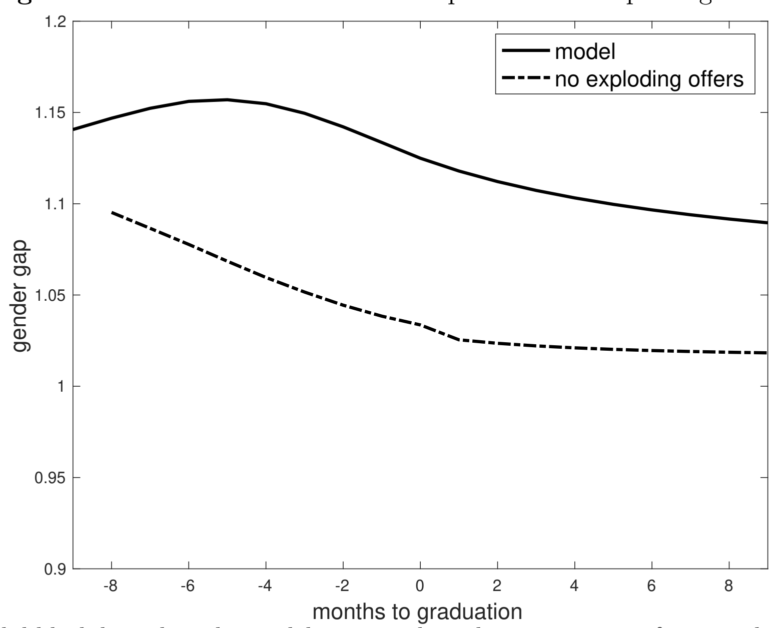
Note: The dotted lines plot the empirical cumulative share of males (blue) and females (red) who have secured a job, while the solid lines plot the model-generated share of males (blue) and females (red) who have secured a job by some date.

Figure 13: 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 line plots the counterfactual gender gap assuming females have the same level of risk aversion as males, which is at the estimated male value in Table 6. The blue lone plots the counterfactual gender gap assuming that both males and females know the true mean log offer in job 2.

Figure 14: Counterfactual Gender Gap Under No Exploding Offers



Note: The solid black line plots the model-generated gender earnings gap from our baseline model. The dashed line plots the gender earnings gap in the model in which students can hold on to offers for a month. Since the optimal strategy is to accept no offers in $t = -9$, no students secure a job in $t = -9$ in the counterfactual environment.

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***	-3952***	-3001**	-2579*
	(1147)	(1146)	(1148)	(1157)	(1397)	(1403)	(1357)
Risk Tolerance			1505***			1780***	
			(453)			(566)	
Risk Tol. ≥ 5				3609**			2220
				(1621)			(2092)
Basic 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	0.538	0.544	0.579
N	1359	1359	1359	1359	1359	1359	1359

Note: The dependent variable is total accepted earnings in the first year of the first job 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: Estimated Model Parameters

Parameter	Description	Value	
β	discount rate	0.996	
σ^*	variance log offer	0.327	
λ_1	search efficiency, job 1	0.176	
λ_2	search efficiency, job 2	0.114	
μ_1^*	mean log offer, job 1	-1.267	
μ_2^*	mean log offer, job 2	-0.916	
ζ	cost of no job	0.854	
ϕ	cost of search	9.353	
ρ	cost of search	4.442	
b	value of leisure	0.092	
		Men	Women
$\hat{\mu}_2$	expected log offer, job 2	-0.706	-0.850
	$\Longrightarrow$bias log wages (percent dev.)	22.918	7.196
ι	risk aversion	1.487	1.738
γ	learning rate	0.080	0.379

Table 7: Counterfactual Gender Gap

	Mean	$T_g - 8$	T_g
Data	1.133	1.174	1.136
Gender gap predicted by:			
Model	1.115	1.147	1.125
no risk differences	1.059	1.087	1.061
perfect information	1.055	1.061	1.062
2-month offers	1.035	1.095	1.034

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, $p = 0.022$).[54] 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.[55] 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

[54] 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.

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

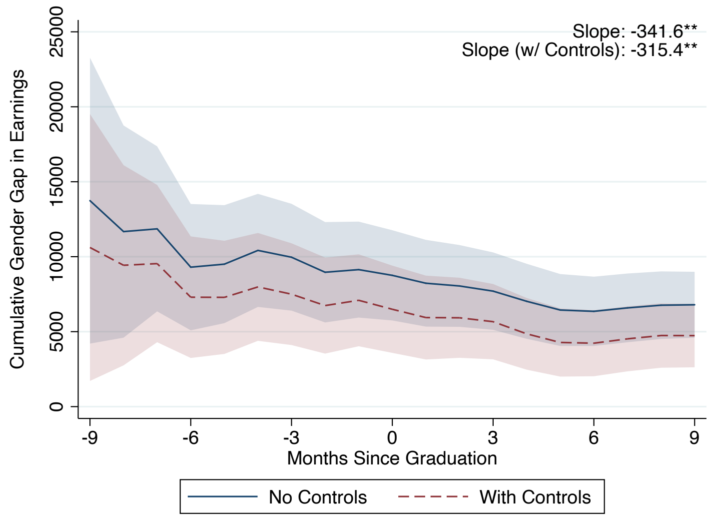
the procrastination index report having accepted their job *earlier*, although the association is not statistically significant. Procrastination is positively (but insignificantly) correlated with accepted earnings (see Figure A.7). Overall, these findings suggest that male students' greater tendency 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 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.7). Therefore, there appears to be no evidence, at least in our data, that women are more rejection averse than men in job search.

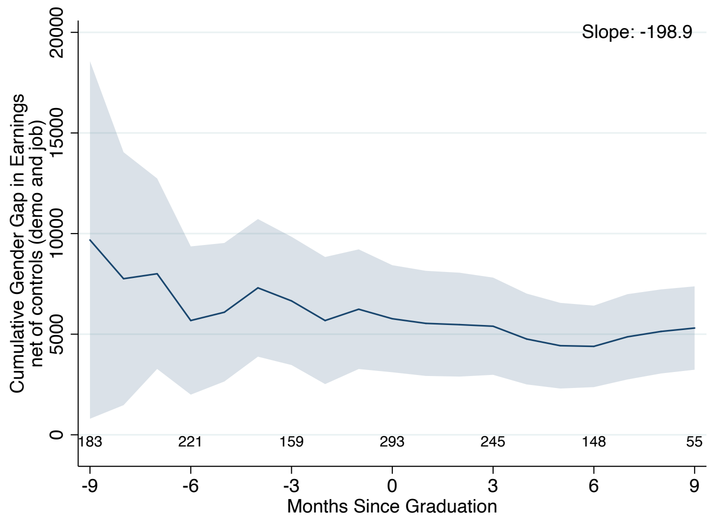
B Appendix: Figures and Tables

Figure A.1: Cumulative Gender Gap in Mean Accepted Offer by Months Since Graduation



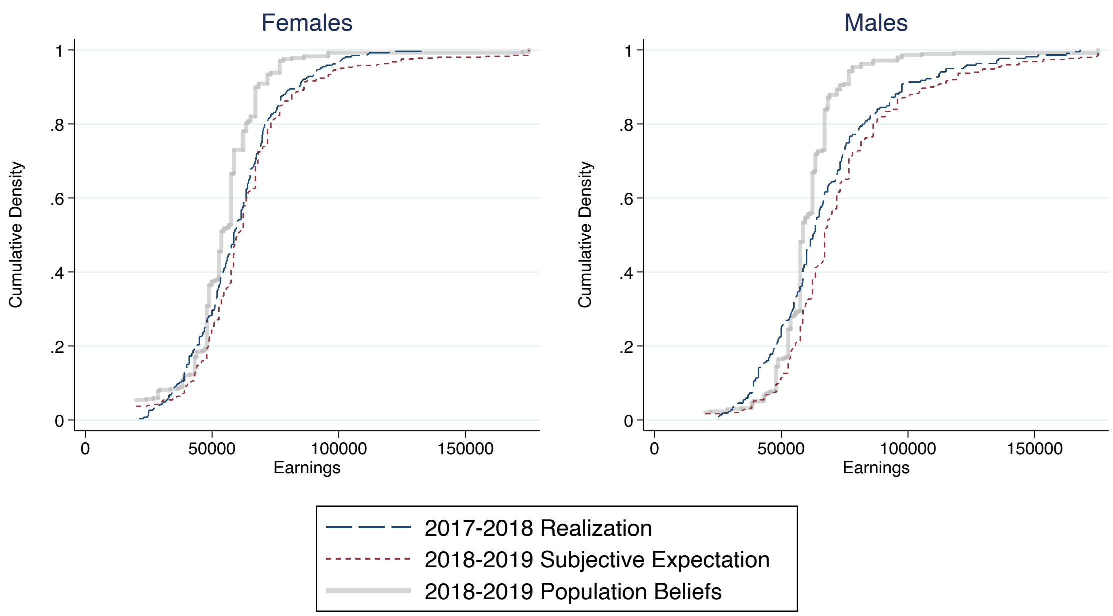
Note: The figure plots the cumulative gender gap in mean accepted earnings as a function of months since graduation. Controls include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education. Months since graduation is defined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

Figure A.2: Cumulative Gender Gap in Mean Accepted Offer by Months Since Graduation (Including Job Controls)



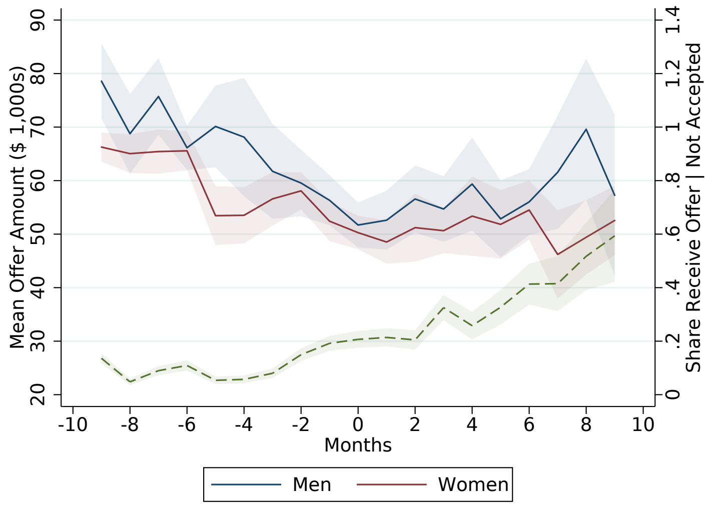
Note: The figure plots the cumulative gender gap in mean accepted earnings as a function of months since graduation net of controls for demographic and job characteristics. In addition to the demographic controls listed in Figure A.1, additoinal controls include job industry fixed effects, dummies for job amenities such as flexible work hours, sick leave, childcare benefits, sick leave, 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.3: Gender Difference in Beliefs Bias – Cross-Cohort Comparison



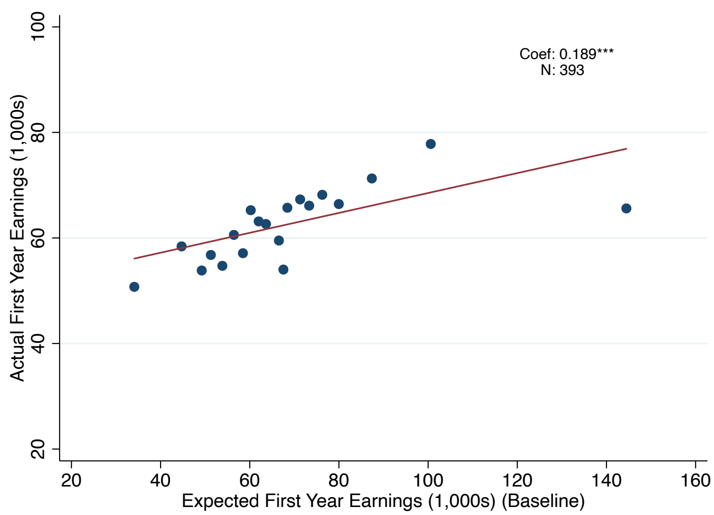
Note: The distribution of expected earnings is constructed based on the earnings expectations (in 2017 dollars) reported by students from the 2018-2019 graduating cohorts. Earnings expectations were elicited during the in-class survey that was conducted in the senior or junior year. The distribution 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.4: Offer Amount and Share Receiving an Offer by Months Since Graduation



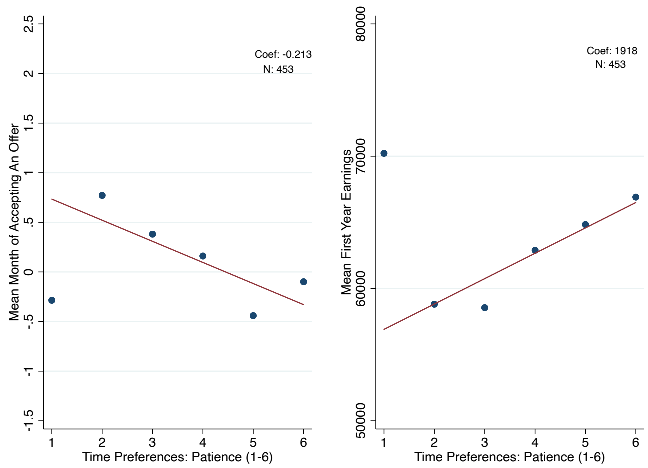
Note: The sample includes individuals from the 2018-2019 graduating cohorts. This figure plots the mean offer amount separately by gender (solid lines) and the share of individuals who received an offer conditional on not having accepted an offer (dashed line) by months since graduation. Months since graduation is defined relative to the month of graduation (indicated as 0).

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



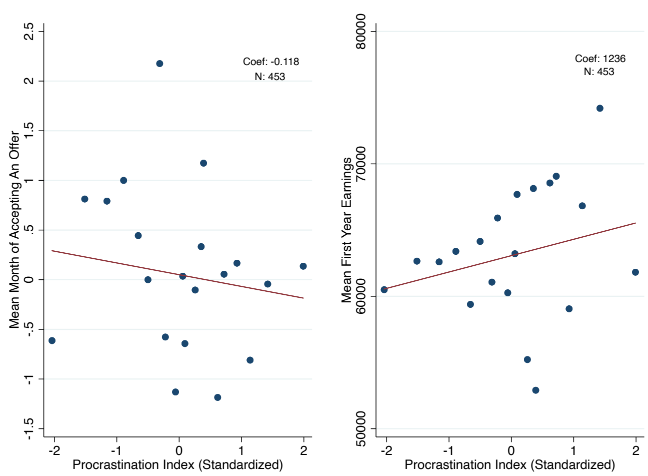
Note: The sample includes individuals from the 2018-2019 graduating cohorts. This figure plots the mean offer amount separately by gender (solid lines) and the share of individuals who received an offer conditional on not having accepted an offer (dashed line) by months since graduation. Months since graduation is defined relative to the month of graduation (indicated as 0).

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



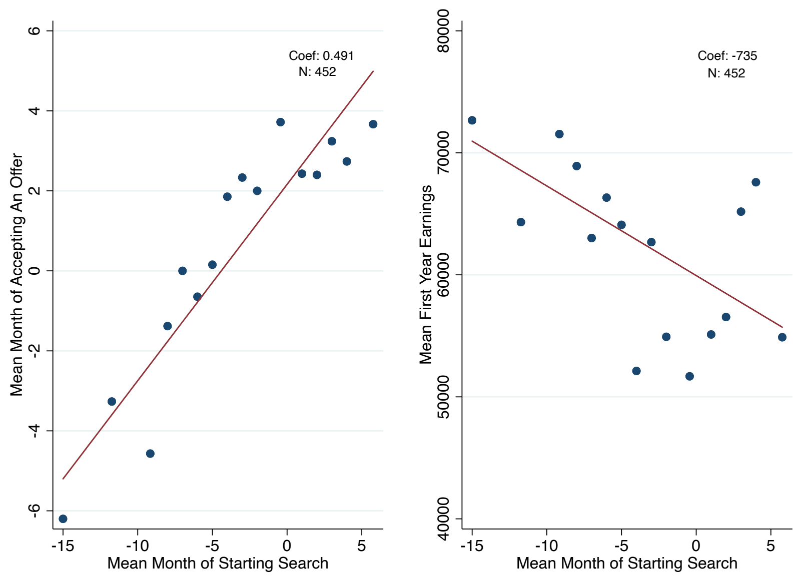
Note: The sample includes individuals from the 2018-2019 graduating cohorts. This figure graphs the binned scatter plot of the month of job offer acceptance (defined relative to the month of graduation) (left panel) and accepted earnings (right panel) on the survey measure of patience. Patience is measured 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 from 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.

Figure A.8: The Role of Search Timing



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 month that individuals report starting job search. The questions on timing when search commenced were fielded to a subset of the "current student" sample.

Table A.1: 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 on a statistical test of the comparison of the gender difference in means between the two samples (full sample vs. accepted sample).

Table A.2: 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.3: 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.4: 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.5: Who Responded to the Surveys?

Outcome:	Female	Foreign Student	GPA	Credit Hours	Accounting	Finance	Marketing	Info Systems
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Survey of Graduates (2017-2019 Cohorts)							
Respondent	0.082***	-0.188***	0.082***	0.028	-0.008	-0.103***	0.045**	0.042**
	(0.022)	(0.019)	(0.016)	(0.163)	(0.017)	(0.022)	(0.019)	(0.018)
N	2,390	2,390	2,390	2,390	2,390	2,390	2,390	2,390
	B. Survey of Current Students, Baseline (2018-2019 Cohorts)							
Respondent	0.070***	-0.132***	0.020	0.583***	-0.041**	-0.054**	0.045**	-0.002
	(0.026)	(0.024)	(0.020)	(0.179)	(0.019)	(0.026)	(0.022)	(0.021)
N	1,538	1,538	1,538	1,538	1,538	1,538	1,538	1,538
Controls:								
Cohort FE	X	X	X	X	X	X	X	X

Note: Each column is a separate regression of a given student characteristic on a dummy variable that equals 1 if the individual had a valid response to the survey (as indicated in each panel), 0 otherwise. The regressions are based on survey data that was merged to administrative data covering 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. Robust standard errors are reported in parentheses. ***significant at the 1% level, **5% level, *10% level.

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***	-0.053**	-0.040*	-0.035
	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)	(0.022)	(0.022)
Risk Tolerance			0.020***			0.025***	
			(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	0.583	0.587	0.605
N	1359	1359	1359	1359	1358	1358	1358

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, 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: 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.8: Model Fit

	Men		Women	
Moment	Data	Model	Data	Model
cumulative mean accepted offer				
$t = -9$	0.412	0.422	0.351	0.370
$t = -8$	0.406	0.416	0.347	0.363
$t = -7$	0.400	0.409	0.344	0.355
$t = -6$	0.395	0.402	0.341	0.348
$t = -5$	0.390	0.395	0.338	0.342
$t = -4$	0.385	0.389	0.335	0.337
$t = -3$	0.381	0.382	0.332	0.332
$t = -2$	0.377	0.376	0.330	0.329
$t = -1$	0.373	0.370	0.327	0.326
$t = 0$	0.369	0.365	0.325	0.324
$t = 1$	0.365	0.361	0.323	0.323
$t = 2$	0.362	0.357	0.320	0.321
$t = 3$	0.359	0.355	0.318	0.320
$t = 4$	0.356	0.352	0.316	0.319
$t = 5$	0.353	0.350	0.315	0.319
$t = 6$	0.351	0.349	0.313	0.318
$t = 7$	0.348	0.347	0.311	0.317
$t = 8$	0.346	0.346	0.310	0.317
$t = 9$	0.344	0.345	0.308	0.317
expected salary				
$t = -8$	0.385	0.394	0.337	0.339
$t = -2$	0.339	0.318	0.307	0.298
cumulative share accepted				
$t = -9$	0.106	0.063	0.117	0.090
$t = 0$	0.539	0.539	0.596	0.608
$t = 10$	0.914	0.795	0.953	0.850
share receive offer				
$t = -9$	0.070	0.078	0.050	0.097
$t = 0$	0.175	0.135	0.163	0.169
$t = 10$	0.216	0.137	0.249	0.169
mean log offer				
$t = -9$	-0.929	-1.011	-1.054	-1.099
$t = 0$	-1.213	-1.244	-1.325	-1.267
$t = 10$	-1.246	-1.256	-1.418	-1.267
rejection rate				
$t = -9$	0.014	0.014	0.026	0.007
$t = 0$	0.056	0.000	0.044	0.000
$t = 10$	0.030	0.000	0.033	0.000