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GENDER DIFFERENCES IN JOB SEARCH AND THE EARNINGS GAP: EVIDENCE FROM THE FIELD AND LAB

Patricia Cortés
Jessica Pan
Ernesto Reuben
Laura Pilossoph
Basit Zafar

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ABSTRACT

This paper investigates gender differences in the job search process, both in the field and lab. First, we collect rich information on initial job offers and acceptances from 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) there is a clear gender earnings gap in accepted offers, which narrows in favor of women over the course of the job search period. To rationalize these patterns, we develop a job search model that incorporates gender differences in risk aversion and over-optimism about prospective offers. We validate the model's assumptions and predictions using the survey data, and present empirical evidence that the job search patterns in the field can be partly explained by the greater risk aversion displayed by women and the higher levels of over-optimism displayed by men. Next, we replicate the findings from the field in a specially-designed laboratory experiment that features sequential job search, and provide direct evidence on the purported mechanisms. Our findings highlight the importance of risk preferences and beliefs for gender differences in job-finding behavior, and consequently, early-career wage gaps among the highly-skilled.

Patricia Cortés
Questrom School of Business
Boston University
595 Commonwealth Avenue
Boston, MA 02215
and NBER
pcortes@bu.edu

Jessica Pan
Department of Economics
National University of Singapore
1 Arts Link
Singapore
and IZA
jesspan@nus.edu.sg

Ernesto Reuben
Columbia University
3022 Broadway
Uris Hall
New York, NY 10027
ereuben@columbia.edu

Laura Pilossoph
Macroeconomics and Monetary Studies Function
Federal Reserve Bank of New York
33 Liberty Street
New York, NY 10045
pilossoph@gmail.com

Basit Zafar
Department of Economics
University of Michigan
611 Tappan Street
Ann Arbor, Michigan 48109
and NBER
basitak@gmail.com

1 Introduction

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

One particular aspect of the labor market where one might expect risk preferences and beliefs about relative ability to matter is job search behavior. 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 how these attributes contribute to gender differences in labor market search behavior and its dynamics, as well as its impact on early-career gender pay gaps. A likely reason for this is that researchers usually have limited information on job search behavior throughout the job search process, the offers that people receive, and measures of risk aversion and biased beliefs. Even in cases where such information is available, the focus is typically on unemployed workers in general and not on the gender dimension.[3] To our knowledge, few studies have systematically documented

[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.

[3]For example, Krueger and Mueller (2011), DellaVigna and Paserman (2005), and Spinnewijn (2015)

gender differences in the dynamics of job search behavior, and specifically explored the roles of preferences and beliefs in explaining the observed dynamics. In this paper, we fill this gap by drawing on rich survey data on the job search behavior of undergraduate business majors and a laboratory experiment on sequential job search to document novel facts about gender differences in the job search process.

Our field evidence comes from self-administered surveys that collect retrospective data on job offers and acceptances from recent undergraduate alumni from Boston University's Questrom School of Business. Specifically, we ask graduates from the 2013–2019 graduating classes details about the job search process that led to their first job after graduating from Questrom, such as the characteristics of their accepted offer (e.g. salary components, job characteristics, timing of the offer, and when the offer was accepted). We also asked similar questions about the characteristics of up to three job offers that were rejected, as well as the reasons for rejecting the offer. To understand how expectations about the job search process evolve, we supplement the alumni survey with a prospective survey of current students from the graduating classes of 2018 and 2019. For these students, we surveyed them at three points in time – twice before they graduated – to ask about their earnings expectations and (intended) job search behavior, as well as eight months post-graduation to ask about the outcomes of their job search process.

We begin by documenting two novel facts regarding gender differences in the job search process using the field data. First, we document a clear gender difference in the timing of acceptance of the first job after graduation – women, on average, accept jobs about one month earlier than their male counterparts (60% of women have accepted a job before graduation, compared to 52% of males). This difference is observed in the raw data and is robust to controlling for concentration (e.g. finance, marketing, etc.), GPA, and standard demographics such as race, cohort, country of birth, and parental education. In addition, this gap does not appear to be driven by gender differences in industry choice. Second, we find a large gender gap in accepted offers, and the gap *narrows* in favor of women over the course of the job search period. For example, the average gender gap (i.e., male-female difference) across all accepted offers starts at around 16% in August of the senior year and declines to about 10% by the following October and thereafter. These patterns are taking into account the aforementioned controls. In addition, we provide evidence suggesting that gender differences in outside options, expected duration at the first job, marriage market considerations, and locational preferences are unlikely to be driving the observed gender

focus on the job search behavior of unemployed workers. More recently, a few papers have also examined job search behavior and the role of learning in the general population of workers (e.g. Faberman et al., 2017, and Conlon et al., 2018).

differences in job search behavior that we document among undergraduates searching for their first job after graduation.

To rationalize these patterns, we develop a model of job search that incorporates gender differences in risk aversion, overoptimism over expected offers, and learning (i.e. updating expectations about job offers) – all assumptions that we show our data support. The model is able to generate the key empirical patterns. Intuitively, if women have higher levels of risk aversion, they will have lower reservation wages, start searching for jobs earlier, and also accept jobs earlier. On the other hand, if men have greater optimism regarding job offers, they will have higher reservation wages and accept jobs later. Learning by both genders lowers reservation wages over the job search period. We show formally how risk preferences and overconfidence theoretically impact reservation wages and search effort and demonstrate that the net effect of these forces can result in a decline in the gender gap in accepted earnings over time which we observe empirically.[4]

We next examine the model mechanisms 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 gender-aggregated 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 find that both men and women update their beliefs downwards as the job search progresses, but that male students' beliefs take longer to converge to the "truth" relative to females' beliefs.

Consistent with the model predictions, we document that both the survey measure of risk

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

[5]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 (Shurchkov and Eckel, 2018). 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., 2013a). 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.

tolerance and the individual-level measure of overoptimism are strongly positively associated with students' reports of their ex-ante reservation earnings. Taken together, both attributes explain a sizable proportion of the observed gender difference in reservation earnings (about 30% of the raw gap and 40% of the residual gap). The model also predicts that more risk averse or overconfident individuals should be more likely to search at a given point in time, with the numerical simulations suggesting an empirically larger role for risk preferences. We confirm these patterns in the data – there is a strong negative relationship between willingness to take risks and the likelihood of starting the job search process before graduation; however, there appears to be no correlation between overoptimism and the timing of starting search. Overall, we find that risk preferences can account for about 20% of the gender gap in job search timing. Empirically, we show that the net effect of the reservation wage and search timing channels results in a positive association between risk tolerance/overconfidence and the timing of job acceptance. Turning to what this implies for the gender gap in accepted earnings, we find that gender differences in risk preferences and proxies for overoptimism account for a non-trivial proportion (about 30%) of the residual gap in accepted earnings.[6] 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 these explanations are not consistent with the full set of empirical patterns observed in the data.

To lend further credence to the job search patterns observed in the field and the proposed mechanisms, we next turn to a controlled laboratory setting to investigate gender differences in sequential job search. The main advantage of the lab setting is that we can abstract from potential confounds in the field such as gender differences in family constraints, outside options, unobservable aspects of the offers, and employer preferences/behavior. The lab setting also allows us to obtain incentivized measures of risk aversion and reservation wages, as well as precise individual-level measures of overconfidence.

The experiment was conducted online in early-2020 with Arizona State University (ASU) undergraduate students, and consists of a real-effort typing task followed by a sequential job search process where participants play the role of a job seeker and have five rounds to find a job. In each round, participants receive a job offer from a discrete distribution ranging from \$2 to \$32 in steps of \$3. The participant's typing speed determines the probability of drawing the different wage offers, with fast typists (that is, those with a typing speed

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

in the top quartile of the typing speed distribution) being more likely to get higher wage draws. Participants are informed of the probabilities of getting each wage offer conditional on being a fast or a slow typist, but they do not know their type with certainty. In each round, participants are asked to report their reservation wage prior to receiving a job offer; the offer is accepted if the reservation wage is less than or equal to the wage offer. This process repeats until an offer is accepted or the experiment ends – at the end of round 5, participants earn the outside option of $2 if no offer has been accepted. The only source of uncertainty in the lab setting comes from not knowing one's own type (and therefore the offer distribution one faces) with certainty. In each round, we also elicit the participant's belief about being a fast typist. This allows us to construct a precise measure of overconfidence at the individual-level, since we know the participant's actual type. Finally, we also elicit risk preferences using an incentivized multiple price list.

The findings from the experiment largely corroborate what we observe in the field and provide direct evidence for the proposed model mechanisms. The average reservation wage is higher for men in each round and, as predicted by the model, we observe average reservation wages for both genders declining over time. As a result of their lower reservation wages in each round, women are significantly more likely to accept a wage offer earlier than men. Consistent with the main model mechanism and what we observe in the field, we find that both risk aversion and overconfidence are correlated with reported reservation wages in the expected direction, and together, explain about a third of the gender gap in reservation wages in the first round. Moreover, among those who accepted a wage offer by round 5, gender differences in risk preferences and prior beliefs can account for about half of the observed gender gap in accepted offers. Another implication of the gender differences in job search behavior is that men are likely to be overrepresented in the tails of the wage distribution. Indeed, we show that men are significantly more likely than women to end up with very high or very low final wages in the experiment, with gender differences in risk preferences and beliefs partially accounting for this pattern.

Finally, we demonstrate that such overconfidence is costly – while overconfidence leads to, on average, higher accepted offers for men, we find that men are much more likely to end up with an accepted wage offer that is *lower* than a previous offer in an earlier round (which they rejected). Once again, this gender difference can be partially accounted for by men's greater risk tolerance and overconfidence. This echoes a similar observation in the field where, relative to women, men report a higher likelihood of having rejected an offer that is higher than the one that they end up accepting, lower satisfaction with the job search process, and a greater likelihood of regretting some aspect of their job search.

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.[7] 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).[8] 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.

Our work is related to three main strands of literature. First, we contribute to the growing literature on the role of psychological attributes and behavioral biases in job-finding behavior. Many of these studies focus on search behavior among unemployed workers and focus on the relationship between job search behavior and behavioral attributes such as time preferences (e.g. DellaVigna and Paserman, 2005; DellaVigna et al., 2017), risk preferences (e.g. Cox and Oaxaca, 1992; Pannenberg, 2010), and biased beliefs (Spinnewijn, 2015).[9] These studies, however, do not focus on gender differences in psychological attributes and job search behavior.

Second, this paper is also related to literature that seeks to explain gender gaps through a search framework. Several papers examine the role of family constraints in the form of non-participation, joint relocation, and commuting time, and find that these factors can account for a non-trivial proportion of the gender wage gap and job application behavior (Bowlus, 1997; Bowlus and Grogan, 2009; Le Barbanchon et al., 2020; Fluchtmann et al., 2020). Other

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

[8]Recent work by Rothstein (2019) suggests even more permanent effects of the Great Recession on college graduates, which he argues might be due, in part to the fact that weaker labor market conditions early in one's career could result in a weak bargaining position that persists throughout the lifecycle (Beaudry and DiNardo, 1991).

[9]Other psychological traits that have been shown to influence job search behavior are internal locus of control (McGee, 2015; Caliendo et al., 2015; McGee and McGee, 2016) and the Big Five personality traits (Flinn et al., 2020).

papers use matched employer-employee data and equilibrium search models to examine the role of compensating differentials resulting from gender differences in preferences for job amenities, statistical discrimination, taste discrimination, and labor market attachment in explaining gender pay gaps over the lifecycle (Morchio and Moser, 2020; Xiao, 2020; Flabbi and Moro, 2012; Flabbi, 2010). Our paper also uses a search framework; however, our focus is on the dynamics of early career job search. 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. More closely related to our work, Vesterlund (1997) extends the Diamond-Mortensen-Pissarides model and shows, theoretically, that gender differences in risk aversion could result in women accepting lower quality matches, and lower wages conditional on productivity.

Finally, our paper contributes to the recent literature that examines less traditional explanations for the persistence of gender differences in labor market outcomes, including the role of gender differences in behavioral traits and psychological attributes. Recent review articles by Shurchkov and Eckel (2018) and Blau and Kahn (2017) summarize the large and growing experimental evidence from both the lab and the field that typically finds that women, on average, tend to exhibit greater risk aversion, lower levels of competitiveness, and a lower willingness to negotiate relative to men.[10] More recent work has sought to link these gender differences in behavioral traits to observed gender gaps in the labor market.[11] Our paper extends this literature by showing how gender differences in two behavioral attributes – risk aversion and overoptimism – affect job search behavior, and consequently, early career wage gaps, among a group of highly-skilled men and women entering the corporate sector.[12]

2 Evidence from the Field

We are interested in exploring whether there are systematic gender differences in initial job search of college graduates and the resulting implications for gender earnings gaps. For

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

[11] Blau and Kahn (2017) provide a summary of the results of several studies that examine the quantitative importance of psychological attributes or non-cognitive skills on the gender pay gap and find that, overall, these traits account for a small to moderate portion of the gender pay gap (about 16% or less).

[12] Several other papers examine the dynamics of the gender gap among professionals and the highly-educated later in the lifecycle and emphasize the role of labor supply and other career adjustments around motherhood as a key explanation for the observed divergence in labor market trajectories between similarly skilled men and women (Bertrand et al., 2010a; 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.

reasons mentioned above, focusing on early-career job search allows us to abstract away from other confounds. More importantly, a better understanding of the origins of initial gender pay gaps is informative of gender disparities later in the lifecycle, as previously discussed. Our field data on initial job search patterns is survey-based. This section describes the survey data, and then documents statistics regarding initial labor market outcomes. We then establish two novel facts regarding gender differences in job search behavior.

2.1 Survey Design and Administration

The field 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 that offers both undergraduate and graduate programs. It has a relatively large undergraduate enrollment of about 3,200 students (across four years of study). Our analysis is based on two main survey instruments: (1) a retrospective survey of recent Questrom alumni ("Survey of Graduates"), and (2) a prospective survey of current Questrom students ("Survey of Current Students"). The online surveys were administered using the SurveyMonkey platform. We next describe each survey in detail.[13]

Survey of Graduates. Our first data source is from the Survey of Graduates, administered to the 2013 to 2017 Questrom graduating classes between April 2017 and February 2018. A total of about 1,000 alumni completed the survey, corresponding to a response rate of about 20%.[14] The survey included questions on demographic and academic background, salary and other job characteristics (for the initial as well as current job), negotiation behavior, perceived ability, salary of peers, and risk attitudes. Central to our analysis, we collected detailed information on the timing of job offers and characteristics not only for the job offer that individuals accepted, but also for offers that individuals ended up rejecting (up to three of such offers) for the initial job search, which starts in college for most students. This allows us to construct a detailed timeline of how the job search process unfolds for each individual in our sample in the months leading up to and after graduation. We supplement this information with data from a similar post-graduation survey of the 2018 and 2019 graduating classes that was conducted in January 2019 and 2020, respectively. Throughout, we will refer to the merged alumni surveys for the 2013-2019 graduating classes as the "Graduate Survey."

[13] The survey questionnaires can be accessed here.

[14] The response rate for our survey is broadly comparable to that of other surveys conducted on similar populations – for example, the response rate for Bertrand et al. (2010b)'s survey of University of Chicago MBA students was 31% while the response rate was around 10% to 12% across the 28 universities that participated in the recent Global COVID-19 Student Survey (Jaeger et al., 2021).

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 against the experimental approach by Dohmen et al. (2011) and Falk et al. (2016).[15] Since very few individuals picked the lowest possible value on the scale for each of the two risk questions, we combine the lowest two values and rescale the responses to be between 1 and 6. For the field 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).

Survey of Current Students. Our second source of data is from a prospective survey of students who graduated in 2018 and 2019. Unlike the alumni survey which is retrospective, these students were surveyed twice before graduation and once after graduation, allowing us to elicit reservation earnings, 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 took the "baseline survey" either in their junior year (2019 cohort) or the start of the senior year (2018 cohort). 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. The survey collected information on demographic characteristics, earnings expectations, reservation earnings, intended job search behavior, and measures of various psychological attributes such as risk preferences, time preferences, and procrastination. The first follow-up survey 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. 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.

We discuss participant compensation, response rates, issues related to the selection of students into the survey, and clarify key data choices in Appendix A. Importantly, relative

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

to the underlying population, we do not find much evidence of differential selection in terms of observables, by gender, into our surveys.

2.1.1 Sample Description

The main characteristics of our analysis sample, which comprises graduates who have accepted an offer by the time of the survey, are shown in Table 1.[16] 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 are comparable in terms of demographics, family background, and GPA – the differences are typically small and not statistically significant. The biggest gender difference is observed in terms of degree concentration. Men are significantly more likely to report concentrating in finance than women (65% vs. 38%), while women are significantly more likely to concentrate in marketing (37% vs. 14%). Women are also significantly more likely to concentrate in law and organizational behavior, although these are relatively small fields of study.[17] 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-fifth of the mean or half of a standard deviation.[18] Men are also more than twice as likely to report an average willingness to take risks of five or more (on a six-point scale) as compared to women (23% vs. 9%). Despite having similar GPAs as men on average, women report significantly lower perceived relative ability, consistent with the previous literature documenting that men tend to be more (over)confident than women.

2.2 Initial Labor Market Outcomes

We next document statistics regarding initial labor market outcomes. This analysis, and the one in the subsequent section, uses the Survey of Graduates from the 2013-2019 graduating cohorts.

Table 2 shows 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

[16] The proportion of students who accepted an offer to work right after graduation does not vary by gender. Summary statistics for the full sample are reported in Table A.5 and are similar to the summary statistics for the sample conditional on having accepted a job.

[17] 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.

[18] 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.

to work after graduating from BU. There is little evidence of significant gender differences in employment status, 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.[19] Nevertheless, there is a large gender gap in earnings, with women earning about 10% less than their male counterparts at their first job; 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 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).[20] Not surprisingly, the observed gender difference in concentration translates to similar differences in industry choice with men significantly more likely to work in financial services, while women are more likely to be in advertising/marketing and consumer products/retail.

The summary statistics also reveal some suggestive gender differences in job search behavior. The average student in the sample accepts their first job about half a month before graduation, with women accepting their first job almost one month before men. Close to 92% of women accept jobs within six months of graduation, compared with 86% of men. These patterns form the basis of our first empirical fact in the next section. Despite the significant gender difference in the timing of job acceptance, on average, women and men receive a similar number of offers (about 1.7) and are equally likely to have rejected at least one offer (approx. 40%). While this may appear to be puzzling, the last panel of Table 2 shows that women start searching for jobs earlier than men and search behavior differs by gender along several dimensions.[21,22]

2.3 Two Novel Facts About Job Search

[19]In this sample, less than 2% of individuals are currently married, and approximately 47% are in a relationship. Women are slightly more likely to be in a relationship than men, but the difference is small (4.4 pp) and marginally significant at the 10% level. Later, in Section 2.3, we discuss the role of marriage market considerations in the job search process.

[20]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).

[21]In the subsample of students ($N = 452$) for whom we have data on both the timing of starting search and job acceptance timing, we find that gender differences in starting search can account for slightly more than half of the observed gender gap in job acceptance timing.

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

2.3.1 Fact 1: Females Accept Jobs Earlier

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

Table 3 shows that the observed gender difference in the timing of job acceptance is robust to the inclusion of controls for background characteristics (e.g. cohort fixed effects, a dummy for US-born, and fixed effects for race and parents' education) and academic background (concentration fixed effects and GPA). Columns (1) to (3) report estimates of the gender difference using a hazard model where the outcome is the probability of accepting a job within six months of graduation, while columns (4) to (6) report estimates from a linear specification using month of job acceptance as the outcome variable. Column (1) indicates that women are 23% more likely to accept a job within six months of graduation relative to men. Column (2) shows that the expected hazard increases to 1.29 with the inclusion of the individual-level covariates. The observed gender difference in job acceptance timing does not appear to be driven by gender differences in industry choice – the hazard odds ratio is slightly lower at 1.24 and remains highly statistically significant with the inclusion of industry fixed effects in column (3).[23] 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 0.84 months. All the estimates are statistically significant at the 5% level.

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

2.3.2 Fact 2: Positive Gender Gap that Narrows Over Job Search Process

The second empirical fact that we observe in the data is that there exists a *cumulative* gender earnings gap in accepted offers in favor of men, and it declines steadily over the job search period. Cumulative mean accepted earnings at a given point in time is constructed as the mean of the first-job accepted earnings among those who have accepted a job *up to that point*; and the cumulative gender earnings gap is defined as the difference between the cumulative mean accepted earnings of men and women at a given point in time.[24]

As observed in Panel (a) of 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 16% 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.[25] Panel (b) of Figure 2 confirms that the observed decline in the cumulative gender earnings gap in accepted offers is robust to the inclusion of controls for background characteristics and academic background, as shown by the red line. Moreover, the green line shows that the decline is robust to the additional inclusion of industry fixed effects.

Table 4 presents the same information in a regression framework. The dependent variable is the cumulative gender earnings gap in each period. Column (1) shows that the gap declines by an economically and statistically significant amount of $340 per month over the course of job search. Columns (2) and (3) show that the slope of the decline is largely unchanged if basic controls and industry fixed effects are added, as we already saw in Panel (b) of Figure 2. Most of the closing of the gender gap in accepted offers happens by the time of graduation, as evidenced in Figure 2. Finally, Appendix Figure E1.1 shows that the qualitative and quantitative conclusions are unchanged if we instead look at the log of accepted earnings.

One may wonder about the extent to which these patterns could be due to gender differences in preferences for non-wage amenities (e.g. Wiswall and Zafar, 2017). Column (4)

[24] This is the relevant object to consider since - once all job seekers have found their first job - it is equivalent to the gender gap in earnings.

[25] This can also be seen in Appendix Figure A.1 which plots the mean accepted earnings by months since graduation and gender, along with the number of observations used to compute each data point. We observe that mean accepted earnings for men starts higher and declines more rapidly than that for women up until about six months post-graduation. Perhaps interestingly, in the later months post-graduation, we observe a divergence in the gender gap in mean accepted earnings. However, it is important to bear in mind that sample sizes are quite small for both genders beyond 6 months post-graduation. Thus, it is not suprising that this apparent divergence in the later months is not large enough to overturn the gender gap in cumulative mean earnings in Figure 2.

of Table 4 shows that the estimated decline in cumulative gender earnings gap decreases by about 25% (from $335 to $255) after controlling for a comprehensive set of job characteristics including work flexibility, availability of sick leave, childcare benefits, and parental leave, as well as expected earnings growth. Nevertheless, the estimated slope net of these amenities remains quantitatively large and statistically significant. This suggests that the observed patterns are not entirely driven by gender-specific changes in the non-wage attributes of accepted jobs over the job search period. These job characteristics are all choices, and thus this analysis should be interpreted only as suggestive. In addition, our data show that the prevalence of non-wage amenities tends to be higher in jobs that are accepted by females: the mean number of non-wage amenities at their jobs is 7.40 versus 6.84 for males ($p < 0.01$). However, the correlation between accepted earnings and the number of non-wage amenities at the job is positive, implying that the observed gender earning gaps is unlikely to be driven by compensating differentials.[26]

The two facts that we have documented are robust to dropping earlier cohorts of students.[27] One might be concerned that, as time progresses, there may be systematic recall bias in the timing of acceptance and accepted wage, and that this bias differs by gender. Appendix Figures E2.1 and E2.2 show that the empirical patterns regarding Facts 1 and 2 are broadly similar if we drop the 2013–2015 graduating classes, that is, the cohorts that were surveyed more than a year after graduation.

2.4 Making Sense of the Patterns

Before we move to the model where we argue that gender differences in overconfidence and risk preferences can explain these patterns, we specifically examine whether the observed gender difference in the timing of job acceptance is driven by factors such as gender differences in outside options, expected duration at the job, and family/marriage market considerations.

Gender differences in the outside option. First, the fact that the gender gap in job acceptance timing is largely unaffected by the inclusion of controls for family background (as proxied for by father's and mother's education) implies that gender differences in liquidity constraints are unlikely to be the reason why women systematically accept jobs earlier than men. Indeed, as observed in Table 1, parental education is very similar across gender.

[26] The positive correlation between earnings and non-wage amenities is observed unconditionally as well as conditional on all sets of controls.

[27] It is not uncommon for surveys to ask for retrospective earnings information for jobs that were held in the past – for example, in their survey of University of Chicago MBAs, Bertrand et al. (2010a) ask participants who graduated from the MBA program between 1 to 15 years ago detailed questions (including earnings) about each of the jobs that they had since graduation.

Further, for a subsample of students for whom we have information on student debt, we also find limited gender differences in the likelihood of having any student debt or the amount of debt. Both genders also report similar importance of having a job by graduation (see Figure A.2).

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

Family/marriage market considerations. It is possible that women's differential job search behavior could be influenced by marriage market considerations and expectations about their future labor supply if married. To investigate this possibility, we examine whether women's self-reported probabilities of working full-time or part-time at age 30 are correlated with the timing of job acceptance and find little evidence of a systematic relationship.[28]

Another aspect related to family/marriage market considerations is the possibility that women may choose to accept jobs earlier as they have stronger geographic preferences or face more geographic constraints in their job search. We find little evidence, however, that women are choosing to accept jobs that are closer to their country of birth or Boston relative to men, suggesting that women do not appear to be placing a higher weight on proximity to family or social connections formed at BU in their job search decisions.[29] Additionally, for a subsample of students who graduated in 2019, we specifically asked students whether factors such as proximity to family and partner location played a role in their job search. Interestingly, we find that while close to half of men and women in the sample indicated that their job search decisions were affected by such considerations, women were, if anything, *less* likely to indicate that family proximity and partner location played a role in their job search

[28] On average, women report a 85% probability of working full-time and a 10% probability of working part time at age 30. The correlations between these probabilities and month of job acceptance are both smaller than 0.05. We also find that women's expectations about future labor supply are uncorrelated with accepted earnings or with risk aversion.

[29] Specifically, both genders are similarly likely to accept their first job in the U.S. (see Table 2) and conditional on accepting a job in the U.S., the gender difference in the distance from the geographic center of the state that their first job is located in and Massachusetts is economically small and statistically insignificant.

(51% for men vs. 43% for women, p-value of the difference = 0.224, $N = 242$).

3 Model of Job Search

We now propose a model in which risk-averse males and females search for their first post-graduation job while they are still in school. The model makes a number of key assumptions that we validate empirically using our survey data in Section 4. For the time being, we abstract from gender when we lay out the model, and later introduce parameter heterogeneity when we discuss the model's prediction for the gender gap.

Time t is discrete and students have preferences over consumption given by $u(c) = \frac{c^{1-\iota}-1}{1-\iota}$; students are risk averse. We denote by $\bar{T} > 1$ the date at which graduation occurs; after $\bar{T}$, we assume that agents are infinitely lived.[30] We assume that from dates $\{1, ..., \bar{T}\}$, students with and without a job earn their value of leisure, b, but that starting from date $t > \bar{T}$, individuals with a job earn the agreed upon wage w, while students without a job continue to earn b. Since all students earn b before graduation regardless of whether they have accepted a job, the risk of not having accepted a job by graduation is foregone wages upon graduating from college.

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

Beliefs. To model biases in beliefs, we assume students have an initial ($t = 1$) belief about the mean log offers they will receive, denoted by μ_1. If the true mean log offer is μ^*, then optimistic individuals have beliefs μ_t at date t such that $\mu_t > \mu^*$.[31] To allow for learning and

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

[31] 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 is itself is a function of both job offer 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 and search decisions. In terms of understanding the job search behavior of college students, we elicited potential biases in earnings expectations (rather than job offer distributions or arrival rates directly) since it seems more natural to elicit earnings expectations than beliefs about the job arrival probability. For example, 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, 2021; Arcidiacono et al., forthcoming).

corrections in the bias about the mean log offer, we model a simple learning rule in which beliefs converge to the true value as time progresses:

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

where γ controls the speed at which learning occurs. This implies that individuals enter with beliefs about the mean log offer given by $\mu_t = \mu_1$ which falls to the true μ^* as t increases. As γ goes to ∞, beliefs converge more quickly.[32]

While we assume that beliefs change over time, we maintain the assumption that students are myopic. That is, when making their decisions, they do so under the assumption that the expected offer is the same forever. As such, behavioral choices (reservation wages and search effort) will be chosen under a fixed belief μ; beliefs are only updated ex-post.

3.1 Values of Employment and Unemployment

At dates $t > \bar{T}$. Starting at date $\bar{T}+1$ and for any given belief μ, agents are infinitely lived and therefore the values of employment and unemployment are stationary for a fixed belief μ. The value of employment at wage w for some belief μ can therefore be solved for explicitly:[33]

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

The value of unemployment for any $t > \bar{T}$ and belief μ is:

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

The value of unemployment depends on beliefs μ, since the expectation is taken over the subjective offer distribution $F(w; \mu, \sigma)$. Given some draw for search costs c, students must decide whether or not to search. If they choose not to search ($s = 0$), they receive no offers, whereas if they search ($s = 1$), they receive offers with probability λ. Plugging in $s = 1$ above and comparing the return to the case when $s = 0$, the student with belief μ will search

[32] While this updating rule is somewhat ad-hoc, at the start of job search, it is consistent with Bayesian updating in the special case where $e^{-\gamma(t-1)}$ equals $\frac{1}{1+\zeta_1}$, where ζ_1 is the variance of the individual's prior about mean offers when they start the job search process. While the time-invariant γ assumption restricts the path of ζ_t, we do not have data on prior variances to discipline it anyway.

[33] The value of employment will be independent of beliefs since we do not allow for search on-the-job or job separations. We include μ as an argument in the value of employment for completeness.

if they draw a cost $c \leq c^*(\mu)$ where $c^*(\mu)$ is defined as:

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

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

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

At dates $t \leq \bar{T}$. Before graduation, the employment and unemployment values are not stationary since students' decisions will depend on the time left until graduation. Let $U_t(\mu)$ denote the value of being a student with some beliefs μ who has not secured a job by date $t \leq \bar{T}$. This value can be written as:

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

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

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

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

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

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

$$W_t(\hat{w}_t(\mu), \mu) - U_t(\mu) = 0. \tag{5}$$

3.2 Implications and Comparative Statics

Our explanation for the job search patterns that we observe in the field is that they are driven by gender differences in risk preferences, biases in beliefs, and by learning. While we will show empirical evidence that these factors are systematically related to job search behavior and outcomes in the next section, we first outline how these factors theoretically impact reservation wages and search effort.

Proposition 1. *Ceteris paribus, reservation wages for* $t > T$, $\hat{w}(\mu)$, *are increasing in beliefs* μ, *that is* $\frac{\partial \hat{w}(\mu)}{\partial \mu} > 0$. *Moreover, the cutoff search draw (below which you decide to search) is increasing in* μ, $\frac{\partial c^*(\mu)}{\partial \mu} > 0$. *The same properties hold for reservation wages and cutoff search draws for every* $t \leq T$.

Proposition 2. *Ceteris paribus, reservation wages for* $t > T$, $\hat{w}(\mu)$, *are decreasing in risk aversion* ι, *that is* $\frac{\partial \hat{w}(\mu)}{\partial \iota} < 0$, *and the cutoff search draw is increasing in* ι, $\frac{\partial c^*(\mu)}{\partial \iota} > 0$. *The same properties hold for reservation wages and cutoff search draws for every* $t \leq T$.

The proofs are contained in Appendix Section C. A direct corollary of these propositions is that - all else equal - if women have higher risk aversion, they will have lower reservation wages and higher probabilities of searching for work *at a given point in time*. Importantly, however, if women are relatively less optimistic compared to men then, all else equal, they will search relatively later than men since they view the return to search to be lower. Therefore, while reservation wages for women will be unambiguously lower if they are more risk averse and less overconfident, theoretically the cutoff search strategy can go in either direction since risk aversion and overconfidence push in different directions. Empirically, the data suggest that the risk channel will dominate, and that women will search earlier relative to men in a calibrated model.

What does the model predict will happen as time progresses toward graduation? Since students choose their reservation wages and search cutoffs under myopia, then for a given belief μ, reservation wages fall and search cutoffs rise as time progresses to graduation due to risk aversion, which should affect women relatively more. Additionally, *realized* reservation wages decline and search cutoffs rise as one progresses to graduation because of the finite time horizon and because of learning, which makes individuals less optimistic.[34] Therefore, whether men or women lower their reservation wages and raise their search cutoffs faster depends on the differences in risk aversion and the speed of learning.

We next show these predictions via comparative statics. Specifically, we examine how risk preferences and biases in beliefs affect search behavior in our model.[35] Figure 3 shows how reservation wages and the probability of receiving an offer change with risk aversion ι and initial biases μ_1. Panel (a) shows that, for a given level of risk aversion, the reservation wage declines rapidly as one approaches the graduation date since students want to avoid

[34]Theoretically, the effect on search cutoffs is again ambiguous since the movement toward graduation raises the cutoff while learning leads to less optimism and thus lower cutoffs. Numerically, we have found that the former mostly dominates.

[35]Details on how we numerically solve the model can be found in Appendix F.

ending up without a job by graduation. As agents become more risk averse (moving from blue to black line), reservation wages drop. Higher degrees of risk aversion imply that agents fear the looming graduation date and its corresponding drop in consumption relatively more; therefore, they lower their reservation wages more to avoid ending up with no job by graduation. For the same reason, Panel (c) shows that students raise the cutoff search cost below which they search as risk aversion rises, leading to higher probabilities of searching for a job.

Changes in the bias of beliefs about the mean log offer have different impacts on search behavior. Panels (b) and (d) in Figure 3 show how reservation wages and the likelihood of searching change as the initial bias in beliefs μ_1 varies. First, as shown in Panel (b), as the bias rises (going from black to blue), the overall option value of search rises, as agents believe they face a more favorable offer distribution. Therefore, reservation wages rise since the option value of search rises. Similarly, as the return to search rises, the probability that students search also rises, albeit slightly (Panel (d)).[36]

The numerical comparative statics show graphically what is described in propositions 1 and 2. Given these results, what does the model predict will happen to the gender gap in cumulative accepted wages over time as the same parameters vary? The effect on the overall slope of the gender gap is ambiguous, since it depends jointly on the relative degrees of risk aversion, relative speeds of learning, relative initial biases, gender differences in offer distributions, and the effects these differences have on reservation wages and the distribution of the timing of job acceptance. Importantly, however, we are able to generate an empirically plausible decline in the gender gap over time in our calibrated model, the details of which are in Online Appendix Section F. The model is able to capture this pattern with higher risk aversion for women, differential rates of learning for men and women, and stronger initial biases for men, all patterns that are consistent with our empirical evidence.[37]

4 Field Evidence for Model Mechanisms and Predictions

In this section, we first show empirical support for the underlying model mechanisms. We then show empirical evidence for the model predictions.

[36]The quantitatively small effect of biases in beliefs on the probability of searching is not a model feature generally, but a result of the fact that the mean search cost we use is high, meaning ϕ is very low. This implies a small effect of changes in the cutoff $c^*(\mu)$ on the probability of searching, $1 - e^{-\phi c^*(\mu)}$.

[37]We also allow for differential mean offer distributions, disciplined by offers observed in the data.

4.1 Empirical Support for Model Mechanisms

Gender Differences in Risk Preferences. One of the mechanisms at play here is that women are more risk averse than men. 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. Furthermore, as we will later show, we also find large gender differences in risk aversion in our experiment using the multiple price list elicitation method.

Gender Differences in Belief Biases. 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., the 2017(2018) graduating cohort. Earnings expectations were elicited using the following question: "*We would next like to ask you about the kind of job that you expect to work at when you first start working after graduation. We would like to know how much you expect to make at this job in the first year.*"[38] This question was asked in the baseline survey for the 2018-2019 cohorts. The distributions of earnings expectations for the 2018-2019 cohorts and the corresponding realizations for the previous cohorts (2017-2018) are shown in Figure 4 separately by gender. The distribution of expectations differs statistically by gender ($p < 0.01$). 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 more pronounced for males: 30% of males expect to make less than the previous cohort median, compared to 37% of females.

One might be concerned that the rightward shift of the expectations distribution relative to the realizations distribution of the previous cohort may not necessarily imply an over-optimism bias if students believe that the earnings distributions are non-stationary and are shifting up over time. However, in order to fully explain the different patterns that we observe by gender in Figure 4, student beliefs' about the non-stationarity of the earnings distributions would have to vary systematically by gender.

To provide additional evidence that beliefs are indeed biased, we use data from the 2018-2019 graduating cohorts and compare the distribution of the ex-ante expectations of students with the distribution of their ex-post realizations. This comparison is possible only for a relatively small subset of students who answered both the baseline and final surveys. Figure A.3 plots the two distributions. Consistent with the cross-cohort comparison, on

[38] While this question does not directly ask about expectations about the job offer distribution (which is the object that features bias in our model), we calculate the same concept in the model-generated data and back out an underlying bias about μ^* that is consistent with the data we have on expected earnings.

average, both men and women overestimate their earnings, with men exhibiting a somewhat greater degree of optimism regarding their future earnings outcomes.[39]

At the aggregate level, expectations are clearly biased upwards (Figures 4 and A.3). In some of the evidence for the model predictions, we also use an *individual-level* measure of overoptimism. Specifically, we construct the individual-level proxy of overoptimism as the percent deviation between the earnings expectations and realizations (with positive values indicating that the individual's earnings expectation exceeds her eventual realization).[40] With the caveat that a positive value of this measure does not necessarily imply overoptimism at the individual level, we find that this measure is positive for 54% of the individuals, consistent with the idea that most individuals overestimate earnings. It is worth noting that, in the subsample of individuals for whom we have data on risk preferences and overoptimism ($N = 392$), we find that risk tolerance and overoptimism are uncorrelated ($r = -0.06, p = 0.209$).

Collectively, the evidence we present here strongly indicates that students' beliefs - in particular, those of male students – are systematically biased upwards.[41]

Gender Differences in 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 may update their beliefs at different speeds. Using data on earnings expectations from two time points, once at the beginning of job search and another mid-search, we are able to observe how earnings expectations evolve. Table 5 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 all three surveys (Panel B). The data for both samples paint a similar picture – both men and women revise their earnings expectations downward over time, and the decline in expectations is statistically significant for both genders and samples ($p < 0.05$). However,

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

[40] As shown in Figure A.5, expectations are indeed predictive of future earnings, though the slope is far from one. This is in line with findings by Conlon et al. (2018) and Wiswall and Zafar (2021) who find that ex-ante earnings expectations of workers and college students, respectively, tend to be predictive of ex-post earnings realizations.

[41] 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. To assess whether the observed patterns are driven by misinformation, we compare the distributions of population earnings beliefs, own-earnings expectations of the 2018-2019 cohort, and the distribution of realized earnings of the 2017-2018 cohort. As observed in Figure A.4, both genders appear to underestimate population earnings. This indicates that the bias in own-earnings expectations is more consistent with overoptimism rather than with misinformed beliefs about population earnings.

looking at the consistent sample, we see that men take longer to approach the "truth". By the mid-search survey, both the mean and median women's earnings expectations have largely converged to the observed realizations (we cannot reject that they are the same; $p = 0.739$). By contrast, men's earnings expectations remain, on average, about 10% higher than eventual realizations, a statistically significant difference ($p < 0.05$).

Importantly, since we only elicit expectations about eventual earnings, the observed decline does not provide direct evidence on the speed of learning by gender, since expected earnings should decline even without learning as students lower their reservation wages. However, we construct earnings expectations in our model and use the aforementioned decline in expected earnings as a way to discipline the rate of learning for each gender. While the calibration allows for a zero rate of learning, we end up with positive rates for both genders, consistent with the results from the field.

4.2 Field Evidence for the Model Predictions

Having presented suggestive evidence on the model assumptions and mechanisms, we next provide empirical evidence in support of the key predictions of the model.

Explaining (Gender) Variation in Reservation Earnings According to the model in Section 3.2, risk preferences and overoptimism affect the timing of job acceptance and accepted earnings 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 graduated between 2018 and 2021. Reservation earnings were elicited using the following survey question: "*What would the lowest annual total compensation (including base pay, signing bonus, and bonus pay) have to be for you to accept a job offer?*"[42] The average reservation wage in the sample is $54,441.

The left panel of Figure 5 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 overoptimism, 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). Even for this small sample of students, there is evidence of a significant relationship between higher reservation earnings and greater

[42]This data was collected for a different project that uses the same survey instruments. We do not use the data from the additional cohorts for the other analyses as the 2020 cohort was affected by the pandemic and we have not yet surveyed the 2021 cohort.

optimism in earnings expectations.[43]

Table 6 further shows that there is a clear gender difference in reservation earnings. Women, on average, report reservation earnings that are about \$3,400 less than men, a statistically significant and economically meaningful gap. This difference is reduced to about \$2,000 after controlling for the standard set of individual-level background controls (column 5). Both risk preferences and overoptimism are positively correlated with reservation earnings, as would be predicted by the model as well. More importantly, the inclusion of the survey measure of risk preferences and overoptimism reduces the raw (residual) gender gap by 30% (42%), indicating that both attributes can account for a sizable portion of the observed gender difference in reservation earnings. The decrease in the raw and residual gender gaps after controlling for our psychological attributes is statistically significant at the 5% level. Taken together, these findings lend further support to the model mechanisms.[44]

Explaining (Gender) Variation in Search Timing Our model predicts that individuals who are more risk averse or more overconfident should be more likely to search at a given point in time. However, recall that the numerical simulations of our calibrated model found a much larger role for risk preferences (Figure 3).

The left panel of Figure 6 presents a binned scatterplot of the relationship between the survey measure of risk tolerance (on the x-axis) and the share who start searching before graduation (on the y-axis). We see that a higher willingness to take risk is negatively related with the likelihood of starting the job search process before graduation. The relationship is economically sizable: a 1-point increase in risk tolerance is associated with a 4.4 percentage point lower likelihood of starting job search before graduation. However, contrary to the model predictions of a positive relationship between overoptimism and the timing of starting search, the right panel of Figure 6 shows no (statistical or economic) significant relationship between overoptimism and the timing of starting search in the field data; this result is, however, in line with the model calibrations.

How these traits affect the gender gap in job search timing is investigated in Table 7, where the dependent variable is an indicator for whether the individual starts searching for a job before graduation. Column (1) shows that females are 11.6 percentage points more likely to do so. In column (2), upon controlling for risk preferences, the estimate on the female indicator falls by nearly 2 percentage points (a drop of almost 20% in the gender

[43] Similar patterns are observed when we use logs, as shown in Appendix Figure E1.2.

[44] Our qualitative conclusions are the same if we instead use log reservation earnings. In that case, the raw gender gap is 5.1% ($p < 0.01$). Controlling for both attributes reduces the gender gap to 3.4% ($p < 0.1$). The patterns are qualitatively similar, albeit not statistically significant for the residual log gender gap (see Appendix Table E1.2).

gap). Column (3) shows that controlling for overconfidence (as measured by the percent gap between expected and realized earnings) has little impact on the estimate on the female indicator. Our conclusions are unchanged if we control for both measures simultaneously (column 4), or include other controls (columns 5 to 8).

So what does this mean for the timing of job acceptance? The model predicts that higher risk aversion should lead to early acceptance (because of both lower reservation wages and starting search early). The impact of overconfidence on the timing of acceptance is ambiguous since, on one hand, it would lead to later acceptance due to higher reservation wages but, on the other hand, to earlier acceptance due to earlier start of job search. However, the model calibration suggests that the latter channel is much weaker. Appendix Figure A.6 shows the relationship between timing of job acceptance and risk preferences (Panel A) and overoptimism (Panel B). Panel A shows that, consistent with our model, higher willingness to take risk is positively related with the mean month of acceptance and with the likelihood of accepting a job 6 months or more after graduation. The estimates are economically meaningful but only the latter relationship is statistically significant. Panel B shows that overconfidence is also positively related with timing of job acceptance; however, only the correlation with month of acceptance is statistically significant.

Explaining the Gender Gap in Earnings Finally, what does all this mean for the gender gap in earnings? This is not as simple as regressing realized earnings onto risk preferences and our individual-level measure of overoptimism. That is because naively regressing accepted earnings on the individual-level measure of overoptimism gives a negative estimate that is largely mechanical since overoptimism is defined as (expectations - accepted earnings). We, therefore, turn to other proxies of overoptimism in the data. One potential proxy is perceived relative ability, while another potential proxy is expected total compensation. Neither is perfect, but *conditional* on GPA and other background characteristics, both measures arguably capture some degree of overoptimism. While the measure of perceived relative ability is available for the full sample of students, expected total compensation is only available for the more recent ("current" student) cohorts who were surveyed prospectively. Therefore, the sample size for the latter proxy is considerably smaller. As mentioned earlier, despite similar GPAs, men tend to rate themselves significantly higher in terms of perceived relative ability (Table 1). Gender differences in belief biases have been discussed in the previous section.

The two panels of Table 8 report OLS estimates of regressions where accepted earnings are regressed onto risk preferences and the alternate measures of overoptimism. Focusing on Panel A (which uses perceived relative ability as the proxy for overconfidence), we see that each of risk tolerance and overoptimism can explain at least 20% of the residual gender gap (columns 2 and 3). Inclusion of both variables reduces the gender gap in earnings by about 37%; this is similar in magnitude to the contribution of these variables in explaining the gender gap in reservation wages (Table 6). The last four columns show that the results remain qualitatively similar even if we include controls for job characteristics such as industry fixed effects, weekly hours of work, and job location fixed effects (these controls are all choices, and hence potentially endogenous). In the last column, we find that gender differences in risk preferences and overconfidence can explain approximately 27% of the residual gender earnings gap (net of job characteristics) in accepted offers. The qualitative patterns in Panel B, which uses expected total compensation as a proxy overconfidence, are similar to Panel A.[45]

In short, gender differences in both risk preferences and overconfidence contribute positively to the gender wage gap. Thus, higher overconfidence for men seems to pay off (on average) in terms of earnings. We, however, do find some suggestive evidence that it might have negatively affected wellbeing. In particular, we find that women are more likely to be satisfied with the job search process than men (5.94 vs. 5.50 on a 10-point scale, $p = 0.068$) and report significantly fewer search regrets (40% vs. 51%, $p = 0.018$).[46] Men are also more likely to have rejected an offer that is higher than the one they end up accepting relative to women (14% vs. 11%, $p = 0.099$ in the full sample; 31% vs. 26%, $p = 0.116$ among those who rejected at least one offer). 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.[47]

[45]The results are similar if we use a log specification for earnings instead of levels (see Appendix Table E1.3) or drop earlier cohorts of students who were surveyed more than a year after graduation (see Appendix Table E2.1).

[46]These questions were asked as part of the Survey of Current Students. The specific questions are: *"How satisfied are you with how the job search process went for you? (1: Not satisfied at all; 10: Absolutely satisfied)"* and *"Do you regret not having started looking for jobs earlier, or not applying to certain jobs earlier on?"* The survey instrument also included a question regarding regret for accepting a job too early for a subset of the current students. We find no gender difference in response to this question: roughly 18% of both genders report regret for accepting a job too early.

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

4.3 Other Potential Explanations

Overall, we find strong support for our model predictions. In Appendix B, 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.

5 Experiment

While we collect very rich survey data, it is impossible to rule out all possible confounds in the field - for example, while we present strong suggestive evidence that different outside options, family constraints, and other (unobservable) aspects of the offers, etc., are unlikely to explain the patterns, we cannot entirely rule them out. Thus, we next move to a controlled laboratory setting to investigate gender differences in sequential job search. Our goal is twofold: First, to show that the gendered patterns that we observe in the field also show up in a stylized setting where, by design, other possible confounds are shut down, and second, to show that our favored explanation – gender differences in overconfidence and risk preferences – are indeed driving a large part of these gender differences.

5.1 Design

Our goal is to design a sequential job search experiment that has some inherent uncertainty. The experiment consists of a real-effort task followed by three independent parts. At the end, participants are paid their earnings in one randomly-selected part. The experimental instructions are available in Appendix G. Throughout the instructions, participants had to answer several understanding checks correctly to ensure they understood the specifics of the experiment.

The experiment begins with a real-effort task. Specifically, participants are asked to type 15 text sequences consisting of randomly generated letters as quickly as possible. They are told that the faster they type, the higher their expected earnings will be in the first part of the experiment. They receive no other information at this point to prevent their performance in the typing task to be affected by the characteristics of the subsequent parts. We chose typing as the real-effort task because (1) there is no widely-held gender stereotype concerning typing speeds, (2) there should be substantial heterogeneity in typing speeds across individuals, and (3) it is a familiar task so that participants should have well-informed priors about their typing speed.

After performing the real-effort task, participants move onto to the job search part of the experiment (part one). In this part, participants play the role of a job seeker. They have a maximum of five rounds to find a job. In each round, they receive a job offer consisting of a wage drawn from a discrete distribution ranging from \$2 to \$32 in steps of \$3. At the beginning of each round, participants report the minimum wage that they are willing to accept (the "reservation wage"). Thereafter, they are informed of the wage drawn that round. If the wage drawn is greater than or equal to the reservation wage, then the offer is accepted, the participant earns the drawn wage, and the job search concludes. Otherwise, the participant moves to the next round and again reports a reservation wage. If a wage offer is not accepted by the end of round 5, the participant earns an outside option of \$2 (for other finite-horizon search experiments, see Cox and Oaxaca (1989), and Cox and Oaxaca (1992)).

The participants' typing speed determines the probabilities of drawing wage offers. Specifically, a participant is either a fast typist or a slow typist. Fast typists are more likely to get draws from the right tail of the wage offer distribution. For example, the likelihood of drawing the highest wage offer of \$32 is 6% for a fast typist versus 1% for a slow typist (see Appendix Figure A.7).[48] Participants are told that they will be classified as a fast typist if their typing speed is in the top quartile of the typing speed observed in a different experiment that was conducted with a similar pool of participants who performed the same task. Participants are informed of the probabilities of getting each wage offer conditional on being a fast or a slow typist, but they are not told their type.

At this stage, participants do not know with certainty whether they are a fast typist or not. Thus, in addition to eliciting reservation wages in each round, we elicit the participants' beliefs about their type. Specifically, in the same screen in which they submit the reservation wage, participants indicate the probability that they are a fast typist.[49]

[48] The mean wage offer for fast typists is \$18.62 while that of slow typists is \$11.48. Moreover, the probabilities are chosen such that each wage offer below \$17 is more likely to be drawn by slow typists while each wage offer above \$17 is more likely to be drawn by fast typists. Because of a mis-declared variable, in a third of the observations, wage offers were drawn using the fast-type probabilities in all rounds but the second irrespective of the individuals' actual type. Participants were unaware that this happened and therefore it is not surprising that there are no statistically significant differences in reservations wages between participants who were exposed to this error and those who were not in the first (p-value = 0.331) or any of the subsequent rounds (p-values from 0.106 and 0.939). Nevertheless, in all regressions we control for these observations using a dummy variable.

[49] We did not incentivize beliefs with monetary payments as doing so can distort incentives by introducing hedging opportunities (Blanco et al., 2010). Moreover, incentivizing belief elicitation is often complex (Danz et al., 2020) and could distract participants from their search decisions. The slider used to indicate beliefs is also linked to a calculator tool that provides detailed information about the likelihood of receiving wage offers over the remaining rounds for their given belief. More specifically, participants see two tables. One

After the job search task, we elicit participants' risk preferences as part two of the experiment. Specifically, we use a multiple price list with 12 choices, one of which is then randomly chosen for payment (see Andersen et al., 2006). Each choice consists of selecting between a lottery and a certain payment. The lottery is the same in all choices: 50% chance of getting $30 and 50% of getting zero. The certain payment starts at $6 and increases by a dollar until $17. Participants who are maximizing expected utility should choose the lottery up to a specific certain payment and then switch to choosing the certain payment thereafter. The lower the certain payment at which a participant switches, the more risk averse the participant is.

We also elicited participants' time preferences as part of the experiment (using a similar multiple price list method). We use these data to obtain an individual-level measure of the certainty equivalent of accepting a payment in 4 weeks or 8 weeks vs. today. Perhaps not surprisingly, time preferences end up not mattering for behavior in our setting. While we control for them in the regression analysis below, we do not report their estimates. At the end of the experiment, we also collected basic demographic and academic data, including gender, race, parental income, SAT scores, high school ranking, GPA, and major.

Before discussing the implementation, it is worth discussing some important features of the job search experiment. In a real job market, a job seeker might be uncertain about their type or the labor market. Just like in the field, job seekers in the experiment are uncertain about their relative ability, which influences the wage offer distribution they face. Moreover, participants in the experiment can also learn and update their beliefs about their type with each new wage offer. Unlike the field, in the experiment there is no uncertainty about receiving an offer every round and receiving an offer does not depend on one's search effort. Since females tend to be more risk averse (Croson and Gneezy, 2009), we believe that shutting down these additional sources of uncertainty in the experiment provides a lower bound on the gender gaps in job search behavior. Another aspect that is shut down in the lab experiment, by design, is that job seekers do not have to decide whether to search or not. Thus, we cannot replicate the job search timing results from the field in the lab.

Finally, our experiment has several advantages over the field. By design, the offer distribution is constant over time (that is, across the five rounds), and other characteristics of the job play no role. The outside option is the same for all participants. Moreover, in terms of measurement, we observe an individual's actual ability (i.e., their typing speed), and have

table shows the probability of receiving each wage offer at least once in the remaining rounds. The other table shows, for each wage offer x, the probability of receiving a wage offer $y >= x$ in the remaining rounds. Participants can see how these computed probabilities change as they input different beliefs of being a fast typist. We provide this information to increase the understanding of the task and reduce mistakes due to calculation errors and to give participants an incentive to think carefully about their beliefs.

incentivized measures of risk aversion and reservation wages. Finally, our setup allows us to construct precise individual-level measures of overconfidence.[50]

Optimal reservation wage policies in this setting decline over time. In the last round, the reservation wage should be \$2 (that is, the same as the outside option). The evolution of optimal reservation wages across rounds depend on one's risk aversion and beliefs about being a fast typist. In line with our model in Section 3,[51] individuals with higher risk aversion have a lower optimal reservation wage in round 1. For instance, assuming a prior belief of 0.25 of being a fast typist, Bayesian updating, and a CRRA utility specification, a risk neutral individual has an optimal reservation wage of \$23 in round 1. On the other hand, an individual with a risk aversion parameter of 0.5 (a value close to the average we find in our sample) has a round 1 optimal reservation wage of \$20. Likewise, higher beliefs of being a fast typist imply higher optimal reservation wages. Consider an individual with a risk aversion parameter of 0.50 (again, assuming a CRRA utility specification and Bayesian updating). Her optimal reservation wage in round 1 is \$20 with a prior of zero of being a fast typist. On the other hand, her optimal reservation wage is \$23 (\$26) if her prior belief of being a fast typist is 0.5 (1.0).

5.2 Administration and Basic Statistics

The experiment was programmed in LIONESS Lab (Giamattei et al., 2020) and conducted online during March and April 2020 with Arizona State University (ASU) undergraduate students. Our invitation email went to all students in the Honors College and a subset of students of the broader student body (based on a random list of undergraduate students provided by the Registrar's Office). Students were able to complete the experiment at any time during a one-week period. Compensation was in the form of an Amazon gift card. Average (median) compensation was \$18.32 (\$20), including a \$5 show-up fee.

Our sample consists of 346 students, of whom 147 (42%) are males.[52] As shown in Appendix Table A.10, males and females in our sample are similar along most dimensions. Males, however, are substantially more likely to major in Engineering/Computing, while females are more likely to major in Humanities. We also see that the parental education of male students is higher. In the analysis below, we will control for these differences in

[50] Our lab design uses an arguably gender-neutral effort task. Whether the lab results hold up in settings that have a gender stereotype associated with them is not clear.

[51] The model arguments in Section 3 also apply to this setting. However, in this case, we have a finite horizon and can solve the model by backward induction.

[52] The actual sample size is much larger (1858 students). However, this includes different treatments designed to evaluate how job search behavior and gender gaps change with different policies. Since that is not the goal here, we only present the results for the baseline treatment. These treatments are analyzed in (Cortes et al., 2022).

observables. Relative to the ASU population, the experimental sample is disproportionately female, Asian, White, has lower family income, has higher ACT scores, and are more likely to major in business/economics and computer science/engineering. Although the experimental sample is selected, importantly for our purposes, as indicated in the last column of Appendix Table A.10, the gender difference in the various observable characteristics are typically not statistically different across the experimental and ASU population samples.[53]

As in the field data, we find that females are substantially more risk averse than males. We assume students have a standard CRRA utility function and use each student's choices in the risk elicitation task to calculate their coefficient of relative risk aversion (ι). More specifically, we use as certainty equivalent (CE) the midpoint between the first certain payment chosen by the students and the certain payment offered just before.[54] Given the \$5 show-up fee, student i's value of ι_i is such that $(5+CE)^{1-\iota_i}/(1-\iota_i) = \frac{1}{2}35^{1-\iota_i}/(1-\iota_i) + \frac{1}{2}5^{1-\iota_i}/(1-\iota_i)$. We find that for the vast majority of students (95%) the coefficient of relative risk aversion is positive, suggesting the presence of risk aversion. Women's mean ι is much larger than men's: 0.70 vs. 0.49 ($p < 0.001$). This gender gap in risk aversion is consistent with the literature on risk preferences using monetary incentives (e.g., Eckel and Grossman, 2002; Eckel and Grossman, 2018; Croson and Gneezy, 2009), as well as our results from the field.

We next turn to beliefs about being a fast typist that are reported at the beginning of the first round. The mean belief of men of being a fast typist is 59 percent, 9.1 points higher than the mean women's belief (gender difference p-value = 0.001). Since students would have had to score in the top quartile of the typing distribution, it is obvious that both genders vastly overestimate their probability of being a high type. In our sample, only 20% of men and 14% of women end up being fast typists.[55] While this gender difference is not statistically significant ($p = 0.141$), on average, men tend to be faster typists. Hence, in our analysis, we will control for actual ability. Note that the gender gap in prior beliefs remains large and significant even after we control for performance (it narrows from 9.1 to 7.7 percentage points; p-value of the gender difference = 0.003). This gender gap in beliefs is consistent with the literature showing that men are more overconfident than women (Barber

[53] The only exception is that the share of sophomores who are female is lower in the experimental sample than in the underlying ASU population.

[54] We use a CE of \$5.50 for students who always chose the certain payment and of \$17.50 for those who always chose the lottery. However, our analysis is not sensitive to these parameterizations. 12% of the students switched more than once between the lottery and the certain payment. There is no consensus about what causes multiple switching or on how to treat these observations (Charness et al., 2013b). In the analysis shown here, we calculate ι for these observations based on the certain payment of the first switch. However, out results are unaffected if these observations are dropped or if we use the number of lottery choices as an alternative measure of risk aversion.

[55] The share of fast typist is less than 25% because the sample of students we use as benchmark came from a different university (Boston University) that happened to have faster typists.

and Odean, 2001; Niederle and Vesterlund, 2007), and with our field evidence where we see that men's beliefs about the offers are substantially higher than ex-post realizations.

5.3 Job Search Results

We start with the analysis of the reservation wages. After all, the other outcomes in the experiment are all a direct consequence of the submitted reservation wages. Moreover, this is the same mechanism that is operational in our model in Section 3, where we argue that women have lower reservation wages. Panel A of Figure 7 shows that the average reservation wages for both genders decline over time.[56] The average reservation wage is higher for men in each round (and statistically different from that of females in the first three rounds, p-values < 0.013). Moreover, the gender gap in reservation wages declines over time. In the first round, the average male (female) reservation wage is \$20.61 (\$17.44). This \$3.17 gender gap, which is both economically and statistically significant, halves to about \$1.60 in round 5 ($p = 0.312$). One needs to be careful when interpreting changes across rounds because of dynamic selection across rounds, which can differ by gender. Therefore, panels B and C of Figure 7 restrict the sample to the set of respondents who make it to rounds 4 and 5, respectively. As can be seen, the results are qualitatively similar even when we look at these subsamples.[57]

Panel A of Appendix Figure A.8 shows that women are more likely to accept a wage earlier. The average round of acceptance for women is 2.4 compared to 2.8 for men ($p = 0.016$). In round 1, 43% of women accept an offer versus 33% of men ($p = 0.061$). This 10 percentage point gender gap in acceptance increases to 13 percentage points by round 3 ($p = 0.009$). This is consistent with the patterns we observed in the field (Figure 1).

Next, Panels (b) and (c) of Appendix Figure A.8 show the cumulative mean accepted

[56] While reservation wages do decline over rounds, it is puzzling that the decline is not sharper. Particularly, in the final round a rational agent should not report a reservation wage of more than \$5, which is the next highest value in the offer distribution above the \$2 outside option. As mentioned before, students had to answer several understanding checks correctly to participate in the job search experiment, so it is unlikely that this is driven by lack of understanding of the experimental instructions. In addition, we find that students who make it to the final round and report a reservation wage of more than \$5 do not have lower ACT scores and GPA than their counterparts, further suggesting that this is not due to lack of understanding. This behavior has also been observed in other search experiments with finite horizons (e.g., Marcu and Noussair, 2018). A potential rationalization is that this behavior is driven by pride (see Strack and Viefers, 2019).

[57] Moreover, consistent with the model predictions, we find that, all else equal, individuals who are more risk averse report larger declines in reservation wages. In addition, individuals who report larger downward revisions in beliefs about their typing speed also report larger declines in reservation wages. Note that because of dynamic selection across rounds, the fact that those who are more risk averse and less overconfident start off with lower reservation wages, and the finite horizon nature of the job search experiment, it is not straightforward to map these predictions to what would happen to the evolution of the gender gap in reservation wages over time.

wage by gender among those who accepted a wage by round 5 and the cumulative mean final wage by gender for the full sample. A direct consequence of the higher reservation wages of men is that they have a higher cumulative accepted wage in the earlier rounds. Among those who accepted a wage by round 5 in Panel (b), we do not observe a gradual closing of the gender gap in cumulative accepted wages. In Panel (c), however, including those who did not accept a wage offer by round 5 and were assigned the outside wage of $2 closes the gender gap in final wages. This is largely because men are more likely to be still seeking an offer in round 5 and are overrepresented among those who are assigned the low outside wage. We argue that, unlike the field patterns, we do not observe a gradual closing of the cumulative gender gap in accepted wages in the lab setting largely because we use a discrete offer distribution. In fact, if we simulate the experiment using a continuous offer distribution, where the continuous distribution is a log-normal fitted to our discrete distribution (but using the same reservation wages), we are able to generate a similar gradual decline in the gender gap (see Appendix Figure A.9).

Next, we turn to an investigation of how much gender differences in risk preferences and overconfidence – the mechanisms that we argue are driving behavior in the field – matter for the gender gap in reservation wages as well as accepted wages in the lab. We focus on the reservation wage reported in the first round, since in later rounds, the selection by gender differs.

We start by regressing the round 1 reservation wage on a female indicator in column (1) of Table 9, controlling for whether the student is a fast typist. The gender gap is $3.05, almost identical to the gender gap in the raw data. Controlling for the risk aversion parameter in column (2) reduces the gender gap by $0.51 (about 16%); not surprisingly, individuals who are more risk averse (i.e., a higher CRRA parameter) have a lower reservation wage. Column (3) investigates the role of beliefs: individuals with a higher prior have a higher reservation wage. Controlling for the prior belief reduces the gender gap in the reservation wage by nearly a quarter. Column (4) shows that controlling for both risk preferences and beliefs can explain about a third of the gender gap in reported reservation wages. The last four columns of Table 9 show that our qualitative conclusions are unchanged if we flexibly control for a rich set of demographics. Turning to accepted offers, as shown in Appendix Table A.6, we find that among those who accepted a wage offer by round 5, controlling for risk preferences and prior beliefs reduces the baseline and residual gender gap in accepted offers of $1.40 by about 50% (this decrease is significant at conventional levels).[58]

[58]For the regressions examining the gender gap in accepted wages, we condition the sample on those who accepted a wage offer by round 5 as individuals with reservation wages above the wage offer in the last round are all assigned the same outside wage of $2. Because the outside wage is the same for everyone, and men are more likely to be in the situation where they are assigned the outside wage, this tends to (mechanically)

Another implication of such gender differences in job search behavior is that we would expect men to be overrepresented in the tails of the wage distribution. This is exactly what we find – the proportion of men who end up with very high accepted offers ($26 or more) is 23%, versus 14% of females (p-value of difference = 0.025). Likewise, the proportion of men who end up with very low final wages ($5 or less) is 16% versus 9.5% for women (p-value of difference = 0.068). As shown in Appendix Table A.7, gender differences in risk preferences and beliefs can account for a significant proportion of the observed overrepresentation of men in the tails of the wage distribution.

Part of our story here is that overconfidence can be costly. Corroborating this, we find that 14% of individuals end up with an accepted wage offer that is lower than an offer in a prior round (which was rejected earlier due to a high reservation wage in that round). Again, consistent with the field data, we find that this likelihood is substantially higher for men: 19% of them end up in such a situation, versus 10% of females (p-value of gender difference = 0.021). In line with the proposed mechanisms, men's greater risk tolerance and overconfidence relative to women can partially account for this observation (see Appendix Table A.8).

These results demonstrate that the mechanisms that we argue are playing a role in job search behavior in the field also manifest themselves in a statistically and economically meaningful way in our lab setting. Interestingly, even in this setting, our measures of risk preferences and overconfidence do not fully explain the gender difference in reservation or accepted wages. We believe this might be due to two factors. First, our measure of risk preferences might not capture all the relevant aspects of decision-making under risk in the experiment. There is increasing evidence of gender differences in loss aversion (Chapman et al., 2019), high-order risk preferences (Schneider and Sutter, 2021), ambiguity aversion (Borghans et al., 2009), and negative reciprocity (Falk and Hermle, 2018) which could be contributing to the gender gap in reservation or accepted wages.[59] Second, there is measurement error in the elicited beliefs and risk preferences. Accounting for measurement error could potentially allow us to explain a significantly larger part of the gender gap, both in the lab and field (Gillen et al., 2019); however, doing so would require multiple elicitations of the underlying quantities, which was simply not feasible for us.

In sum, the lab setting replicates our findings from the field, and provides direct evidence for the mechanisms that we believe are partly driving gender differences in labor market

shrink the gender gap in final wages at the end of the experiment (in the full sample, the female-male gender gap in final wages is $0.41 and not statistically significant, see Panel (c) of Appendix Figure A.8).

[59]While including experimental tasks to measure these differences would be interesting, we opted not to do so because it would make the experiment considerably more complex and time consuming, which is problematic in online settings.

search behavior and outcomes. Since our experiment abstracts from uncertainty along other dimensions (such as the likelihood of receiving an offer), we believe that the experimental estimates provide a lower bound for the role of risk preferences and beliefs in job search.

6 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 particular at the early career stage. In this paper, using rich survey and lab experimental data, we document novel facts about the job search behavior of male and female college graduates in the entry labor market.

Using survey data on job search behavior of business undergraduate majors, we find that women accept jobs earlier than comparable men and the cumulative gender gap in accepted offers declines over the job search period. Furthermore, we provide evidence that men's greater degree of risk tolerance and overconfidence relative to women play a role in explaining the observed gender differences in reservation wages, job search and acceptance timing, and the resulting gender earnings gap.

While our field data are unusually rich, we acknowledge that based on the observational data, we cannot entirely rule out some of the confounds/alternative explanations. To lend further credibility to the field evidence and to provide direct evidence on the underlying mechanisms, we then design a lab experiment of sequential job search. Consistent with the field data, we find that females report lower reservation wages, and hence accept jobs significantly earlier. Not only can we replicate the field evidence in our stylized lab setting, we also find strong evidence of gender differences in risk preferences and overconfidence explaining a non-trivial part of the gender gap. Our lab results are also more general in the sense that they are based on a representative sample of college students (opposed to the field evidence that comes from business undergraduates).

We believe that our results have implications for sequential job search with exploding offers, a setting that mimics the initial job search for college students. By highlighting that gender differences in psychological attributes affect how female and male students search for jobs and impact their early career earnings, we offer a novel explanation for gender gaps among the highly-skilled. While our field analysis focuses on the point of entry in the labor market, understanding disparities in the initial conditions is important since they tend to have long-lasting effects on workers (Rothstein, 2019).

Our findings suggest that policies aimed at reducing biased beliefs, especially that of men, can lead to 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 though, the general equilibrium consequences are not clear. 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, although this could worsen the gender gap at graduation.

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, and do not take a stand for why that may be the case. Survey evidence suggests that this could partially be because men and women gather information differently (e.g., Table 2 shows that men are more likely to rely on referrals, and women find the career center more useful). Future work that tries to understand the origins and persistence of such biases would be valuable.

References

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

Andersen, Steffen, Glenn Harrison, Morten Lau, and Elisabet Rutstrom, “Elicitation using multiple price list formats,” *Experimental Economics*, 2006, *9* (4), 383–405.

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

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

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

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

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

Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet, “Gender Differences in Job Search: Trading off Commute Against Wage,” *Quarterly Journal of Economics*, 2020, *136* (1), 381–426.

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

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

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

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

_ , _ , and _ , "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors," *American Economic Journal: Applied Economics*, 2010, *2* (3), 228–255.

Blanco, Mariana, Dirk Engelmann, Alexander K. Koch, and Hans Theo Normann, "Belief elicitation in experiments: Is there a hedging problem?," *Experimental Economics*, December 2010, *13* (4), 412–438.

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

Borghans, Lex, Bart H Golsteyn, James J Heckman, and Huub Meijers, "Gender Differences in Risk Aversion and Ambiguity Aversion," *Journal of the European Economic Association*, 2009, *7* (2-3), 649–658.

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

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

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

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

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

Chapman, Jonathan, Erik Snowberg, Stephanie Wang, and Colin Camerer, "Loss Attitudes in the U.S. Population: Evidence from Dynamically Optimized Sequential Experimentation (DOSE)," Working Paper, New York University Abu Dhabi 2019.

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

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

— , — , and — , "Experimental methods: Eliciting risk preferences," *Journal of Economic Behavior & Organization*, 2013, *87* (C), 43–51.

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

Cortes, Paricia, Jessica Pan, Laura Pilossoph, Ernesto Reuben, and Basit Zafar, "Sequential Job Search Under Counterfactual Regimes: Evidence From the Laboratory," *Working Paper*, 2022.

Cox, James C. and Ronald L. Oaxaca, "Laboratory Experiments with a Finite-Horizon Job-Search Model," *Journal of Risk and Uncertainty*, 1989, *2* (3), 301–329.

— and — , "Direct Tests of the Reservation Wage Property," *Economic Journal*, 1992, *102*, 1423–1432.

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

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

Danz, David, Lise Vesterlund, and Alistair J Wilson, "Belief Elicitation: Limiting Truth Telling with Information on Incentives," Working Paper 27327, National Bureau of Economic Research June 2020.

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

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

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

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

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

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

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

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

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

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

Falk, Armin and Johannes Hermle, "Relationship of Gender Differences in Preferences to Economic Development and Gender Equality," *Journal of Political Economy*, 2018, *362* (6512), eaas9899.

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

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

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

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

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

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

Fluchtmann, Jonas, Anita M. Glenny, Nikolaj Harmon, and Jonas Maibom, "The Gender Application Gap: Do Men and Women Apply for the Same Jobs?," Working Paper 2020.

Giamattei, Marcus, Kyanoush Seyed Yahosseini, Simon Gächter, and Lucas Molleman, "LIONESS Lab: a free web-based platform for conducting interactive experiments online," *Journal of the Economic Science Association*, 2020, *6* (1), 95–111.

Gillen, Ben, Erik Snowberg, and Leeat Yariv, "Experimenting with Measurement Error: Techniques with Applications to the Caltech Cohort Study," *Journal of Political Economy*, 2019, *127* (4), 1826–1863.

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

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

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

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

Marcu, Emanuel and Charles Noussair, "Sequential Search with a Price Freeze Option - Theory and Experimental Evidence," *SSRN Electronic Journal*, 2018.

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

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

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

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

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

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

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

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

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

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

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

Schneider, Sebastian O. and Matthias Sutter, "Higher Order Risk Preferences: Novel Method, New Measures, Determinants and Field Behavior.," Discussion Paper, Max Planck Institute for Research on Collective Goods 2021.

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

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

Steel, Piers, "Arousal, Avoidant and Decisional Procrastinators: Do They Exist?," *Personality and Individual Differences*, 2010, *48* (8), 926–934.

Strack, Philipp and Paul Viefers, "Too Proud to Stop: Regret in Dynamic Decisions," *Journal of the European Economic Association*, 12 2019, *19* (1), 165–199.

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

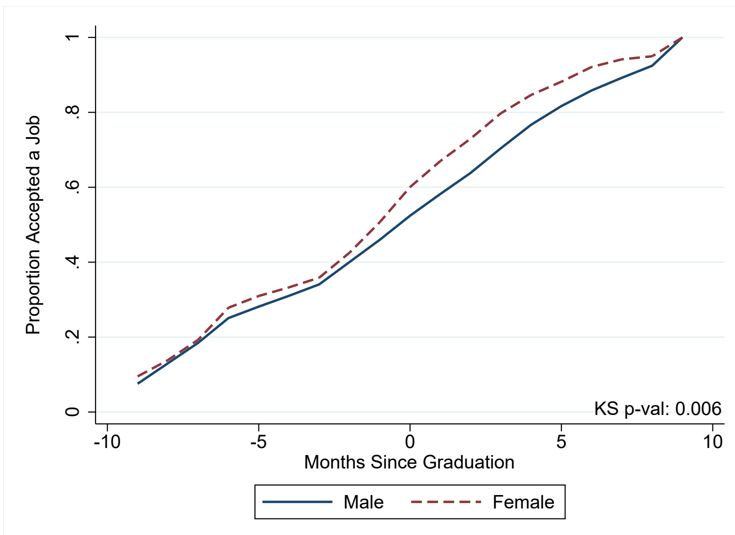
Wee, Shu Lin, "Delayed learning and human capital accumulation: The cost of entering the job market during a recession," 2016. Unpublished manuscript.

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

_ **and** _ , "Human Capital Investments and Expectations about Career and Family," *Journal of Political Economy*, 2021, *129* (5), 1361–1424.

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

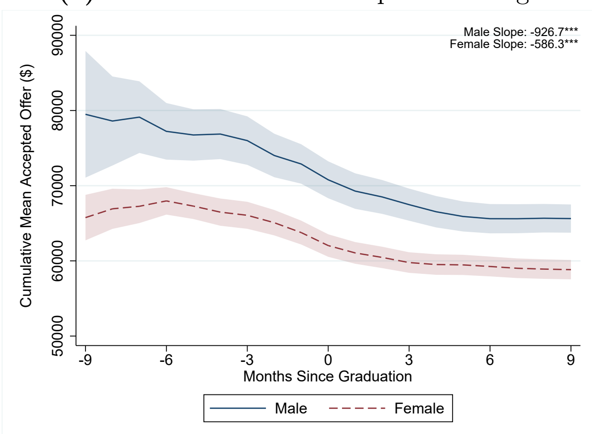
Figure 1: CDF of Job Acceptance Timing, By Gender



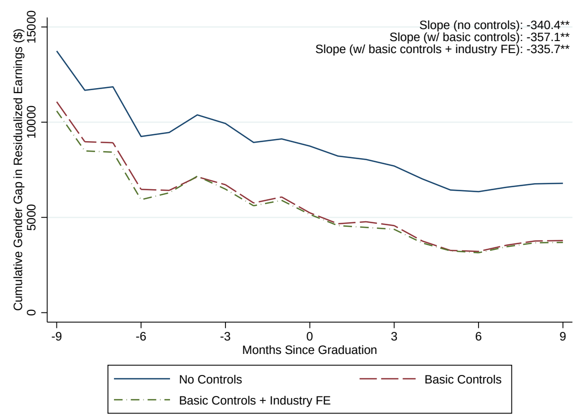
Note: This figure plots the proportion of males and females who accepted a job in each month relative to the month of graduation (indicated as 0). Months since graduation = 9 and -9 includes individuals who accepted a job 10 or more months after or before graduation, respectively.

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

(a) Cumulative Mean Accepted Earnings

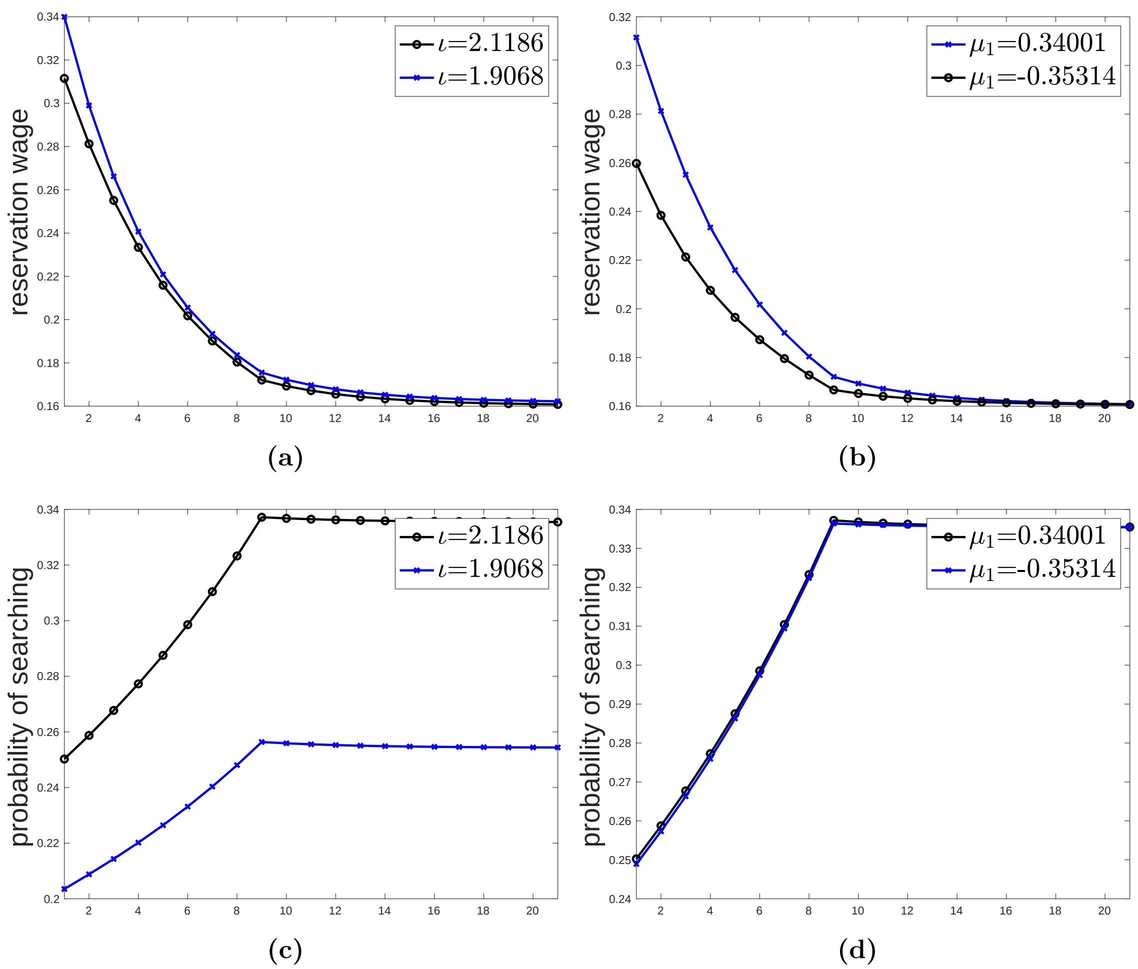


(b) Cumulative Gender Earnings Gap (M-F)



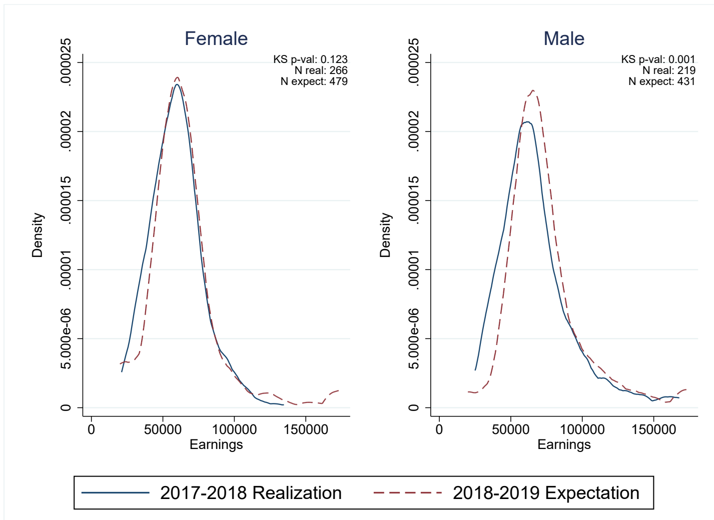
Note: Months since graduation is defined relative to the month of graduation (indicated as 0). Panel (a) plots the cumulative mean accepted earnings as a function of months since graduation separately for males (solid blue line) and females (dashed red line). The cumulative mean accepted earnings at a given point in time is constructed as the mean of the first-job accepted earnings among those who have accepted a job up to that point. The 95% confidence interval bands are based on bootstrapped standard errors. Panel (b) plots the cumulative gender gap in mean accepted earnings as a function of months since graduation. The cumulative gender earnings gap is defined as the difference between the cumulative mean accepted earnings of men and women at a given point in time. The solid line plots the unconditional cumulative gender earnings gap, while the two dashed lines plot the cumulative gender gap in earnings that have been residualized of (1) basic controls that include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education (red line) and (2) basic controls plus industry fixed effects (19 groups) (green line). Earnings are expressed in 2017 dollars.

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



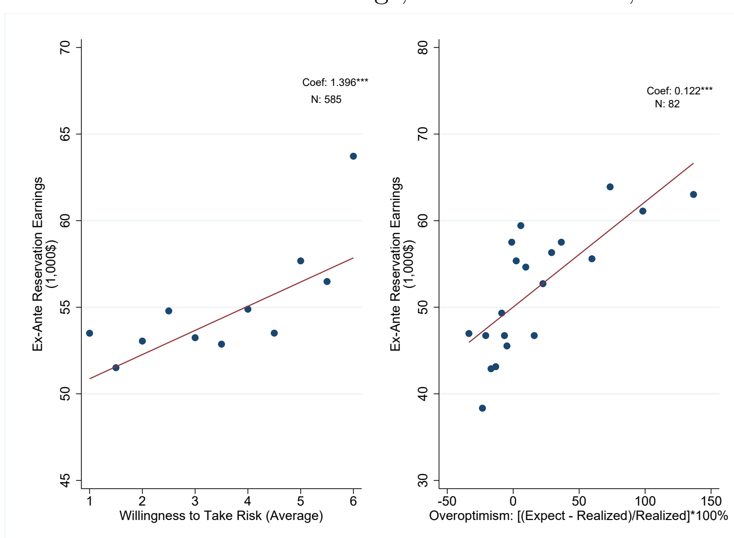
Note: This figure shows how reservation wages (Panels a and b) and the probability of searching (Panels c and d) change over the job search period as risk aversion varies (left two panels) and biases vary (right two panels). The scale on the x-axis (in months) matches the timing in the model, where the graduation date is set to $\bar{T} = 10$ and the model begins at $t = 1$, 9 months before graduation. For these numerical exercises, we use the estimated parameter values for males; ι and μ_1 vary around their respective estimated male values as depicted above.

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



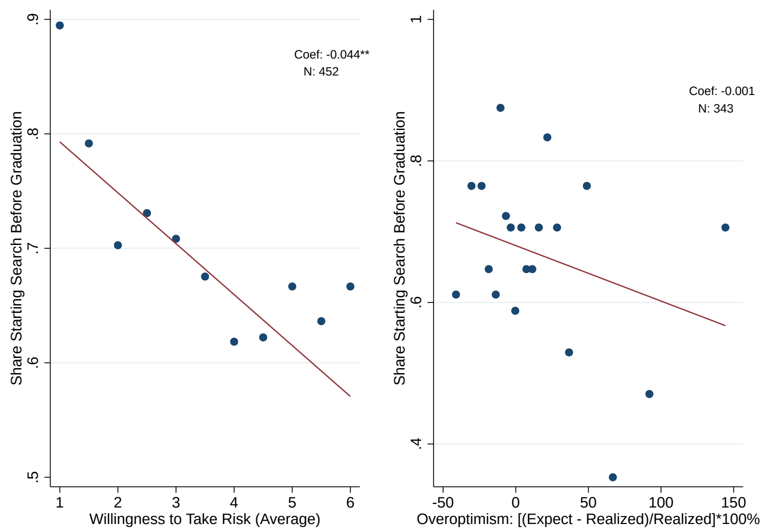
Note: The distribution of expected earnings is constructed based on the earnings expectations reported by students from the 2018-2019 graduating cohorts. Earnings expectations were elicited during the in-class survey that was conducted in the senior or junior year. The distribution of realized (actual)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

Figure 5: Ex-Ante Reservation Earnings, Risk Preferences, and Overoptimism



Note: This figure is a binned scatter plot of reported ex-ante reservation earnings (expressed in 2017 dollars) from the in-class survey on risk preferences (left panel) and overconfidence (right panel). For risk preferences, we use all available data from students who completed the in-class survey and answered the reservation earnings question. These students are expected to graduate between 2018 and 2021. For overconfidence, we are limited to students for whom we have data on earnings expectations and realizations. To account for outliers, we winsorize the top and bottom 2.5% of reservation earnings and the overconfidence measure. We also restrict the sample to students with reservations earnings above $20,000 and whose reported reservation earnings are lower than their expected earnings.

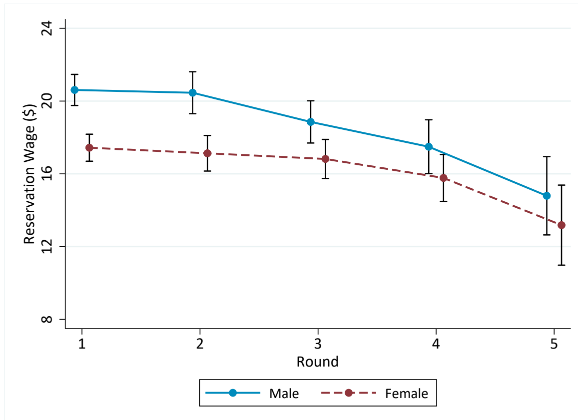
Figure 6: Timing of Search, Risk Preferences, and Overoptimism



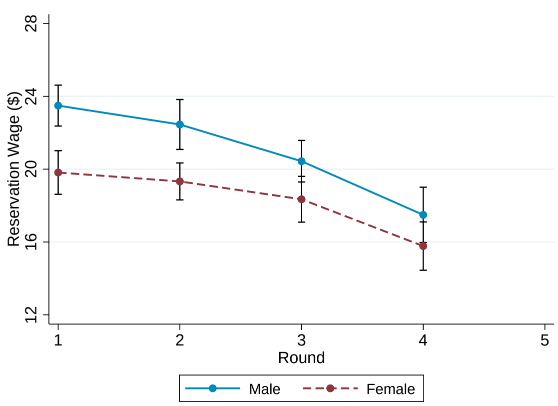
Note: This figure shows binned scatter plots of share of students starting search before graduation on the survey measure of risk preferences (left panel) and the individual-level measure of the extent of biased beliefs (i.e. overoptimism). The willingness to take risks is the average of two survey questions 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. The overoptimism measure 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 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 7: Job Search Experiment – Mean Reservation Wage in Each Round by Gender

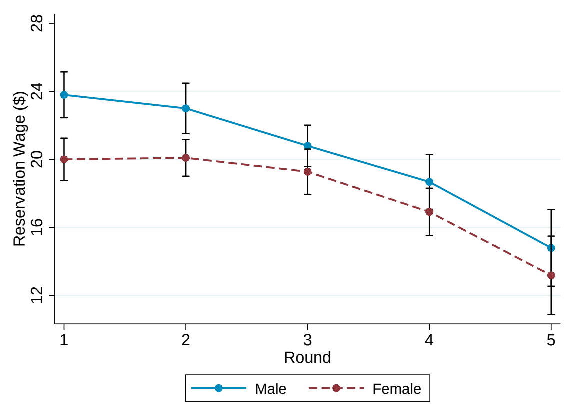
(a) All Participants



(b) Participants who Reach Round 4 ($N = 104$)



(c) Participants who Reach Round 5 ($N = 67$)



Note: Panel (a) plots the mean reservation wage among participants in the job search experiment who are still searching in a given round (i.e. have not accepted a wage) separately for males (solid blue line) and females (dashed red line). Panel (b) is similar except that the sample is restricted to the 104 participants (55 males and 49 females) who reach round 4 (i.e. those who have not accepted a wage by round 4). Panel (c) restricts the sample to the 67 participants (34 males and 33 females) who reach round 5 (i.e. those who have not accepted a wage by round 5).

Table 1: Sample Characteristics of Graduates

	All	Men	Women	p-value
Observations	1358	622	736	
Age	22.58	22.78	22.42	0.001
	(2.00)	(2.04)	(1.95)	
White/Caucasian	50.9%	53.6%	48.7%	0.075
Black/ African American	4.3%	3.2%	5.2%	0.077
American Indian	0.4%	0.6%	0.1%	0.124
Hispanic/ Latino	11.2%	10.6%	11.7%	0.521
Asian/ Pacific Islander	33.2%	32.0%	34.3%	0.370
Born in U.S.	75.3%	76.4%	74.3%	0.384
Father BA+	78.0%	80.2%	76.1%	0.278
Mother BA+	74.4%	74.3%	74.5%	0.959
GPA	3.32	3.31	3.33	0.204
	(0.34)	(0.35)	(0.33)	
Concentration:				
Accounting	17.1%	18.8%	15.6%	0.120
Entrepreneurship	3.8%	4.7%	3.0%	0.106
Finance	50.4%	65.4%	37.8%	0.000
General Management	2.7%	2.7%	2.7%	0.986
International Management	5.9%	2.1%	9.1%	0.000
Law	9.3%	7.2%	11.0%	0.017
Management Info. Systems	19.0%	20.4%	17.8%	0.221
Marketing	26.2%	13.8%	36.7%	0.000
Operations & Tech. Mgmt.	10.9%	9.8%	11.8%	0.236
Organizational Behavior	3.9%	1.9%	5.6%	0.001
Cohort:				
2013	11.0%	11.3%	10.7%	0.760
2014	10.6%	11.4%	9.9%	0.373
2015	10.5%	10.1%	10.7%	0.717
2016	14.9%	17.2%	13.0%	0.032
2017	14.5%	14.0%	14.9%	0.618
2018	21.2%	21.2%	21.2%	0.991
2019	17.3%	14.8%	19.4%	0.024
Perceived Relative Ability (1-5)	3.90	4.01	3.79	0.000
	(0.81)	(0.84)	(0.76)	
Risk Tolerance (1-6)	3.48	3.83	3.19	0.000
	(1.22)	(1.20)	(1.15)	
High Risk Tolerance (≥ 5)	15.3%	22.8%	9.0%	0.000

Note: The last column reports the p-value of the test of equality of means across gender. "Risk Tolerance" is the average of the responses to two questions on self-reported willingness to take risks regarding financial matters and daily activities. The responses to both questions have been re-scaled to be between 1 and 6, with 1 indicating low willingness to take risks and 6 indicating a very high willingness to take risks. "High Risk Tolerance" is a dummy variable indicating a value of 5 or 6 on the risk tolerance measure. "Perceived Relative Ability" is based on the following question where respondents were asked, on a 5-point scale (increasing in perceived ability): *"Relative to your peers with the same concentration in BU, how would you rate your ability?"*

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

	All	Men	Women	p-value
Observations	1358	622	736	
First Job in U.S.	94.9%	94.2%	95.5%	0.288
Currently Employed Full-Time	94.4%	94.2%	94.6%	0.778
Industry:				
Accounting	9.4%	7.4%	11.0%	0.023
Advertising/Marketing	8.9%	5.3%	12.0%	0.000
Consulting Services	12.7%	13.3%	12.1%	0.490
Cons. Products/Retail	9.4%	5.6%	12.5%	0.000
Entertainment Media	1.9%	1.8%	2.0%	0.718
Financial Services	24.3%	30.7%	18.9%	0.000
Government/Education	2.4%	2.7%	2.2%	0.505
Health	3.2%	2.7%	3.7%	0.332
Other	27.7%	30.3%	25.6%	0.054
First Year Total Pay	\$61,711	\$65,352	\$58,634	0.000
	(20,840)	(23,567)	(17,659)	
Current Job Total Pay	\$66,962	\$72,186	\$62,689	0.000
	(27,890)	(33,201)	(21,752)	
Interned for First Job	28.7%	29.3%	28.1%	0.624
Referral Helped Get Job	25.2%	31.0%	20.9%	0.009
Month Accept Offer	-0.47	0.02	-0.89	0.006
	(6.00)	(6.26)	(5.73)	
Accept Job Before Grad	56.6%	52.4%	60.1%	0.005
Accept Job within 6 mo. of Grad	89.2%	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	0.649
	(0.95)	(0.95)	(0.95)	
Rejected Any Offer	42.6%	43.4%	42.0%	0.597
Search Behavior (2018/2019 cohorts only)[a]				
Observations	452	193	259	
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 Under-Qualified for	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)	

Note: [a]Variables in this panel were collected in the post-graduation survey and refer to the entire job search period. The last column reports the p-value of the test of equality of means across gender. Earnings measures are expressed in 2017 dollars.
"Accept Job Before Grad" is a dummy variable indicating the respondent had accepted a job offer before graduation. "Month Accept Offer" and "Month Start Active Job Search" are defined relative to the month of graduation (indicated as 0). "Time Given to Consider" is the deadline in weeks that the employer gave the respondent to accept or reject an offer. "Referral Helped Get Job" is a dummy variable indicating that a referral helped the respondent get their first job. "Usefulness of Career Center in Search" is based on the question of how useful the career center was in helping the respondent get their first job on a 1 (not useful at all) to 5 (extremely useful) scale. "Proportion of Jobs Under-qualified" is based on the reported answers to the survey question: *"Of the jobs that you applied for, what proportion of jobs (out of 100) did you feel: (1) You were over-qualified for, (2) You had the right qualifications for, and (3) You were underqualified for."*

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	1.226***	1.287***	1.240***	-0.905***	-1.125***	-0.837**
	(0.067)	(0.078)	(0.079)	(0.328)	(0.331)	(0.328)
Basic Controls		X	X		X	X
Industry FE			X			X
Mean	0.892	0.892	0.892	-0.473	-0.473	-0.473
R^2				0.006	0.157	0.202
N	1358	1358	1358	1358	1358	1358

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: Relationship Between Cumulative Gender Earnings Gap and Month Since Graduation

	Dependent Variable: Cumulative Gender Earnings Gap			
		Residualized of:		
	No Controls	Basic Controls	Basic Controls + Industry FE	Basic Controls + Industry FE + Job Amenities
	(1)	(2)	(3)	(4)
Months Since Graduation	-340.41**	-357.09**	-335.73**	-254.78*
	(166.27)	(154.21)	(146.09)	(140.45)
R^2	0.864	0.849	0.843	0.799
N	19	19	19	19

Note: The dependent variable is the cumulative gender earnings gap in levels. The cumulative gender earnings gap is defined as the difference between the cumulative mean accepted earnings of men and women at a given point in time. Earnings measures are expressed 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. Industry fixed effects include 19 groups. Job amenities include indicator variables for whether the job offers flexible work hours, sick leave, childcare benefits, maternity leave, paternity leave, and the expected earnings growth over the next 12 months in the job. Bootstrapped standard errors reported in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table 5: Learning Process

		Baseline Expectations	Mid-Search Expectations	Realizations	p-value Base = Real	p-value Mid = Real
A. Full Sample						
Men	Mean	73,938	68,079	66,918		
	Median	67,098	62,305	65,389		
	Std. Dev.	27,466	26,750	22,926		
	N	431	97	203		
Women	Mean	64,746	55,374	59,926		
	Median	61,395	54,174	59,877		
	Std. Dev.	26,835	10,935	17,008		
	N	479	122	266		
B. Consistent Sample						
Men	Mean	71,084	64,837	58,610	0.005	0.033
	Median	64,811	60,933	54,122	0.001	0.003
	Std. Dev.	24,246	19,238	23,983		
	N	52	52	52		
Women	Mean	60,713	55,033	54,358	0.012	0.739
	Median	58,566	55,356	53,295	0.008	0.378
	Std. Dev.	15,778	9,881	16,659		
	N	77	77	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 the baseline, mid-search, and post-graduation surveys, had not accepted a job by the mid-search survey, and revised their expectations by less than 100 percent. Actual and expected earnings measures are expressed in 2017 dollars.

Table 6: Gender Gap in Reservation Earnings

	Dependent Variable: Ex-Ante Reservation Earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-3430***	-2798***	-3100***	-2435**	-1967*	-1469	-1644	-1144
	(1046)	(1043)	(1041)	(1033)	(1099)	(1092)	(1088)	(1079)
Risk Tolerance		1082**		1133**		1092**		1116**
		(511)		(504)		(531)		(522)
Overoptimism (%)			118***	120***			134***	135***
			(36)	(36)			(32)	(32)
Controls					X	X	X	X
Mean	54441	54441	54441	54441	54441	54441	54441	54441
R^2	0.017	0.025	0.041	0.050	0.132	0.139	0.157	0.165
N	585	585	585	585	585	585	585	585
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.007				0.014		

Note: The dependent variable is ex-ante reservation earnings in 2017 dollars. Risk tolerance is the average of two survey questions that . ask respondents to rate their willingness to take on financial risks and daily risks and is measured on a 1 to 6 scale that is increasing in willingness to take risks. Overoptimism is measured as the percent gap between ex-ante expected earnings and ex-post realized earnings at the individual-level (i.e. $Overoptimism = (\frac{Expect-Realized}{Realized}) * 100\%$). Controls include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table 7: Gender Gap in Timing of Starting Search

	Dep. Var: Starting Search Before Graduation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.116***	0.095**	0.114**	0.093**	0.088*	0.074	0.086*	0.071
	(0.044)	(0.047)	(0.044)	(0.046)	(0.051)	(0.053)	(0.051)	(0.053)
Risk Tolerance		-0.032*		-0.034*		-0.027		-0.029
		(0.018)		(0.019)		(0.020)		(0.021)
Overconfidence (%)			-0.001	-0.001			-0.001	-0.001
			(0.001)	(0.001)			(0.001)	(0.001)
Controls					X	X	X	X
Mean	0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688
R^2	0.015	0.021	0.025	0.032	0.104	0.108	0.107	0.111
N	452	452	452	452	452	452	452	452

Note: The dependent variable is a dummy variable for starting search before graduation. Basic controls include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table 8: Gender Gap in Accepted Earnings, Controlling for Risk Preferences and Proxies for Biased Beliefs

	Dep. Var: Accepted Earnings in the First Job							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel (a): Controlling for Risk Preferences and Perceived Relative Ability							
Female	-4531***	-3617***	-3450***	-2869**	-3517***	-2968***	-2912***	-2549**
	(1147)	(1148)	(1141)	(1151)	(1036)	(1056)	(1053)	(1071)
Risk Tolerance		1654***		1231***		1056**		798*
		(468)		(468)		(452)		(449)
Perceived Relative Ability (1-5)			3961***	3596***			2558***	2336***
			(781)	(782)			(778)	(777)
Mean	61711	61711	61711	61711	61711	61711	61711	61711
R^2	0.170	0.179	0.189	0.194	0.397	0.400	0.404	0.406
N	1358	1358	1358	1358	1358	1358	1358	1358
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.000				0.001		
	Panel (b): Controlling for Risk Preferences and Expected Total Compensation							
Female	-6419.9***	-5782.9***	-5492.7**	-4757.5**	-5173.1**	-4479.1**	-4769.5**	-4008.4*
	(2247.7)	(2225.7)	(2191.9)	(2166.2)	(2067.9)	(2094.2)	(2037.0)	(2066.5)
Risk Tolerance		1329.1		1466.1*		1332.3		1405.6
		(878.2)		(866.4)		(851.5)		(854.0)
Expected Total			0.1**	0.1**			0.1	0.1
Compensation			(0.0)	(0.0)			(0.0)	(0.0)
Mean	62506	62506	62506	62506	62506	62506	62506	62506
R^2	0.166	0.171	0.183	0.189	0.439	0.443	0.442	0.447
N	392	392	392	392	392	392	392	392
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.012				0.043		
Controls	X	X	X	X	X	X	X	X
Add. controls					X	X	X	X

Note: The dependent variable is total accepted earnings in the first year in 2017 dollars. Risk tolerance is the average of two survey questions that ask respondents to rate their willingness to take on financial risks and daily risks and is measured on a 1 to 6 scale that is increasing in willingness to take risks. Perceived relative ability is based on the following question where respondents were asked, on a 5-point scale (increasing in perceived ability): *"Relative to your peers with the same concentration in BU, how would you rate your ability?"*. Expected total compensation refers to how much respondents expect to make at their first job after graduation in the first year. 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), dummies for the location of the first job (country/state), and weekly hours of work. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table 9: Gender Gap in Reservation Wage in Round 1 (Lab)

	Dependent Variable: Reservation Wage in Round 1							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-3.05***	-2.54***	-2.36***	-2.09***	-2.73***	-2.26***	-1.89***	-1.66***
	(0.57)	(0.56)	(0.52)	(0.52)	(0.65)	(0.63)	(0.59)	(0.58)
Fast Typist	1.85***	1.69***	-0.14	-0.08	1.50**	1.47**	-0.57	-0.45
	(0.67)	(0.64)	(0.68)	(0.66)	(0.69)	(0.67)	(0.71)	(0.69)
CRRA Coefficient		-1.16***		-0.74**		-1.11***		-0.69**
		(0.31)		(0.30)		(0.33)		(0.31)
Prior of Being a Fast Typist			2.15***	1.97***			2.29***	2.14***
			(0.34)	(0.33)			(0.37)	(0.36)
Controls					X	X	X	X
Mean	18.79	18.79	18.79	18.79	18.79	18.79	18.79	18.79
R^2	0.10	0.14	0.23	0.24	0.13	0.17	0.27	0.28
N	346	346	346	346	346	346	346	346
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.000				0.000		

Note: The dependent variable is reservation wages in round 1. Controls include dummies for year of study, GPA, dummy for US-born, race dummies, dummy variables for college-graduate father/mother, separate indicator variables for majoring in engineering/computing and business/economics, and controls for time preferences (measured as the certainty equivalent of accepting a payment in 4 weeks or 8 weeks vs. today). Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Online Appendix

A Appendix: Survey Compensation, Response Rates, Selection into the Survey and Data Choices

A.1 Survey Compensation

We compensated alumni who responded to the Survey of Graduates with a $20 Amazon gift card. The survey took about 20 minutes. For the baseline and mid-search surveys that required approximately 10 minutes to complete, we offered a $10 Amazon gift card.

A.2 Response Rates for Survey of Current Students

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). The baseline survey, which took about 10 minutes to complete, was conducted in-class in two mandatory courses that Questrom undergraduates typically take in their junior and senior years. Course instructors set aside 10 minutes at the end of class and provided students with the link to the online survey, which students could complete using a smartphone or a laptop. The response rate for the baseline survey was high – approximately 85% of those enrolled in the class completed the survey.[60] We also sent the survey to students in the 2019 cohort who were not enrolled in the mandatory module in October 2018.[61] Overall, approximately 1,055 students completed the baseline survey, representing about 50%(65%) of the 2018 (2019) graduating classes.[62] In terms of background characteristics, the sample of students who responded to more than one survey is disproportionately female, Hispanic, less likely to concentrate in finance, and less risk tolerant, compared to those who responded only to the baseline survey. They are also slightly more likely to be US-born and less likely to have a father with a bachelor's degree. There appears to be little difference across the samples in terms of ability proxies such as GPA, perceived relative ability, and expected total pay (see Table A.2).

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

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

[62] 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.

A.3 Selection into the Survey and Sample Selection

The voluntary nature of the survey naturally raises the question of the extent to which the survey samples are representative of the underlying population of BU undergraduate business students. To provide a sense of how respondents compare with non-respondents, we would ideally use administrative student-level information for all the eligible cohorts of students. Unfortunately, we have limited administrative data from the undergraduate student office that only includes some background information (e.g. gender, current GPA, international student, concentration, etc.) on all students enrolled as business majors in a given semester from Spring 2017 to Fall 2018. As such, we examine selection into the baseline (in-class) survey for the Survey of Current Students (i.e., the 2018–2019 cohorts).[63]

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

A.4 Data Choices

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. Individuals' salaries are also adjusted based on reported work hours to reflect full-time equivalent earnings. To handle outliers in yearly earnings, we drop observations where the reported total first year earnings are less than \$20,000 and more than \$175,000.[64] We winsorize the top and bottom 2.5% of reservation earnings and further restrict the sample to students with reservations earnings above \$20,000, those whose reported reservation earnings are lower than their expected earnings, and indicate that they plan to work immediately after graduation.[65] 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

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

[64]This criterion drops about 7% of our main analysis sample (i.e. those who have accepted an offer). The main results are robust to winsorizing earnings (above 175,000 and below 20,000) instead of dropping the outliers (see Appendix E.3).

[65]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.

of graduation.

B Appendix: Other Potential Explanations

B.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, $p = 0.022$).[66] The relationships between patience, and our main variables of interest – ex-ante reservation earnings, search timing, job acceptance timing, and earnings – are shown in Appendix Figure A.10. As observed in Panel (a), patience is largely uncorrelated with reservation earnings and search timing. We find that individuals who are more patient, if anything, accept jobs earlier rather than later (see left figure in Panel (b)). The estimated relationship, however, is small and not statistically significant. Turning to the right panel of Panel (b), 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.

[66] 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.

B.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, $p = 0.032$). As observed in Panel (a) of Appendix Figure A.11, we find little evidence of a correlation between reservation earnings and procrastination. Students who score higher on the procrastination index are less likely to start search before graduation, however, the relationship is not statistically significant. Turning to Panel (b), we find that, if anything, higher procrastination is associated with accepting a job *earlier*, although the association is not statistically significant. Procrastination is positively (but insignificantly) correlated with accepted earnings. Overall, these findings suggest that male students' greater tendency to procrastinate is unlikely to be a key driver of the observed patterns.

B.3 Rejection Aversion

Another alternative explanation is that women may accept jobs earlier than men because they are rejection averse. While we are not aware of any work that systematically documents gender differences in rejection aversion, there is an emerging literature that suggests that women tend to be more averse to negative feedback (e.g. Buser and Yuan, 2019; Avilova and Goldin, 2018). While we cannot fully dispel this alternative mechanism, we provide some suggestive evidence that rejection aversion is unlikely to be a first-order explanation. First, we find that a large share of males and females in our sample reject jobs, and the gender difference in the likelihood of rejecting a job is small (43.4% of men vs. 41.9% of women rejected at least one offer, $p = 0.582$). Therefore, it is not the case that women are simply accepting *any* job. If women are more rejection averse than men, we might expect women to be more likely to apply to jobs for which they (think they) are overqualified; however, in the data, we observe that both genders apply at fairly similar rates to jobs for which they are overqualified. Furthermore, we find that over time, job search behavior does not appear to change differentially by gender. Women who accept earlier are not more likely to be over-qualified for the job relative to women who accept later (see Table A.9). Therefore, there appears to be no evidence, at least in our data, that women are more rejection averse than men in job search.

C Appendix: Proofs

Proof of Proposition 1.

Proof. The value of unemployment for someone with belief μ can be rewritten using the reservation wage rule and the optimal cutoff for search as:

$$U(\mu) = u(b) + \beta U(\mu) + H(c^*(\mu))\, c^*(\mu) - \int^{c^*(\mu)} c dH(c),$$

where $c^*(\mu)$ and $\hat{w}(\mu)$ are as described in the text.

Differentiating this value with respect to μ gives:

$$\begin{aligned} \frac{\partial U(\mu)}{\partial \mu}(1-\beta) &= \left[h(c^*(\mu))\frac{\partial c^*(\mu)}{\partial \mu}c^*(\mu) + H(c^*(\mu))\frac{\partial c^*(\mu)}{\partial \mu}\right] - \left[c^*(\mu)\, h(c^*(\mu))\frac{\partial c^*(\mu)}{\partial \mu}\right] \\ &= H(c^*(\mu))\frac{\partial c^*(\mu)}{\partial \mu}. \end{aligned}$$

Differentiating the policy function $c^*(\mu)$ gives:

$$\begin{aligned} \frac{\partial c^*(\mu)}{\partial \mu} &= \frac{\partial}{\partial \mu}\beta\lambda \int_{\hat{w}(\mu)} [W(w,\mu) - U(\mu)]\, dF(w;\mu,\sigma) \\ &= \beta\lambda \int_{\hat{w}(\mu)} \frac{\partial U(\mu)}{\partial \mu} f(w;\mu,\sigma)\, dw + \beta\lambda \int_{\hat{w}(\mu)} [W(w,\mu) - U(\mu)]\frac{\partial f(w;\mu,\sigma)}{\partial \mu}dw \\ &= \beta\lambda \frac{\partial U(\mu)}{\partial \mu}[1 - F(\hat{w}(\mu))] + \beta\lambda \int_{\hat{w}(\mu)} [W(w,\mu) - U(\mu)]\frac{\partial f(w;\mu,\sigma)}{\partial \mu}dw. \end{aligned} \tag{6}$$

Plugging the expression for $\frac{\partial c^*(\mu)}{\partial \mu}$ into the expression for $\frac{\partial U(\mu)}{\partial \mu}$ gives:

$$\begin{aligned}\frac{\partial U(\mu)}{\partial \mu} &= \frac{\beta\lambda H(c^*(\mu))\left\{\int_{\hat{w}(\mu)}[W(w,\mu)-U(\mu)]\frac{\partial f(w;\mu,\sigma)}{\partial \mu}dw\right\}}{(1-\beta(1-\lambda H(c^*(\mu))[1-F(\hat{w}(\mu))]))}] \\ &= \frac{\beta\lambda H(c^*(\mu))\left\{\int_{\hat{w}(\mu)}\left\{[W(w,\mu)-U(\mu)]\frac{1}{\sigma}\left[\frac{w-\mu}{\sigma}\right]f(w;\mu)\right\}dw\right\}}{(1-\beta(1-\lambda H(c^*(\mu))[1-F(\hat{w}(\mu))]))} > 0.\end{aligned}$$

Differentiating the function implicitly defining the reservation wage gives:

$$\frac{\partial W(\hat{w}(\mu))}{\partial w}\frac{\partial \hat{w}(\mu)}{\partial \mu} = \frac{\partial U(\mu)}{\partial \mu}.$$

Since the right-hand side is positive and $\frac{\partial W(\hat{w}(\mu))}{\partial w} > 0$, $\frac{\partial \hat{w}(\mu)}{\partial \mu} > 0$. From 6, it follows that $\frac{\partial c^*(\mu)}{\partial \mu} > 0$.

□

Proof of Proposition 2.

Proof. Start from $t \geq \bar{T}$. Differentiate the value of employment with respect to ι, letting $x = 1-\iota$:

$$\begin{aligned}\frac{\partial W(w)}{\partial \iota} =& \frac{\partial x}{\partial \iota}\frac{\partial W(w)}{\partial x} = -\frac{\partial}{\partial x}\left[\frac{w^x-1}{x(1-\beta)}\right] \\ &= -\left[\frac{x^2\ln(w)-(w^x-1)}{x^2(1-\beta)}\right] \\ &= -\frac{\ln(w)}{(1-\beta)} + \frac{u(w)}{(1-\iota)(1-\beta)} \\ &= \frac{1}{1-\beta}\left(\frac{u(w)-(1-\iota)\ln(w)}{1-\iota}\right) > 0.\end{aligned}$$

Differentiating the equation which implicitly defines reservation wages:

$$\frac{\partial W(\hat{w}(\mu),\mu)}{\partial \iota} - \frac{\partial U(\mu)}{\partial \iota} = \frac{\partial \hat{w}(\mu)}{\partial \iota}\frac{1}{1-\beta}\left(\frac{u(\hat{w}(\mu))-(1-\iota)\ln(\hat{w}(\mu))}{1-\iota}\right) - \frac{\partial U(\mu)}{\partial \iota} = 0.$$

Now differentiate the optimal search cutoff rule with respect to the risk aversion parameter:

$$\begin{aligned}
\frac{\partial c^*(\mu)}{\partial \iota} &= \int_{\hat{w}(\mu)} \left[W(w,\mu) - U(\mu)\right] dF(w;\mu,\sigma) \\
&= -\left[W(\hat{w}(\mu),\mu) - U(\mu)\right] f(\hat{w}(\mu)) \frac{\partial \hat{w}(\mu)}{\partial \iota} + \int_{\hat{w}(\mu)} \left[\frac{\partial W(w,\mu)}{\partial \iota} - \frac{\partial U(\mu)}{\partial \iota}\right] f(w;\mu,\sigma)\, dw \\
&= \beta\lambda \int_{\hat{w}(\mu)} \left[\frac{\partial W(w,\mu)}{\partial \iota} - \frac{\partial U(\mu)}{\partial \iota}\right] f(w;\mu,\sigma)\, dw.
\end{aligned}$$

Finally, differentiate $U(\mu)$ with respect to ι:

$$\frac{\partial U(\mu)}{\partial \iota}(1-\beta) = \frac{u(b) - (1-\iota)\ln(b)}{1-\iota} + \frac{\partial c^*(\mu)}{\partial \iota} H(c^*(\mu)).$$

Plugging in for $\frac{\partial c^*(\mu)}{\partial \iota}$ gives:

$$\frac{\partial U(\mu)}{\partial \iota} = \frac{\frac{u(b)-(1-\iota)\ln(b)}{1-\iota} + H(c^*(\mu))\,\beta\lambda \int_{\hat{w}(\mu)} \frac{\partial W(w,\mu)}{\partial \iota} f(w;\mu,\sigma)}{\left(1 - \beta\left(1 - H(c^*(\mu))\,\lambda\left(1 - F(\hat{w}(\mu))\right)\right)\right)}.$$

Since $\frac{\partial W(w,\mu)}{\partial \iota} > 0$, the above implies $\frac{\partial U(\mu)}{\partial \iota} > 0$. Using the derivative of the reservation wage equation, if $\frac{\partial U(\mu)}{\partial \iota} > 0$, then $\frac{\partial \hat{w}(\mu)}{\partial \iota}$ is < 0 since $1 - \iota < 0$. Finally, note that:

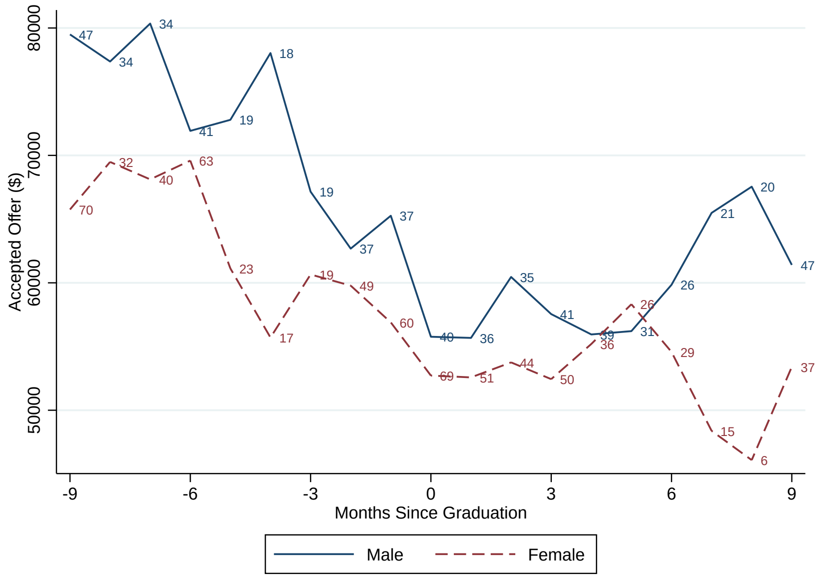
$$\begin{aligned}
\frac{\partial^2 W(w,\mu)}{\partial w \partial \iota} &= \frac{1}{1-\beta}\left(\frac{u'(w) - (1-\iota)\frac{1}{w}}{1-\iota}\right) \\
&= \frac{1}{1-\beta}\frac{w^{-\iota} - (1-\iota)\frac{1}{w}}{1-\iota} > 0,
\end{aligned}$$

and that $\frac{\partial^2 U(\mu)}{\partial w \partial \iota} = 0$. Therefore it must be that $\frac{\partial c^*(\mu)}{\partial \iota} = \beta\lambda \int_{\hat{w}(\mu)} \left[\frac{\partial W(w,\mu)}{\partial \iota} - \frac{\partial U(\mu)}{\partial \iota}\right] f(w;\mu,\sigma)\, dw > 0$.

$\square$

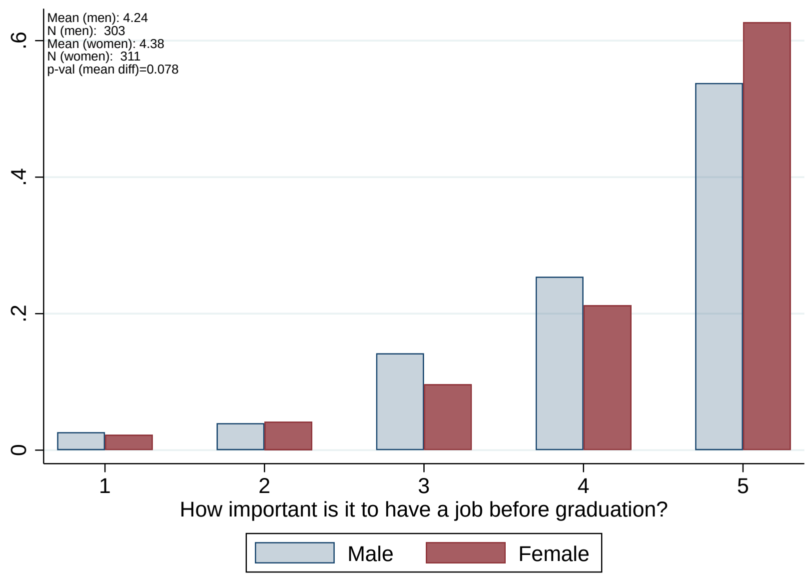
D Appendix: Figures and Tables

Figure A.1: Mean Accepted Earnings by Months Since Graduation and Gender



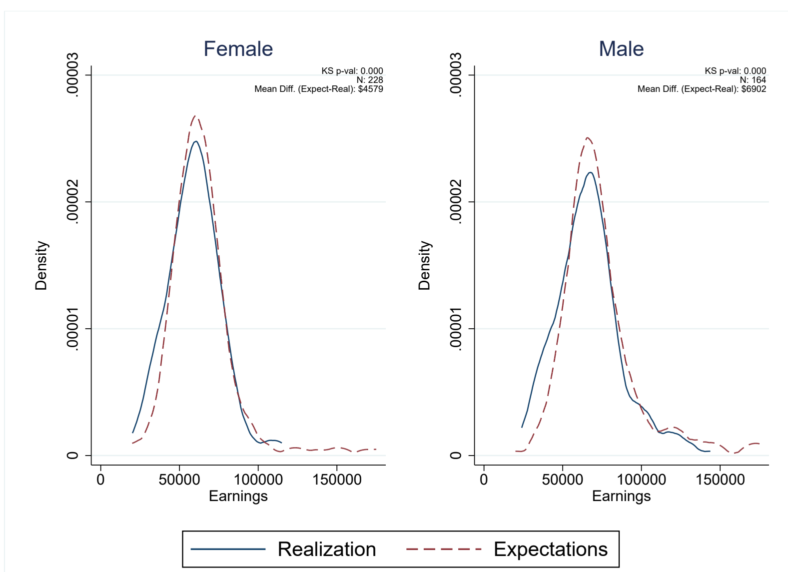
Note: This figure plots the mean accepted earnings (in 2017 dollars) as a function of months since graduation (0 indicates the month of graduation) separately for males (solid blue line) and females (dashed red line). The number of observations for each month and gender is shown above each data point in the figure.

Figure A.2: Importance of Having a Job by Graduation



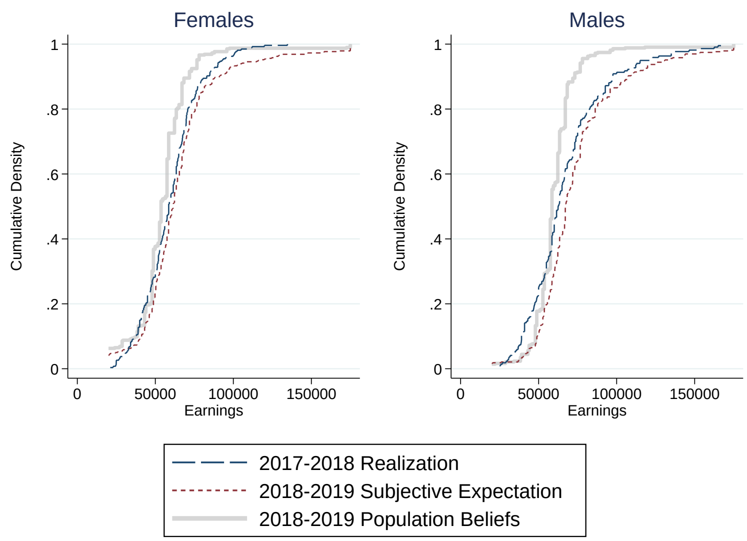
Note: This figure plots the distribution of male and female responses to the following question that was asked to students as part of the in-class survey: *"On a 5-point scale, how important is it to you that you have a job lined up before the end of your senior year (that is, before you graduate)?"*

Figure A.3: Gender Difference in Beliefs Bias – Within Individual Comparison



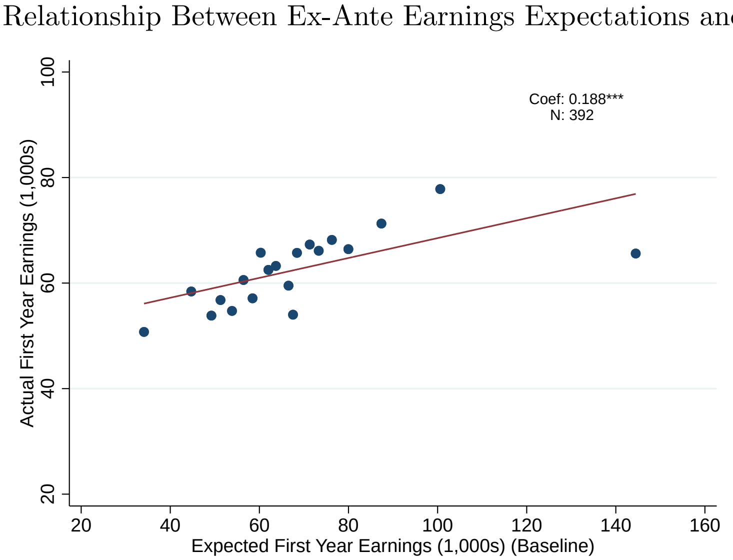
Note: The sample is restricted to individuals for whom we have data on both earnings expectations and realizations. The figure plots the distribution of the difference between ex-ante earnings expectations and ex-post earnings expectations separately by gender. Earnings expectations and realizations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

Figure A.4: CDF of Beliefs Bias by Gender – Cross-Cohort Comparison



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

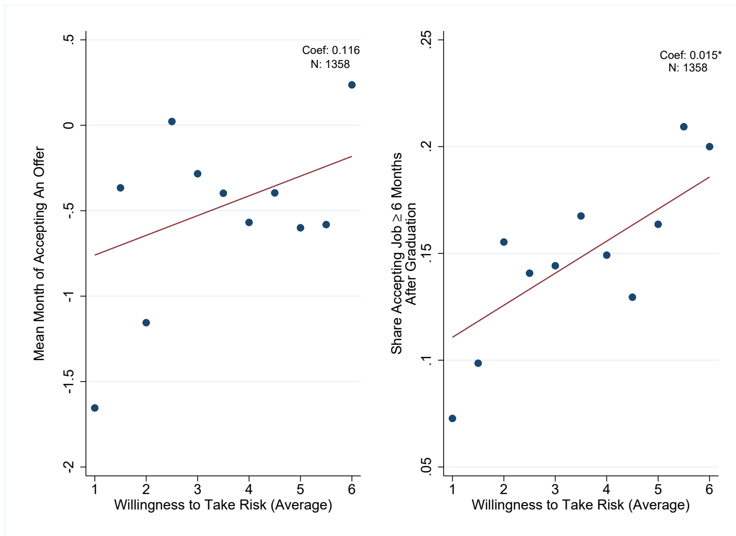
Figure A.5: Relationship Between Ex-Ante Earnings Expectations and Realizations



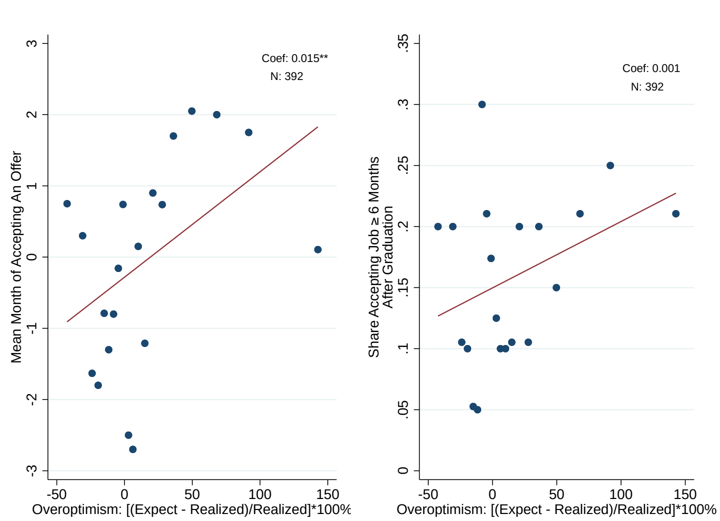
Note: This figure is a binned scatter plot of accepted earnings in the first year on students' ex-ante earnings expectations elicited in the baseline "Survey of Current Students." Both measures are in 2017 dollars.

Figure A.6: Timing of Job Acceptance, Risk Preferences, and Overoptimism

(a) Relationship Between Timing of Job Acceptance and Risk Preferences



(b) Relationship Between Timing of Job Acceptance and Biased Beliefs



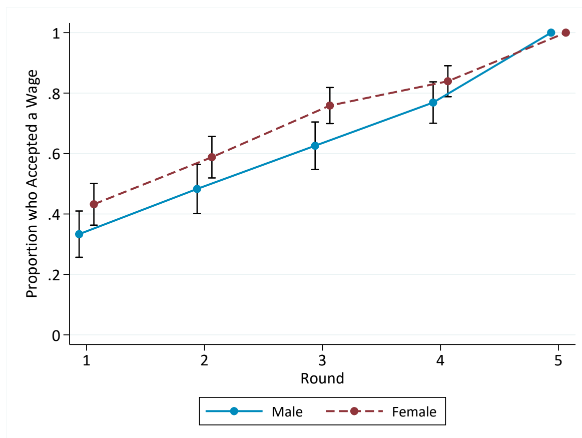
Note: Each graph is a binned scatter plot of a measure of the timing of job acceptance on the survey measure of risk preferences (Panel (a)) or overoptimism (Panel (b)). The y-axis for the graphs in the left panel plot the mean month of accepting an offer (defined relative to the month of graduation) while the y-axis for the graphs in the right panel plot the share accepting a job within six months of graduation. For Panel (a), 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. For Panel (b), 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 A.7: Distribution of Wage Offers in Job Search Experiment

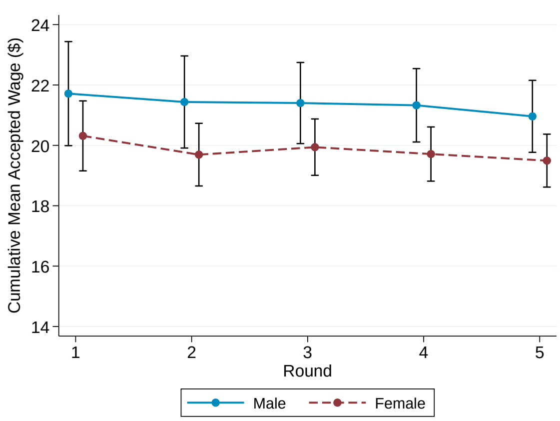
Wage offer	\$2	\$5	\$8	\$11	\$14	\$17	\$20	\$23	\$26	\$29	\$32
Probability if you are a fast typist	3%	4%	7%	8%	10%	10%	20%	20%	6%	6%	6%
Probability if you are a slow typist	15%	15%	15%	15%	12%	10%	7%	6%	2%	2%	1%

Figure A.8: Acceptance Rates and Cumulative Mean Accepted Wage Across Rounds by Gender

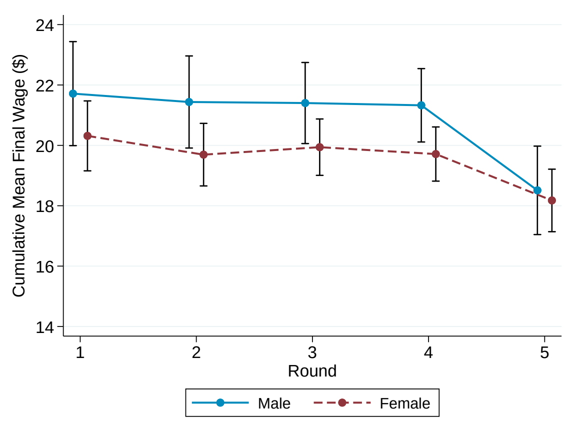
(a) Proportion who Have Accepted a Wage



(b) Cumulative Mean Accepted Wage

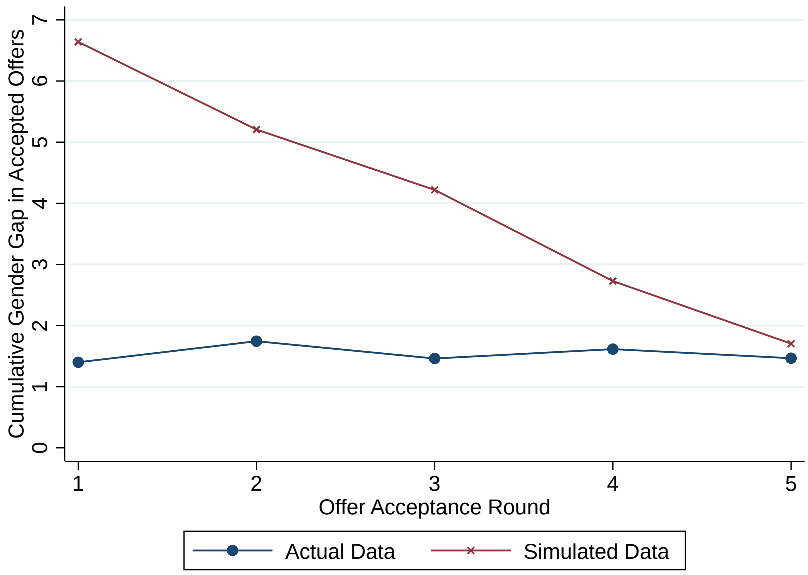


(c) Cumulative Mean Final Wage



Note: Panel (a) plots the proportion of males (solid blue line) and females (dashed red line) who have accepted a wage in each round. Panel (b) plots the cumulative mean accepted wage across rounds separately for males (solid blue line) and females (dashed red line) excluding those who had not accepted a wage by round 5. Panel (c) plots the cumulative mean accepted wage across rounds separately for males (solid blue line) and females (dashed red line) for the full sample, including those (34 participants) who had not accepted a wage by round 5 and were assigned the outside wage of \$2. The cumulative mean accepted wage at a given point in time is constructed as the mean of the accepted wages among those who have accepted a wage offer up to that point.

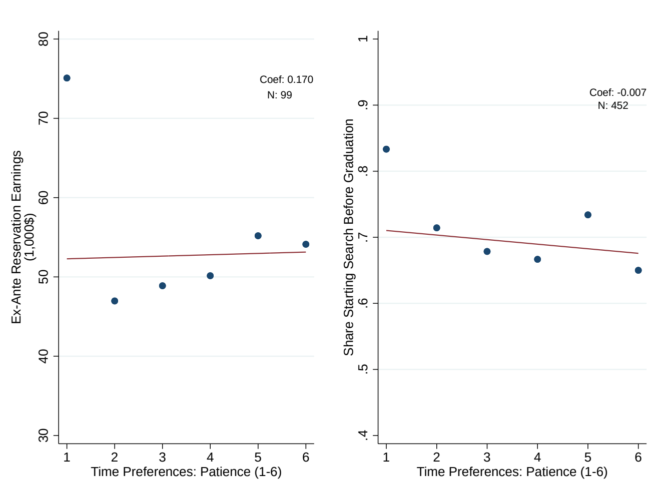
Figure A.9: Simulation of the Gender Gap in Cumulative Mean Accepted Offers



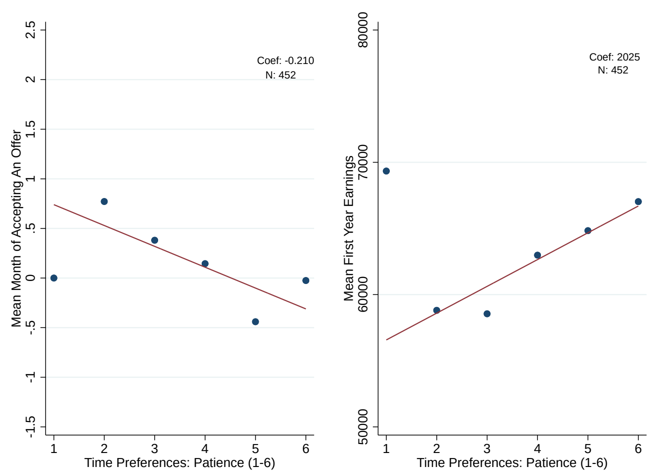
Note: The gender gap in cumulative mean accepted offers is defined as the difference between the cumulative mean accepted offer of men and women in a given round. The cumulative mean accepted offer at a given point in time is constructed as the mean of the wage offer among those who accepted a wage offer up to that point. The figure plots the cumulative gender gap in mean accepted offers as a function of experiment round using both the actual wage data and simulated wage data. The simulated wage data is obtained by simulating the lab experiment using a continuous wage offer distribution. To do so, we take the discrete offer distributions for each skill-type (fast vs. slow) from the experiment and fit it to a log-normal distribution. We then create a sample of males and females with the same initial beliefs as our experimental sample and the same reservation wages reported in each round. For each round, we simulate a wage offer from the log-normal above the individual's reservation wage, and then plot the cumulative gender gap in wage offers received in each round using the actual set of people who found a job in each round.

Figure A.10: Correlations with Patience

(a) Reservation Earnings, Search Timing, and Patience



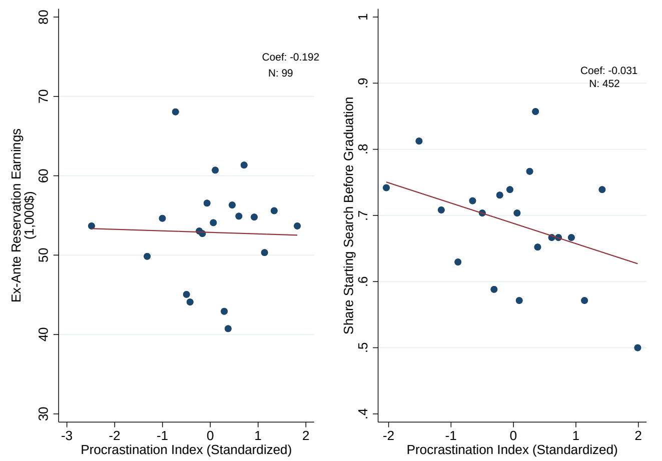
(b) Job Acceptance Timing, Earnings, and Patience



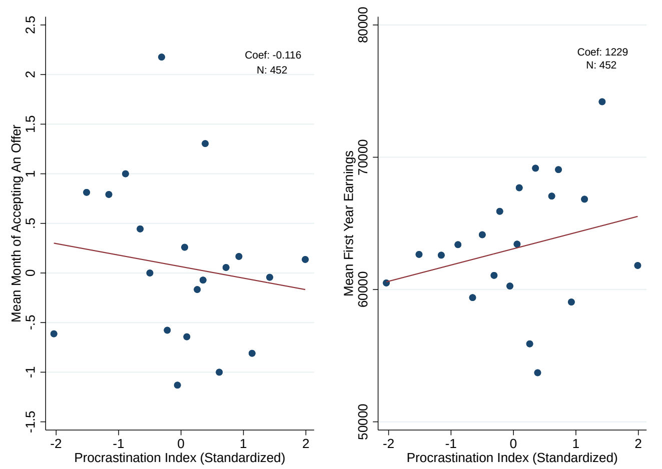
Note: The sample includes individuals from the 2018-2019 graduating cohorts. This figure graphs the binned scatter plot of ex-ante reservation earnings, share starting search before graduation, month of job offer acceptance (defined relative to the month of graduation), and accepted earnings on the survey measure of patience (a higher value of the patience variable indicates more patience). There are fewer observations for reservation earnings as patience was not elicited in the baseline survey for the two additional 2020 and 2021 cohorts. Patience is measured using the following question "On a scale from 1 (not willing at all) to 7 (very willing), how would you rate your willingness to give up something that is beneficial for you today in order to benefit more from that in the future?." Due to the small number of responses for the bottom two options, we combine them into a single category and re-scale the responses to the question to be between 1 and 6. The patience question was fielded to a subset of the "current student" sample. Earnings are expressed in 2017 dollars.

Figure A.11: Correlations with Procrastination

(a) Reservation Earnings, Search Timing, and Procrastination



(b) 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 ex-ante reservation earnings, share starting search before graduation, month of job offer acceptance (defined relative to the month of graduation), and accepted earnings on the procrastination index (a higher value of the procrastination index indicates a higher tendency to procrastinate). There are fewer observations for reservation earnings as procrastination was not elicited in the baseline survey for the two additional 2020 and 2021 cohorts. 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. Earnings are expressed in 2017 dollars.

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

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

Table A.2: Responses Across Waves

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

Note: The table reports the means and standard deviations of the background characteristics of the students from the 2018-2019 graduating cohorts who responded to various components of the "Survey of Current Students" as indicated in the columns. The stars indicate the p-value of the difference in means for the respective sample relative to the mean for students who responded to baseline survey (i.e. Column (1)). ***significant at the 1% level, **5% level, *10% level. Earnings are expressed in 2017 dollars.

Table A.3: Response Rates Based on Administrative Data

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

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

Table A.4: Who Responded to the Surveys?

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

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

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

		Full sample		Accepted		
		Men	Women	Men	Women	p-value
Observations		744	869	622	736	
Age		22.56	22.30	22.78	22.42	0.467
		(2.02)	(1.92)	(2.04)	(1.95)	
Race	White/Caucasian	51.2%	46.2%	53.6%	48.7%	0.976
	Black/ African American	3.3%	4.5%	3.2%	5.2%	0.628
	American Indian	0.7%	0.1%	0.6%	0.1%	0.905
	Hispanic/ Latino	10.8%	11.0%	10.6%	11.7%	0.710
	Asian/ Pacific Islander	34.1%	38.2%	32.0%	34.3%	0.622
Born in U.S.		72.3%	69.6%	76.4%	74.3%	0.844
Father BA+		79.8%	75.3%	80.2%	76.1%	0.932
Mother BA+		73.8%	73.1%	74.3%	74.5%	0.845
GPA		3.29	3.32	3.31	3.33	0.759
		(0.35)	(0.33)	(0.35)	(0.33)	
Concentration	Accounting	17.9%	16.3%	18.8%	15.6%	0.553
	Entrepreneurship	5.2%	3.3%	4.7%	3.0%	0.873
	Finance	65.9%	37.9%	65.4%	37.8%	0.924
	General Management	2.4%	2.9%	2.7%	2.7%	0.693
	International Management	2.7%	8.9%	2.1%	9.1%	0.628
	Law	8.2%	10.7%	7.2%	11.0%	0.557
	Management Info. Systems	19.4%	18.5%	20.4%	17.8%	0.536
	Marketing	13.3%	35.9%	13.8%	36.7%	0.933
	Operations & Tech. Mgmt.	9.3%	11.6%	9.8%	11.8%	0.884
	Organizational Behavior	2.0%	5.1%	1.9%	5.6%	0.672
Accepted Job Offer to Work after Grad		84.7%	83.6%			0.549
Cohort	2013	9.8%	9.7%	11.3%	10.7%	0.868
	2014	9.8%	8.6%	11.4%	9.9%	0.886
	2015	9.3%	9.9%	10.1%	10.7%	0.994
	2016	15.9%	12.0%	17.2%	13.0%	0.918
	2017	14.0%	14.8%	14.0%	14.9%	0.972
	2018	21.8%	23.7%	21.2%	21.2%	0.523
	2019	19.5%	21.3%	14.8%	19.4%	0.327
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	3.21	3.83	3.19	0.684
		(1.20)	(1.15)	(1.20)	(1.15)	
Percent High Risk (≥ 5)		22.8%	9.0%	22.8%	9.0%	0.997

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

Table A.6: Gender Gap in Accepted Wage (Lab)

	Dependent Variable: Accepted Wage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-1.448**	-0.887	-1.181	-0.750	-1.395*	-0.804	-1.079	-0.630
	(0.716)	(0.751)	(0.720)	(0.759)	(0.781)	(0.809)	(0.779)	(0.812)
Fast Typist	3.625***	3.444***	2.711***	2.775***	3.638***	3.609***	2.686**	2.894***
	(0.868)	(0.847)	(0.990)	(0.968)	(0.923)	(0.892)	(1.055)	(1.030)
CRRA Coefficient		-1.178***		-1.043**		-1.260***		-1.123***
		(0.398)		(0.409)		(0.408)		(0.423)
Prior of Being a Fast Typist			0.933**	0.704*			0.975**	0.736*
			(0.409)	(0.403)			(0.423)	(0.424)
Controls					X	X	X	X
Mean	20.10	20.10	20.10	20.10	20.10	20.10	20.10	20.10
R^2	0.10	0.13	0.12	0.14	0.11	0.15	0.13	0.16
N	312	312	312	312	312	312	312	312
P-value: Equality of Female Coeff	(1) vs. (4)				(5) vs. (8)			
	0.010				0.005			

Note: The dependent variable is accepted wage. The sample includes those who accepted a wage offer by round 5. Controls include dummies for year of study, GPA, dummy for US-born, race dummies, dummy variables for college-graduate father/mother, separate indicator variables for majoring in engineering/computing and business/economics, and controls for time preferences (measured as the certainty equivalent of accepting a payment in 4 weeks or 8 weeks vs. today). Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level

Table A.7: Gender Gap in the Likelihood of Being in the Tails of the Wage Distribution (Lab)

	Panel (a): Dep. Var: Accepted a High Wage ($\geq$ \$26)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.096**	-0.081*	-0.088**	-0.076*	-0.094**	-0.076*	-0.082*	-0.069
	(0.042)	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)
CRRA Coefficient		-0.035		-0.031		-0.044**		-0.039*
		(0.021)		(0.021)		(0.022)		(0.022)
Prior of Being a Fast Typist			0.027	0.020			0.034	0.026
			(0.021)	(0.021)			(0.022)	(0.022)
Mean	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
R^2	0.04	0.04	0.04	0.05	0.06	0.07	0.06	0.07
p-value: equality of Female coeff	(1) vs. (4)				(5) vs. (8)			
	0.092				0.030			
	Panel (b): Dep. Var: Obtained a Low Final Wage ($\leq$ \$5)							
Female	-0.065*	-0.053	-0.045	-0.040	-0.068*	-0.062	-0.049	-0.048
	(0.036)	(0.038)	(0.035)	(0.038)	(0.038)	(0.041)	(0.038)	(0.040)
CRRA Coefficient		-0.026		-0.014		-0.014		-0.004
		(0.019)		(0.019)		(0.019)		(0.020)
Prior of Being a Fast Typist			0.061***	0.058***			0.053**	0.052**
			(0.020)	(0.020)			(0.020)	(0.021)
Mean	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
R^2	0.07	0.08	0.10	0.10	0.14	0.14	0.16	0.16
P-value: Equality of Female Coeff	(1) vs. (4)				(5) vs. (8)			
	0.033				0.063			
Controls					X	X	X	X
N	346	346	346	346	346	346	346	346

Note: The dependent variables in Panels (a) and (b) are a dummy for accepting a high wage (i.e., $\geq$ \$26) and a dummy for obtaining a low final wage (i.e. $\leq$ \$5), respectively. Controls include dummies for being a fast typist, year of study, GPA, dummy for US-born, race dummies, dummy variables for college-graduate father/mother, separate indicator variables for majoring in engineering/computing and business/economics, and controls for time preferences (measured as the certainty equivalent of accepting a payment in 4 weeks or 8 weeks vs. today). Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table A.8: Gender Gap in the Likelihood of Obtaining a Final Wage Less than a Previously Offered Wage (Lab)

	Dependent Variable: Final Wage < Previously Offered Wage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.087**	-0.080**	-0.062*	-0.062	-0.089**	-0.085**	-0.060	-0.063
	(0.038)	(0.040)	(0.037)	(0.039)	(0.039)	(0.041)	(0.037)	(0.040)
Fast Typist	-0.123***	-0.125***	-0.195***	-0.195***	-0.149***	-0.149***	-0.219***	-0.220***
	(0.043)	(0.043)	(0.048)	(0.048)	(0.046)	(0.046)	(0.051)	(0.052)
CRRA Coefficient		-0.016		0.000		-0.009		0.006
		(0.019)		(0.019)		(0.019)		(0.019)
Prior of Being a Fast Typist			0.078***	0.078***			0.077***	0.079***
			(0.020)	(0.021)			(0.020)	(0.021)
Controls					X	X	X	X
Mean	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
R^2	0.07	0.07	0.11	0.11	0.14	0.14	0.18	0.18
N	346	346	346	346	346	346	346	346
P-value: Equality of Female Coeff	(1) vs. (4)				(5) vs. (8)			
	0.042				0.035			

Note: The dependent variable is an indicator for ending up with a final wage that is lower than a previously offered wage. Controls include dummies for year of study, GPA, dummy for US-born, race dummies, dummy variables for college-graduate father/mother, separate indicator variables for majoring in engineering/computing and business/economics, and controls for time preferences (measured as the certainty equivalent of accepting a payment in 4 weeks or 8 weeks vs. today). Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level

Table A.9: Qualification By Acceptance Month

			Accept Offer Before Grad	Accept Offer After Grad	p-value
Both [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.10: Experimental Sample Compared to the ASU Population

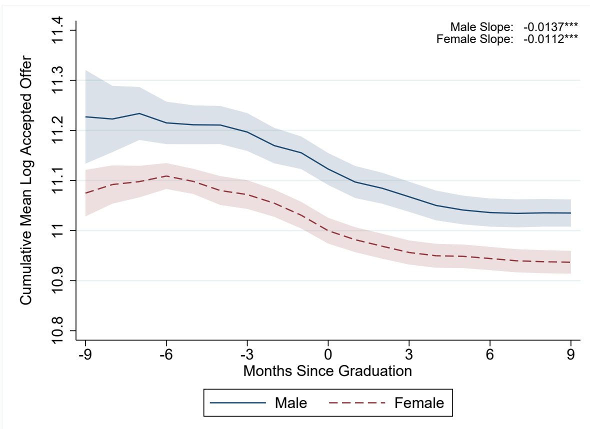
	Experiment			ASU			P-value[c]
	Female	Male	Gender P-val	Female	Male	Gender P-val	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Asian	0.23	0.28	0.249	0.11	0.11	0.002	0.166
White	0.64	0.65	0.878	0.55	0.55	0.118	1.000
First Generation[a]	0.23	0.20	0.451	0.23	0.19	0.000	0.806
Family Income[b]	102.85	129.34	0.001	122.29	134.89	0.000	0.307
Freshman	0.25	0.23	0.670	0.27	0.26	0.000	0.894
Sophomore	0.26	0.35	0.050	0.25	0.24	0.141	0.020
Junior	0.24	0.22	0.718	0.22	0.23	0.361	0.570
Business/Econ	0.21	0.24	0.507	0.16	0.23	0.000	0.420
Comp Sci/Engin	0.20	0.47	0.000	0.16	0.41	0.000	0.724
ACT	29.21	30.62	0.004	26.50	27.82	0.000	0.861
Sample Size	199	147		19,199	20,043		0.001[d]

Notes: ASU data includes everyone taking at least one class for credit during the Spring semester of 2018 and attended ASU as their first full-time university. Income and first generation variables for the ASU data are constructed with the data of the first available year, which it is not the first year of college for most of the sample.
[a] Students with no parent with a college degree.
[b] Family income in thousands of dollars.
[c] P-value for whether the gender differences in the experiment sample and the ASU population are different.
[d] P-value for the difference in females proportion between the experiment sample and ASU population.

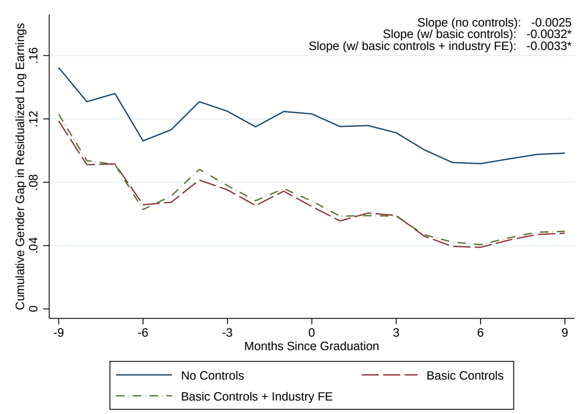
E Appendix: Robustness of Empirical Results

E.1 Using Logs vs. Levels for Earnings Outcomes

Figure E1.1: Cumulative Mean Accepted Earnings and Gender Gap by Months Since Graduation (in Logs)



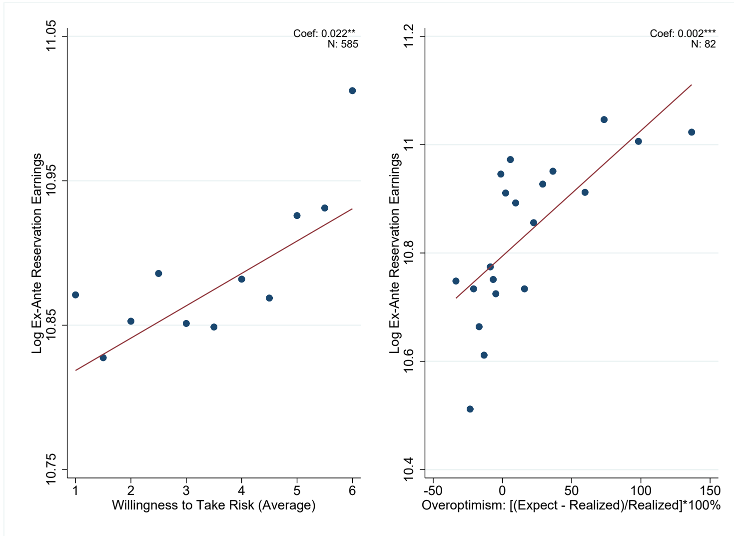
(a) Cumulative Mean Log Accepted Earnings



(b) Cumm. Log Gender Earnings Gap (M-F)

Note: Months since graduation is defined relative to the month of graduation (indicated as 0). Panel (a) plots the cumulative mean log accepted earnings as a function of months since graduation separately for males (solid blue line) and females (dashed red line). The cumulative mean log accepted earnings at a given point in time is constructed as the mean of the natural log of the first-job accepted earnings among those who have accepted a job up to that point. The 95% confidence interval bands are based on bootstrapped standard errors. Panel (b) plots the log cumulative gender earnings gap in mean accepted offers as a function of months since graduation. The cumulative log gender earnings gap is defined as the difference between the cumulative mean log accepted earnings of men and women at a given point in time. The solid line plots the unconditional cumulative gender gap in logs, while the two dashed lines plot the cumulative log gender earnings gap that have been residualized of (1) basic controls that include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education (red line) and (2) basic controls plus industry fixed effects (19 groups) (green line). Earnings measures are expressed in 2017 dollars.

Figure E1.2: Ex-Ante Log Reservation Earnings, Risk Preferences, and Overoptimism



Note: This figure is a binned scatter plot of reported ex-ante log reservation earnings from the in-class survey on risk preferences (left panel) and overconfidence (right panel). For risk preferences, we use all available data from students who completed the in-class survey and answered the reservation earnings question. These students are expected to graduate between 2018 and 2021. For overconfidence, we are limited to students for whom we have data on earnings expectations and realizations. To account for outliers, we winsorize the top and bottom 2.5% of reservation earnings and the overconfidence measure. We also restrict the sample to students with reservations earnings above $20,000 and whose reported reservation earnings are lower than their expected earnings. Earnings measures are expressed in 2017 dollars.

Table E1.1: Relationship Between Cumulative Log Gender Earnings Gap and Month Since Graduation

	Dependent Variable: Cumulative Log Gender Earnings Gap			
		Residualized of:		
	No Controls	Basic Controls	Basic Controls + Industry FE	Basic Controls + Industry FE + Job Amenities
	(1)	(2)	(3)	(4)
Months Since Grad	-0.002***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.001)
R^2	0.697	0.781	0.764	0.658
N	19	19	19	19

Note: The dependent variable is the cumulative log gender earnings gap, defined as the difference between the cumulative mean log accepted earnings of men and women at a given point in time. Earnings measures are expressed 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. Industry fixed effects include 19 groups. Job amenities include indicator variables for whether the job offers flexible work hours, sick leave, childcare benefits, maternity leave, paternity leave, and the expected earnings growth over the next 12 months in the job. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

Table E1.2: Gender Gap in Log Reservation Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.051***	-0.041**	-0.045**	-0.034*	-0.023	-0.015	-0.017	-0.009
	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)
Risk Tolerance		0.018*		0.019**		0.018*		0.018**
		(0.009)		(0.009)		(0.009)		(0.009)
Overoptimism (%)			0.002***	0.002***			0.003***	0.003***
			(0.001)	(0.001)			(0.001)	(0.001)
Controls					X	X	X	X
Mean	10.876	10.876	10.876	10.876	10.876	10.876	10.876	10.876
R^2	0.011	0.017	0.036	0.043	0.129	0.135	0.156	0.162
N	585	585	585	585	585	585	585	585
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.009				0.020		

Note: The dependent variable is the natural log of ex-ante reservation earnings (in 2017 dollars). Risk tolerance is the average of two survey questions that ask respondents to rate their willingness to take on financial risks and daily risks and is measured on a 1 to 6 scale that is increasing in willingness to take risks. Overoptimism is measured as the percent gap between ex-ante expected earnings and ex-post realized earnings at the individual-level (i.e. $Overoptimism = (\frac{Expect-Realized}{Realized}) * 100\%$). Controls include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

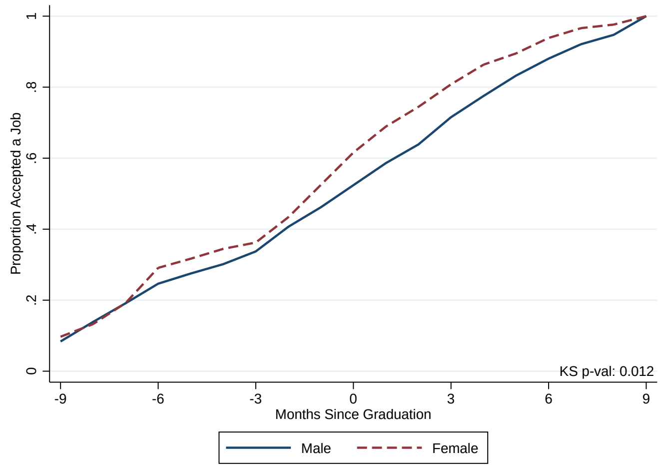
Table E1.3: Gender Gap in Log Earnings, Controlling for Risk Preferences and a Proxy for Biased Beliefs

	Dep. Var: Log Accepted Earnings in the First Job							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel (a): Controlling for Risk Preferences and Perceived Relative Ability							
Female	-0.058***	-0.045**	-0.041**	-0.033*	-0.047***	-0.039**	-0.037**	-0.032*
	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)	(0.017)	(0.017)	(0.017)
Risk Tolerance		0.023***		0.016**		0.015**		0.011
		(0.007)		(0.007)		(0.007)		(0.007)
Perceived Relative Ability (1-5)			0.062***	0.057***			0.042***	0.039***
			(0.013)	(0.013)			(0.012)	(0.012)
Mean	10.98	10.98	10.98	10.98	10.98	10.98	10.98	10.98
R^2	0.179	0.185	0.197	0.200	0.426	0.428	0.433	0.435
N	1358	1358	1358	1358	1358	1358	1358	1358
P-value: Equality of Female Coeff	(1) vs. (4)				(5) vs. (8)			
	0.000				0.001			
	Panel (b): Controlling for Risk Preferences and Expected Total Compensation							
Female	-0.090**	-0.081**	-0.073**	-0.062*	-0.066**	-0.054*	-0.061*	-0.048
	(0.037)	(0.037)	(0.036)	(0.035)	(0.032)	(0.032)	(0.032)	(0.032)
Risk Tolerance		0.019		0.021		0.023*		0.024*
		(0.013)		(0.013)		(0.013)		(0.013)
Log Expected Total Compensation			0.154**	0.158**			0.055	0.061
			(0.064)	(0.063)			(0.055)	(0.054)
Mean	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00
R^2	0.169	0.173	0.187	0.192	0.500	0.506	0.502	0.508
N	392	392	392	392	392	392	392	392
P-value: Equality of Female Coeff	(1) vs. (4)				(5) vs. (8)			
	0.008				0.034			
Controls	X	X	X	X	X	X	X	X
Add. controls					X	X	X	X

Note: The dependent variable is the natural log of total accepted earnings in the first year (in 2017 dollars). Risk tolerance is the average of two survey questions that ask respondents to rate their willingness to take on financial risks and daily risks and is measured on a 1 to 6 scale that is increasing in willingness to take risks. Perceived relative ability is based on the following question where respondents were asked, on a 5-point scale (increasing in perceived ability): *"Relative to your peers with the same concentration in BU, how would you rate your ability?"*. Expected total compensation refers to how much respondents expect to make at their first job after graduation in the first year. 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), dummies for the location of the first job (country/state), and weekly hours of work. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

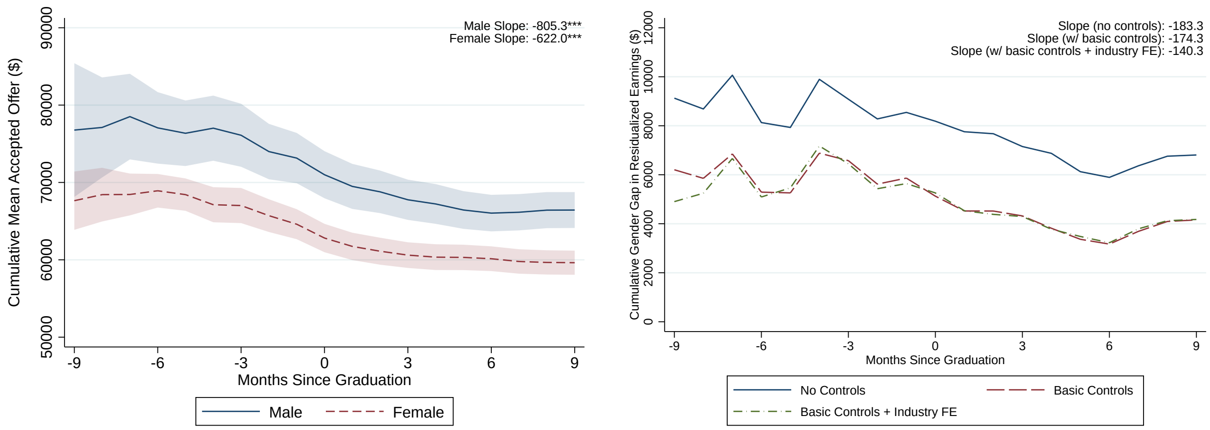
E.2 Omitting Earlier (2013 to 2015) Cohorts

Figure E2.1: CDF of Job Acceptance Timing, By Gender



Note: The sample is restricted to the 2016 to 2019 cohorts. This figure replicates Figure 1 for the 2016 to 2019 cohorts. See notes to Figure 1.

Figure E2.2: Cumulative Mean Accepted Earnings and Gender Gap by Months Since Graduation



(a) Cumulative Mean Accepted Earnings

(b) Cumulative Gender Earnings Gap (M-F)

Note: The sample is restricted to the 2016 to 2019 cohorts. This figure replicates Figure 2 for the 2016 to 2019 cohorts. See notes to Figure 2. Earnings are expressed in 2017 dollars.

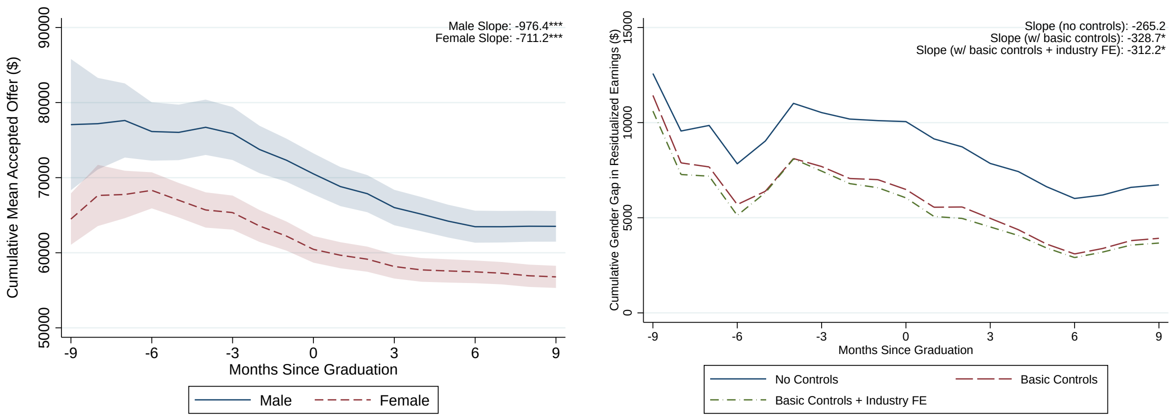
Table E2.1: Gender Gap in Accepted Earnings, Controlling for Risk Preferences and a Proxy for Biased Beliefs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel (a): Controlling for Risk Preferences and Perceived Relative Ability							
Female	-5354***	-4580***	-3925***	-3529**	-3981***	-3623***	-3106**	-2955**
	(1460)	(1469)	(1431)	(1455)	(1316)	(1341)	(1311)	(1344)
Risk Tolerance		1447**		889		720		362
		(620)		(610)		(598)		(585)
Perceived Relative Ability (1-5)			4867***	4594***			3220***	3115***
			(961)	(959)			(949)	(940)
Mean	62677	62677	62677	62677	62677	62677	62677	62677
R^2	0.155	0.161	0.181	0.184	0.400	0.401	0.411	0.411
N	923	923	923	923	923	923	923	923
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.000				0.011		
	Panel (b): Controlling for Risk Preferences and Expected Total Compensation							
Female	-6419.9***	-5782.9***	-5492.7**	-4757.5**	-5173.1**	-4479.1**	-4769.5**	-4008.4*
	(2247.7)	(2225.7)	(2191.9)	(2166.2)	(2067.9)	(2094.2)	(2037.0)	(2066.5)
Risk Tolerance		1329.1		1466.1*		1332.3		1405.6
		(878.2)		(866.4)		(851.5)		(854.0)
Expected Total Compensation			0.1**	0.1**			0.1	0.1
			(0.0)	(0.0)			(0.0)	(0.0)
Mean	62506	62506	62506	62506	62506	62506	62506	62506
R^2	0.166	0.171	0.183	0.189	0.439	0.443	0.442	0.447
N	392	392	392	392	392	392	392	392
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.012				0.043		
Controls	X	X	X	X	X	X	X	X
Add. controls					X	X	X	X

Note: The dependent variable is total accepted earnings in the first year in 2017 dollars. Risk tolerance is the average of two survey questions that ask respondents to rate their willingness to take on financial risks and daily risks and is measured on a 1 to 6 scale that is increasing in willingness to take risks. Perceived relative ability is based on the following question where respondents were asked, on a 5-point scale (increasing in perceived ability): *"Relative to your peers with the same concentration in BU, how would you rate your ability?"*. Expected total compensation refers to how much respondents expect to make at their first job after graduation in the first year. 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), dummies for the location of the first job (country/state), and weekly hours of work. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

E.3 Winsorizing vs. Omitting Outliers

Figure E3.1: Cumulative Mean Accepted Earnings and Gender Gap by Months Since Graduation



(a) Cumulative Mean Accepted Earnings **(b)** Cumulative Gender Earnings Gap (M-F)

Note: To construct the outcome variables (cumulative mean accepted offer and cumulative gender gap in mean accepted offer), instead of dropping outliers (individuals who earn below \$20,000 and above \$175,000), we winsorize earnings above \$175,000 and below \$20,000. Months since graduation is defined relative to the month of graduation (indicated as 0). Panel (a) plots the cumulative mean accepted earnings as a function of months since graduation separately for males (solid blue line) and females (dashed red line). The cumulative mean accepted earnings at a given point in time is constructed as the mean of the first-job accepted earnings among those who have accepted a job up to that point. The 95% confidence interval bands are based on bootstrapped standard errors. Panel (b) plots the cumulative gender gap in mean accepted earnings as a function of months since graduation. The cumulative gender earnings gap is defined as the difference between the cumulative mean accepted earnings of men and women at a given point in time. The solid line plots the unconditional cumulative gender earnings gap, while the two dashed lines plot the cumulative gender gap in earnings that have been residualized of (1) basic controls that include cohort fixed effects, major fixed effects, GPA, dummy for US-born, and fixed effects for race, father's education, and mother's education (red line) and (2) basic controls plus industry fixed effects (19 groups) (green line). Earnings are expressed in 2017 dollars.

Table E3.1: Gender Gap in Accepted Earnings (Winsorized), Controlling for Risk Preferences and a Proxy for Biased Beliefs

	Dep. Var: Accepted Earnings in the First Job							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel (a): Controlling for Risk Preferences and Perceived Relative Ability							
Female	-4612***	-3888***	-3497***	-3094**	-3240**	-2882**	-2651**	-2451*
	(1295)	(1309)	(1303)	(1315)	(1289)	(1319)	(1303)	(1326)
Risk Tolerance		1275**		826		662		419
		(510)		(518)		(489)		(499)
Perceived Relative Ability (1-5)			4193***	3948***			2523***	2412***
			(874)	(891)			(831)	(852)
Mean	59592	59592	59592	59592	59592	59592	59592	59592
R^2	0.145	0.149	0.161	0.162	0.370	0.371	0.376	0.376
N	1462	1462	1462	1462	1462	1462	1462	1462
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.000				0.01		
	Panel (b): Controlling for Risk Preferences and Expected Total Compensation							
Female	-7002.5***	-6796.2***	-5742.7**	-5437.0**	-5767.3**	-5596.8**	-5009.0**	-4747.5*
	(2526.8)	(2609.5)	(2451.0)	(2529.3)	(2536.8)	(2682.4)	(2492.3)	(2633.9)
Risk Tolerance		420.6		600.0		305.9		449.3
		(1088.0)		(1055.6)		(964.1)		(940.1)
Expected Total Compensation			0.2***	0.2***			0.1*	0.1**
			(0.1)	(0.1)			(0.1)	(0.1)
Mean	60524	60524	60524	60524	60524	60524	60524	60524
R^2	0.149	0.150	0.179	0.180	0.449	0.449	0.458	0.459
N	415	415	415	415	415	415	415	415
P-value: Equality of Female Coeff		(1) vs. (4)				(5) vs. (8)		
		0.036				0.096		
Controls	X	X	X	X	X	X	X	X
Add. controls					X	X	X	X

Note: The dependent variable is total accepted earnings (winsorized) in the first year in 2017 dollars. For this outcome, instead of dropping outliers (individuals who earn below $20,000 and above $175,000), we winsorize earnings above $175,000 and below $20,000. Risk tolerance is the average of two survey questions that ask respondents to rate their willingness to take on financial risks and daily risks and is measured on a 1 to 6 scale that is increasing in willingness to take risks. Perceived relative ability is based on the following question where respondents were asked, on a 5-point scale (increasing in perceived ability): *"Relative to your peers with the same concentration in BU, how would you rate your ability?"*. Expected total compensation refers to how much respondents expect to make at their first job after graduation in the first year. 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), dummies for the location of the first job (country/state), and weekly hours of work. Robust standard errors in parentheses. ***significant at the 1% level, **5% level, *10% level.

F Numerical Solution and Model Calibration

F.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 $\hat{\mu} \in \{\hat{\mu}_1, ..., \hat{\mu}_{N_\mu}\}$.[67] 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" values of unemployment over time are dictated by equation (1) so that:

$$\bar{U}_t = U_t\left(\hat{\mu}_t\right) \quad \text{for} \quad t = \{1, 2, .., T\} \tag{7}$$

F.2 Calibration

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

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

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

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

[67]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).

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

For the empirical moments contained in M, we use data on the evolution of earnings expectations (for which we have information at two points in time, $\bar{T} - 8$ and $\bar{T} - 2$) to inform the learning rule and overconfidence,[68] and information on the time path of cumulative mean accepted offers by gender and the share of students who have accepted offers over time to inform the preference and search parameters.[69] Throughout, and consistent with the evidence outlined above, we impose the restriction that risk aversion for women is larger than for men, in line with the reduced-form evidence.

The estimated parameters are summarized in Table F.1. The top panel reports the gender-neutral parameters, while the bottom panel reports the gender-specific parameters. The risk aversion parameter for men is $\iota^m = 2.12$ with a larger value for women of $\iota^f = 2.24$. While at face value the difference may appear small, what matters is how these differences translate into differential behavior in the model. Figure 3 shows that reservation wages move significantly for this quantitative move in risk aversion. The value of leisure (net of search costs) before graduation is 0.018% of offered wages; given that students do not receive unemployment benefits, it is natural that this parameter should be significantly below the usual 40% replacement rate used in the search literature. The average cost of search is roughly 8 times the flow value of leisure for women and men, respectively. The mean annual salary offer is $\$66,068$ for men and $\$59,848$ for women. Men have more optimistic beliefs about the mean offer that they will receive relative to women; the implied bias in wages at graduation is 13% for men and less than 9% for women. Moreover, the learning rate of women is about 5% higher than that of men. At the beginning of job search, men believe the mean offer they will receive is $\$282,760$ while women believe it is $\$173,790$.

The model is able to broadly match the key empirical patterns observed in the data. For example, we capture the decline in the gender gap in accepted earnings and the fact that women accept jobs earlier than men. While the model overpredicts the likelihood of searching initially (something not targeted in the estimation), it generates the observation that women are more likely to search for jobs earlier than men, and that search probabilities are rising over time. Figure F.1a plots the implied gender gap in cumulative mean accepted offers in our estimated model. The model is able to capture the decline in the gender gap as

[68]Note that we elicit beliefs about the earnings that respondents expect to have, not about the mean of the offer distribution, μ^*. The elicited expectations are thus a function of several of the model parameters.

[69]Specifically, for the former we use the value for each gender at $t = 2, 5, 11, 15, 20$; for the latter, we use the cumulative share that have accepted jobs at dates $t = 2$ and $t = \bar{T} + 1$ for each gender.

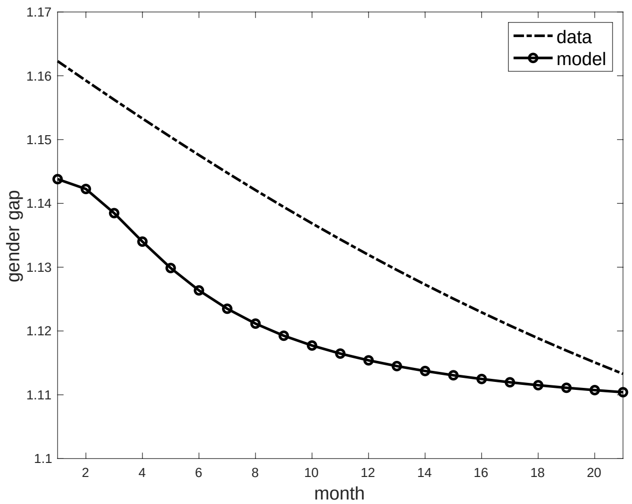
Table F.1: Model Parameters

Parameter	Description	Value	
β	discount rate	0.996	
σ^*	variance log offer	0.307	
ϕ	mean cost of search (utils)	586.950	
b	value of leisure	0.027	
λ	returns to search	0.269	
		Men	Women
μ^*	mean log offer	-1.114	-1.213
μ	expected log offer	0.340	-0.147
	$\Longrightarrow$implied bias in wages (percent dev.) at graduation	13.525	8.589
ι	risk aversion	2.119	2.241
γ	learning rate	0.271	0.284

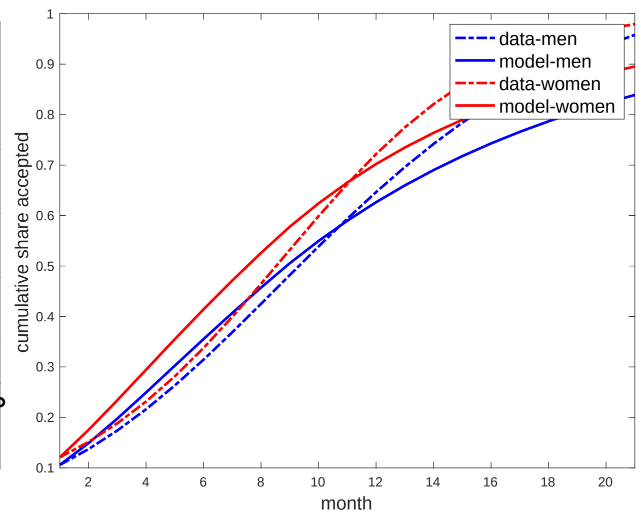
graduation nears, though it under-predicts the level at earlier dates.

Figure F.1b plots the cumulative share of men and women who have accepted jobs over the job search period, in both the model and the data. The model captures the fact that females accept jobs earlier than males, driven by the fact that they are more likely to search earlier. Importantly, only the shares at the beginning of search and at graduation (month 10) were targeted, not the entire curve. Finally, while women are always less likely to reject an offer in a particular period, the composition of job acceptance dates implies that, overall, men and women are likely to reject at least one offer at similar rates; this is consistent with the raw data as well, where we see similar likelihood of rejecting any offer by gender (see Table 2). Specifically, at $t = -9$, the probability that a female student searches is 30% while the probability a male student searches is 29%.

Figure F.1: Model-Generated Gender Earnings Gap and Cumulative Job Acceptance Rate



(a) Gender Earnings Gap



(b) Cumulative Share Who Have Accepted a Job

Note: The scale on the x-axis (in months) matches the timing in the model, where the graduation date is set to $\bar{T} = 10$ and the model begins at $t = 1$, 9 months before graduation. For Panel (a), 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. For Panel (b), 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.

G Appendix: Experiment Instructions

Welcome

You have been invited to take part in an online study of decision making. The study takes around 25 minutes to complete.

In this online study, you will be asked to complete **three tasks**. Once you start the study, it is important that you **complete all the three tasks without interruptions**. Excessive delays might result in you being disconnected from the server, which means that your progress will be lost. Note that Task 1 will take the most time to complete. Tasks 2 and 3 are fairly quick and should take less than two minutes each.

At the end of the study, you will receive a participation fee of $5. In addition, the **computer will randomly select one of the three tasks and pay you your earnings in that task**. Hence, your total earnings at the end of the study will be your payment for the randomly-selected task plus your $5 participation fee. The average total payment is $18.25. Since you will not know which of the three tasks will be selected for payment until the end of the study, you should treat each task as if you will receive payment for it.

Note that to qualify for payment, you must complete all three tasks. Importantly, please do not close your browser window until you have completed the study. If you close your browser, you will not be able to re-enter, and we will not be able to pay you. You will be paid through an **Amazon gift card**. To be able to send you the Amazon Gift Card, you will be asked to enter your **ASURITE User ID**. Remember that your ASURITE ID is **not** the same as your ASU ID number. Your ASURITE ID is what you use to log in. Please note that **you will be paid only your first participation**. Your first participation starts when you click on the button below and the first page of the study appears. If, by accident, you participate more than once in a task, please let us know immediately. Finally, to participate, **you must be a current undergraduate ASU student**, if you are not, we will not be able to compensate you.

This study is an individual task. You should not communicate with other people while you are taking part in the study. You will receive the instructions for each task right before you start the task.

Taking part in this study is completely voluntary. Your responses will be kept strictly confidential, and digital data will be stored in secure computer files. Any report of this research that is made available to the public will not include your name or any other individual information by which you could be identified. If you have questions or want a copy or summary of this study's results, you can contact Professor Basit Zafar at bzafar@asu.edu. If you have concerns about your rights as a research subject or want to speak with someone independent of the research team, you may contact the Institutional Review Board directly at 617-358-6115.

By clicking on the "Start the study" button below, you indicate that you are 18 years of age or older and that you consent to participate in this study.

Please enter your ASURITE ID below.

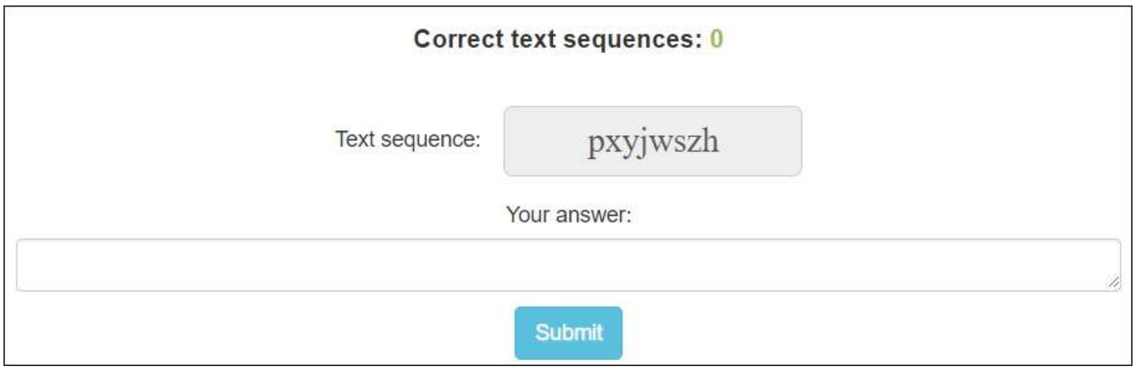
Start the study

Typing Assignment

Before we describe your choices in Task 1, you will perform a **typing assignment**. Specifically, you will be given sequences of random letters. An example of such a sequence can be seen below. **You will have four minutes to correctly type 15 text sequences as quickly as possible**. Note that each letter must be correct. To submit a text sequence, you must click on the "Submit" button (pressing the enter key will not submit the text sequence). Once you submit a text sequence, you will be able to see whether the text sequence was correct. Subsequently, irrespective of whether the text sequence was correct or incorrect, a new text sequence will appear. You will see the remaining time at the bottom of the screen.

You can see an example of the typing assignment's screen below.

Example: Screenshot of the typing assignment



Note that, the faster you type, the higher you can expect your earnings to be in Task 1. Importantly, your typing speed is measured by the moment you leave the typing screen. More specifically, once you finish typing correctly the 15th text sequence, a red button labeled "Finished" will appear. **Your time will be recorded the moment you press the "Finished" button**.

Click on the button below once you are ready to start the typing assignment.

Start the typing assignment

Typing Assignment

Correctly type up to 15 text sequences.

Correct text sequences: 0

Text sequence: jzcyfbaj

Your answer:

Submit

Remaining time: **03:53**

Typing Assignment

Correctly type up to 15 text sequences.

Correct text sequences: 15

You solved 15 text sequences, click on the button below to go to finish the typing assignment.

Finished

Remaining time: **00:15**

Task 1

Your role in Task 1 is that of a **job seeker**. You will have a **maximum of 5 rounds** to find a job. In each round, you will receive a **wage offer**. Wage offers can be either $2, $5, $8, $11, $14, $17, $20, $23, $26, $29, or $32.

At the beginning of each round, you will report the **minimum wage you are willing to accept**. This means that, in each round, there are two possibilities:

1. The **wage offer is equal to or larger than your minimum acceptable wage**, which means that you automatically **accept** the wage offer. In this case, your earnings are equal to the **offered wage** and no further rounds are played.
2. The **wage offer is less than your minimum acceptable wage**, which means that you **reject** the wage offer. In this case, you will proceed to the next round. Importantly, if you do not accept a wage offer by the end of round 5, your earnings will be $2.

Examples

- Suppose you are in round 1, and you report a minimum acceptable wage of $23. After that, you learn that the wage offer in round 1 is $29. Since your minimum acceptable wage is lower than the wage offer, you accept the wage offer and earn $29 in Task 1.
- Suppose you are in round 3, and you report a minimum acceptable wage of $14. After that, you learn that the wage offer in round 3 is $8. Since your minimum acceptable wage is higher than the wage offer, you reject the wage offer and continue to round 4.
- Suppose you are in round 5, and you report a minimum acceptable wage of $8. After that, you learn that the wage offer in round 5 is $5. Since your minimum acceptable wage is higher than the wage offer, you reject the wage offer. Since round 5 is the last round, there are no further wage offers, and you earn $2 in Task 1.

Understanding check: Suppose that you are in round 4 and report a minimum acceptable wage of $14. After that, you learn that the wage offer in round 4 was $23. What happens next?

- You reject the wage offer and continue to round 5
- You accept the wage offer and earn $14 for Task 1
- You reject the wage offer, there are no further rounds, and you earn $2 in Task 1
- You accept the wage offer and earn $23 for Task 1

Probabilities of receiving different wage offers

The wage offers you receive depend on the speed at which you correctly typed 15 text sequences. Specifically, in a separate study, we asked students from a comparable 4-year university in the US to perform the same typing assignment you just did. We will compare the time you took to correctly type 15 text sequences to the time taken by the 476 students who completed the typing assignment.

- If your typing speed is among the **fastest 25%** students, then you are classified as a **fast typist**, and you will receive wage offers according to the probabilities in the first row of Table 1.
- If your typing speed is among the **slowest 75%** students, then you are classified as a **slow typist**, and you will receive wage offers according to the probabilities in the second row of Table 1.

Table 1: Probability of getting a particular wage offer in a round

Wage offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability if you are a fast typist	3%	4%	7%	8%	10%	10%	20%	20%	6%	6%	6%
Probability if you are a slow typist	15%	15%	15%	15%	12%	10%	7%	6%	2%	2%	1%

For example, if you are a fast typist, then 20% of the time, you will receive a wage offer of exactly $20. On the other hand, if you are a slow typist, then you will receive a wage offer of exactly $20 only 7% of the time.

Another way to think about the information in Table 1 is to think about the chance of receiving a wage offer that is at least $X in a round. For example, if you are a fast typist, then the chance that the wage offer is $20 or higher is 58% (20% + 20% + 6% + 6% + 6%). On the other hand, if you are a slow typist, then the chance that the wage offer is $20 or higher is only 18% (7% + 6% + 2% + 2% + 1%).

Understanding check: Which statement is true:

- Fast typists will always get higher wage offers than slow typists
- Fast typists are more likely to get higher wage offers than slow typists
- Fast typists are more likely to get lower wage offers than slow typists
- Fast typists will always get lower wage offers than slow typists

Understanding check: What is the probability that you receive a wage offer of $14 in Round 1 if:

You are a fast typist? _______ %

You are a slow typist? _______ %

Understanding check: Suppose that you are in round 1 and report a minimum acceptable wage of $23.

What is the probability that you **accept** a wage offer in round 1 if you are a fast typist?

_______ %

Wage offers over rounds

An important consideration when choosing a minimum acceptable wage is that you can receive wage offers in subsequent rounds. For example, when making your choice in round 1, you know that could receive up to 5 wage offers (one per round). Hence, even though the probability of receiving a wage offer of $32 in one particular round is low, the probability of receiving a wage offer of $32 at least once in 5 rounds is considerably higher. To illustrate this more clearly, in Table 2 below, we calculate the **probability of receiving each wage offer at least once in 5 rounds**.

Table 2: Probability of getting a particular wage offer at least once in 5 rounds

Wage Offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability if you are a fast typist	14%	18%	30%	34%	41%	41%	67%	67%	27%	27%	27%
Probability if you are a slow typist	56%	56%	56%	56%	47%	41%	30%	27%	10%	10%	5%

The calculations used to compute probabilities like the ones in Table 2 are sometimes unwieldy. Therefore, to help choose your minimum acceptable wage, every round we will ask you the following question: **"How likely do you think it is that you are a fast typist?"** You can then use a slider to answer the question with a percentage between 0% and 100%. Importantly, by answering the question above, the computer will be able to compute the following information:

- The probability that you receive each wage offer at least once in the remaining rounds (assuming no acceptances).
- The probability that you receive a wage offer that is at least $X in the remaining rounds (assuming no acceptances).

Example

The following screenshot serves as an example. It illustrates these probabilities for a job seeker making a decision for round 3 who thinks he or she has a 40% chance of being a fast typist.

By looking at the green table, this job seeker can see that he or she has 30% chance of receiving a wage offer of exactly $14 at least once in the remaining rounds (either in round 3, round 4, or round 5).

Moreover, by looking at the orange table, this job seeker can see that he or she has an 87% chance of receiving a wage offer equal to $14 or more ($14, $17, $20, $23, $26, $29, or $32) at least once in the remaining rounds (either in round 3, round 4, or round 5).

How likely do you think it is that you are a fast typist?

0% 100%

Current answer 40 %

Given your answer above, below is the **probability of receiving each possible wage offer at least once** in the remaining 3 rounds (in either round 3, 4, or 5).

Wage Offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	27%	28%	31%	32%	30%	27%	31%	30%	10%	10%	9%

Given your answer above, below is the **probability of receiving a wage offer that is at least $X** in the remaining 3 rounds (in either round 3, 4, or 5).

Wage offer of at least:	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	100%	100%	98%	94%	87%	76%	64%	48%	27%	18%	9%

Are you a fast or a slow typist?

Note that you will **not** be informed whether you are a fast typist or a slow typist until the end of the study. In other words, you will not know what type of typist you are while you are choosing your minimum acceptable wages.

Understanding check: Use the screenshot below to answer the following questions.

What is the probability that you receive a wage offer of $29 at least once in the remaining rounds? _______ %

What is the probability that you receive a wage offer equal to $20 or more at least once in the remaining rounds? _______ %

How likely do you think it is that you are a fast typist?

0% 100%

Current answer 60 %

Given your answer above, below is the **probability of receiving each possible wage offer at least once** in the remaining 4 rounds (in either round 2, 3, 4, or 5).

Wage Offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	26%	28%	34%	36%	37%	34%	46%	44%	16%	16%	15%

Given your answer above, below is the **probability of receiving a wage offer that is at least $X** in the remaining 4 rounds (in either round 2, 3, 4, or 5).

Wage offer of at least:	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	100%	100%	100%	98%	95%	89%	80%	66%	40%	29%	15%

Go to Round 1

Task 1 - Round 1

You **took 234 seconds** to finish the typing assignment.

Table 1: Probability of getting a particular wage offer in a round

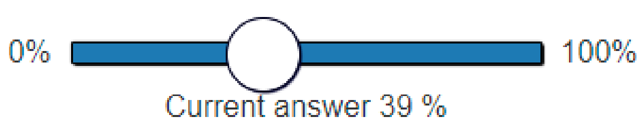
Wage offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability if you are a fast typist	3%	4%	7%	8%	10%	10%	20%	20%	6%	6%	6%
Probability if you are a slow typist	15%	15%	15%	15%	12%	10%	7%	6%	2%	2%	1%

What is the minimum wage you are willing to accept in round 1?

$2
$5
$8
$11
$14
$17
$20
$23
$26
$29
$32

Please answer the following question with a number between 0% and 100%:

How likely do you think it is that you are a fast typist?



Given your answer above, below is the **probability of receiving each possible wage offer at least once** in the remaining 5 rounds (in either round 1, 2, 3, 4, or 5).

Wage Offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	39%	41%	46%	47%	45%	41%	45%	42%	16%	16%	13%

Given your answer above, below is the **probability of receiving a wage offer that is at least $X** in the remaining 5 rounds (in either round 1, 2, 3, 4, or 5).

Wage offer of at least:	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	100%	100%	100%	99%	95%	88%	77%	62%	38%	27%	13%

Continue

Task 1 - Round 2

In round 1 you received a wage offer of $14, which you rejected because it is below your minimum wage of $20.

Table 1: Probability of getting a particular wage offer in a round

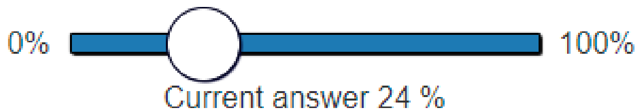
Wage offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability if you are a fast typist	3%	4%	7%	8%	10%	10%	20%	20%	6%	6%	6%
Probability if you are a slow typist	15%	15%	15%	15%	12%	10%	7%	6%	2%	2%	1%

What is the minimum wage you are willing to accept in round 2?

$2
$5
$8
$11
$14
$17
$20
$23
$26
$29
$32

In the previous round, you reported a **39%** chance that you are a fast typist. Please consider the wage offer you got and answer the following question with a number between 0% and 100%. Note that, to ensure that participants consider the question, the slider must be moved to continue. If your answer to the question has not changed from the previous round, then you must move the slider away from its current value and then move it back to 39%.

Now, how likely do you think it is that you are a fast typist?



Given your answer above, below is the **probability of receiving each possible wage offer at least once** in the remaining 5 rounds (in either round 1, 2, 3, 4, or 5).

Wage Offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	39%	40%	42%	43%	39%	34%	33%	31%	11%	11%	8%

Given your answer above, below is the **probability of receiving a wage offer that is at least $X** in the remaining 5 rounds (in either round 1, 2, 3, 4, or 5).

Wage offer of at least:	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	100%	100%	99%	97%	90%	79%	65%	49%	27%	18%	8%

Continue

Task 1 - Round 3

You received a wage offer of $8.

Since your minimum wage is $2, this offer has been accepted.

Your earnings for Task 1 are therefore $8.

Table 1: Probability of getting a particular wage offer in a round

Wage offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability if you are a fast typist	3%	4%	7%	8%	10%	10%	20%	20%	6%	6%	6%
Probability if you are a slow typist	15%	15%	15%	15%	12%	10%	7%	6%	2%	2%	1%

In the previous round, you reported a **24%** chance that you are a fast typist. Please consider the wage offer you got and answer the following question with a number between 0% and 100%. Note that, to ensure that participants consider the question, the slider must be moved to continue. If your answer to the question has not changed from the previous round, then you must move the slider away from its current value and then move it back to 24%.

Now, how likely do you think it is that you are a fast typist?

0% 100%

Current answer 15 %

Given your answer above, below is the **probability of receiving each possible wage offer at least once** in the remaining 5 rounds (in either round 1, 2, 3, 4, or 5).

Wage Offer	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	34%	35%	36%	36%	31%	27%	24%	22%	8%	8%	5%

Given your answer above, below is the **probability of receiving a wage offer that is at least $X** in the remaining 5 rounds (in either round 1, 2, 3, 4, or 5).

Wage offer of at least:	$2	$5	$8	$11	$14	$17	$20	$23	$26	$29	$32
Probability	100%	100%	98%	92%	81%	68%	52%	37%	19%	12%	5%

Continue

Task 2

In Task 2, you make 12 simple decisions. Each decision consists of a choice between two options: A and B. If you choose Option A, you earn a specified amount of money with certainty. If you choose Option B, a random draw determines your earnings: with 50% probability you earn $30 and with 50% probability you earn $0. Once you have made your choices, one of the 12 decisions will be randomly selected by the computer to determine your earnings for Task 2.

Continue

Task 2

Please select either A or B in each decision.

Decision 1	A: $6 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 2	A: $7 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 3	A: $8 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 4	A: $9 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 5	A: $10 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 6	A: $11 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 7	A: $12 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 8	A: $13 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 9	A: $14 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 10	A: $15 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 11	A: $16 with certainty	B: $0 with 50% probability and $30 with 50% probability
Decision 12	A: $17 with certainty	B: $0 with 50% probability and $30 with 50% probability

Submit choices for Task 2

Task 3

In Task 3, you decide when you want to receive a specified amount of money. More precisely, you will make 24 choices between two options: A and B. An option specifies an amount of money and the time when you would be paid the specified amount. The amounts of money range from $13.00 to $18.50 and the payment times include "today", "in 4 weeks", and "in 8 weeks". Once you have made your choices, one of the 24 decisions will be randomly selected by the computer to determine your earnings for Task 3. If this task is picked for payment, you will receive your earnings at the date based on your choice.

Continue

Task 3

Please select either A or B in each decision.

Decision 1	A: $13.50 today	B: $13.00 in 4 weeks
Decision 2	A: $13.50 today	B: $13.50 in 4 weeks
Decision 3	A: $13.50 today	B: $14.00 in 4 weeks
Decision 4	A: $13.50 today	B: $14.50 in 4 weeks
Decision 5	A: $13.50 today	B: $15.00 in 4 weeks
Decision 6	A: $13.50 today	B: $15.50 in 4 weeks
Decision 7	A: $13.50 today	B: $16.00 in 4 weeks
Decision 8	A: $13.50 today	B: $16.50 in 4 weeks
Decision 9	A: $13.50 today	B: $17.00 in 4 weeks
Decision 10	A: $13.50 today	B: $17.50 in 4 weeks
Decision 11	A: $13.50 today	B: $18.00 in 4 weeks
Decision 12	A: $13.50 today	B: $18.50 in 4 weeks

Decision 13	A: $13.50 in 4 weeks	B: $13.00 in 8 weeks
Decision 14	A: $13.50 in 4 weeks	B: $13.50 in 8 weeks

Decision 15	A: $13.50 in 4 weeks	B: $14.00 in 8 weeks
Decision 16	A: $13.50 in 4 weeks	B: $14.50 in 8 weeks
Decision 17	A: $13.50 in 4 weeks	B: $15.00 in 8 weeks
Decision 18	A: $13.50 in 4 weeks	B: $15.50 in 8 weeks
Decision 19	A: $13.50 in 4 weeks	B: $16.00 in 8 weeks
Decision 20	A: $13.50 in 4 weeks	B: $16.50 in 8 weeks
Decision 21	A: $13.50 in 4 weeks	B: $17.00 in 8 weeks
Decision 22	A: $13.50 in 4 weeks	B: $17.50 in 8 weeks
Decision 23	A: $13.50 in 4 weeks	B: $18.00 in 8 weeks
Decision 24	A: $13.50 in 4 weeks	B: $18.50 in 8 weeks

Submit choices for Task 3

Thank you for your participation

The experiment has concluded.

We will pay you your earnings plus the $5 participation fee with an **Amazon gift card**. You will receive your payment at the ASU email you provided.

The task that was randomly chosen for payment is **Task 1**.

In Task 1, your earned **$8**, plus the $5 participation fee.

You will receive your payment in the next 24 hours. Please contact Professor Basit Zafar at bzafar@asu.edu if you have any questions.

In case you are curious about your typing speed, you were among the slowest 75 percent students, and therefore, you were classified as a **SLOW** typist.

You can close this window.