

Job Applications and Labor Market Flows*

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Abstract

Improvements in search technology have led to an increase in worker applications over time. Concomitantly, unemployment inflow rates have declined sharply, with no long-run change in job-finding rates. To explain these trends, we introduce a search model with multiple applications and costly information acquisition. When workers send more applications, the model predicts that firms invest more in finding good matches, leading to fewer separations, while workers become choosier about which offers they accept, mitigating the rise in job-finding rates. Quantitatively, the model replicates the empirical trends in unemployment flows both in the aggregate and across groups. To validate our model's mechanisms, we present new facts on the variation in job offers, acceptance rates, and reservation wages over time. Importantly, it is the model's ability to reproduce these empirical changes that enables it to generate the observed trends in unemployment flows.

Keywords: Multiple Applications, Inflows, Outflows, Unemployment, Costly Information
JEL Codes: E24, J63, J64

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1 Introduction

Improvements in search technology with the widespread adoption of the internet and online job platforms have led to a rise in worker applications over time. Alongside this change, the U.S. has seen a steady decline in the unemployment inflow (job separation) rate since the 1980s, while the unemployment outflow (job-finding) rate has not exhibited any long-run trend. Given that unemployment flows are inextricably tied to job-search behavior, we ask how an increase in the number of applications can lead to differential trend behaviors in inflow and outflow rates.

In addressing this question, we make two contributions. First, we empirically document the trends in unemployment flows and worker applications. Using data from the Current Population Survey (CPS), we show that the decline in the unemployment inflow rate is largely driven by a sharp decline in the inflow rate for workers without a college degree, whom we define as “non-college workers”. In contrast, the inflow rate of workers with a college degree – whom we define as “college workers” – observes a much smaller decline. Further, unemployment outflow rates for both non-college and college workers observe no long-run changes. We also provide novel findings on how worker applications have changed over time using information from the Employment Opportunity Pilot Project (EOPP) and the Survey of Consumer Expectations (SCE). In particular, we find that the median number of applications submitted per month has doubled since the 1980s for both non-college and college unemployed workers.

Second, we build a tractable equilibrium labor search model to quantitatively analyze how a doubling in the number of applications can generate differential declines in the unemployment inflow rates of non-college and college workers without precipitating simultaneous trend declines in unemployment outflow rates. Our model departs from the standard labor search model in two ways. First, to explore the consequences of rising applications, we allow workers to send multiple applications and vacancies to be contacted by multiple applicants. Second, we introduce information frictions in the form of costly information acquisition by firms. The assumption of costly information captures the notion that a rising number of applications increases the firm’s burden of identifying the best applicant for the job. We highlight that the endogenous change in firms’ hiring behavior is a key channel through which increased applications can generate the observed empirical changes in labor market flows over time. Crucially, we provide new evidence on how job offer and acceptance rates as well as reservation wages – outcomes which directly affect inflow and outflow rates – have changed over time. We validate our model’s predictions against these application outcomes observed in the data.

In our model, workers submit multiple applications to separate vacancies and costlessly observe the match quality drawn for each application. Match quality evolves over time but is persistent as future draws are correlated with current values and high-productivity matches are less susceptible to match quality shocks. Firms can receive more than one application. Unlike

workers, firms can only observe the match quality of their applicants at the time of meeting if they pay a fixed cost of acquiring information. Firms' incentives to acquire information increase with the number of worker applications, as a higher number of applicants per vacancy increases the probability that a firm has at least one high-productivity applicant. Firms, however, can only exploit this benefit if they acquire information and are able to rank applicants. Further, the probability that an offer is rejected is minimized when firms extend offers to their highest quality applicants, as wages are rising in match productivity.

Having developed our model, we apply our framework to the data. We assume that workers can differ by education and that labor markets are segmented across education groups. We calibrate our model to match labor market moments and application outcomes both in the aggregate and across education groups for the period 1976-1985.¹ Our main quantitative exercise consists of two parts. First, we use our calibrated model to analyze how the unemployment inflow and outflow rates of non-college and college workers change when *only* the number of applications that workers can send increases. Second, we use our empirical findings in the EOPP and SCE to validate our model's predictions on application outcomes such as the offer probability, the acceptance rate as well as the reservation wage.

Our model captures the differential decline in unemployment inflow rates between non-college and college workers. In particular, our model predicts that the inflow rate of non-college workers falls 59 percent, similar to the 50 percent decline observed in the data. For college workers, our model predicts a modest increase in the inflow rate from 1.7 percent to 1.9 percent, while in the data it declined from 1.4 percent to 1.1 percent.² How does the model generate differential trends in inflows despite a similar increase in applications across educational groups? In the model, an increase in applications affects the inflow rate in two opposing ways. On one hand, a higher number of applicants per vacancy raises firms' incentives to acquire information and thus, the share of informed firms. More informed firms lead to a greater formation of high-productivity matches that are less susceptible to job destruction, reducing inflows. However, the ability to contact more vacancies also elevates workers' outside options. This raises workers' selectivity, leading to higher reservation match quality and more job destruction. Quantitatively, the effects from an improved distribution of realized match quality dominate the rise in worker selectivity for non-college workers. As such, the model generates a sharp decline in their inflow rate. Notably, the effect of worker selectivity manifests through changes in the reservation wage. Thus, changes in our model-implied reservation wages can be tested against its empirical counterpart in the EOPP and SCE. Overall, we find that our model's prediction of a muted

¹We use this time period because the EOPP is a cross-sectional dataset that provides information for the period 1979-1980. Since we are interested in long-run comparisons, we treat the 10-year period around 1979-1980 as our steady-state period.

²These data moments are obtained for the 1976-1985 period and the 2010-2019 period, respectively. The former period covers the EOPP survey while the latter covers the SCE.

increase in the reservation wage for non-college workers is consistent with the stagnant growth in reservation wages for non-college workers in the data.

Unlike non-college workers, the worker selectivity effect is stronger for college workers. Given their access to jobs with higher match quality, each additional application raises the college worker's probability of drawing a high-quality match and attaining a job, thus elevating their outside options. Consequently, our model predicts a slight increase in the inflow rate of college workers. Notably, when we increase both the number of applications *and* the average productivity of college workers such that the model also replicates the rise in the college premium over time, the model is able to generate a decline in the inflow rate of college workers, as in the data. This reversal occurs because the sharp improvement in the distribution of realized match quality now outweighs the effect of higher worker selectivity.

For outflow rates, our model predicts that a rise in applications causes only slight changes for both non-college (47 percent to 43 percent) and college (60 percent to 63 percent) workers. These results are in line with the fact that outflow rates exhibit no long-run change over time, a finding we highlight in greater detail in Section 2. How is the model able to generate a muted response of outflow rates despite the rise in applications? Similar to inflows, an increase in applications has an ambiguous effect on outflows. While outflow rates can rise due to the increased contact between job-seekers and vacancies, whether job-finding rates actually increase ultimately depends on the probability that these contacts are converted into offers and acceptances. The probability a single application yields an offer falls when there is increased competition amongst workers, while the probability that an offer is accepted falls when workers contact more vacancies and can choose from more options. The decline in offer and acceptance probabilities is sizeable, and counteracts the worker's benefit from contacting more vacancies. These offsetting forces cause increased applications to have a negligible impact on outflows. We *validate* our model-implied changes in job offer and acceptance probabilities against our empirical findings from the EOPP and SCE. As in the data, our model predicts that the rise in worker applications has been accompanied by an overall decline in job offer and acceptance rates.

Finally, we demonstrate why endogenizing the firm's information acquisition problem is a necessary feature to understand how a rise in applications affects trends in labor market flows. We consider two thought experiments: a case where information about a firm's applicants is free, and a case where information is infinitely costly. We find that both models predict counterfactual unemployment flows, especially for inflow rates. Intuitively, in the zero-cost environment, all firms always make an offer to the highest quality applicant in their pool, while in the infinite-cost environment, all firms randomly hire a job-seeker from their applicant pool. As such, in both these environments, an increase in the number of applications results in a weak improvement in the distribution of realized match quality relative to the rise in worker selectivity. Importantly, the firm's investment in information does not vary with the number of applications in both of

these models. In contrast, our baseline model observes the share of informed firms endogenously varying with the number of worker applications. The share of informed firms in our model has a non-trivial effect on the concentration of high-quality matches and aggregate job longevity, suggesting that the interaction between the firms' information problem and the workers' application behavior is necessary to explain the trends in labor market flows.

Related literature We are not the first to examine how improvements in search technology affect labor market flows. [Martellini and Menzio \(2020\)](#) study an economy with search frictions along a balanced growth path and show how *both* inflow and outflow rates can remain unchanged over the long-run even if search technology improves. In contrast, our paper highlights that the improvement in search technology since the 1980s has been accompanied by a secular decline in inflow rates with no long-run change in outflow rates, findings which are consistent with recent evidence by [Crump, Eusepi, Giannoni, and Şahin \(2019\)](#). [Martellini and Menzio \(2020\)](#) show that the outflow rate remains constant when lower acceptance rates counteract the improvement in search efficiency. Importantly, the fall in acceptance rates in their model is driven by a rise in reservation match quality and thus, reservation wages. While the reservation wage has risen for college workers in the data, there has been little change in the reservation wage of non-college workers over time. Thus, their model cannot generalize to *all* workers. Our model with its focus on heterogeneous workers and multiple applications can reconcile the differential growth in reservation wages across education groups. Although acceptance rates also decline in our model, they fall because workers reject offers more often when they can contact more vacancies and select from more options. Our model can thus generate a large decline in acceptance rates without simultaneously precipitating a large increase in the reservation wage of non-college workers, consistent with the data. Finally, [Martellini and Menzio \(2020\)](#) predict a constant share of employed being displaced each period as the distribution of realized match quality and reservation match productivity improve at the same rate. Our framework instead accommodates declines in inflow rates whenever the rise in reservation match quality is muted relative to the improvement in the distribution of realized match quality. As such, our model accounts for the differential declines in inflow rates across groups since the 1980s. Overall, we argue that any model that analyzes the long-run changes in inflow and outflow rates should also account for changes in job offer and acceptance rates as well as reservation wages – factors that have a first order effect on unemployment flows.

Our work contributes to the literature on the secular changes in labor market flows. [Engbom \(2019\)](#) extends the labor search model to incorporate rich firm dynamics and entrepreneurial choice, and shows how an aging workforce contributes to the decline in worker dynamics over time. We focus on how changes in application behavior have led to changes in labor market flows through their effects on household job search and firm hiring decisions. [Mercan \(2017\)](#)

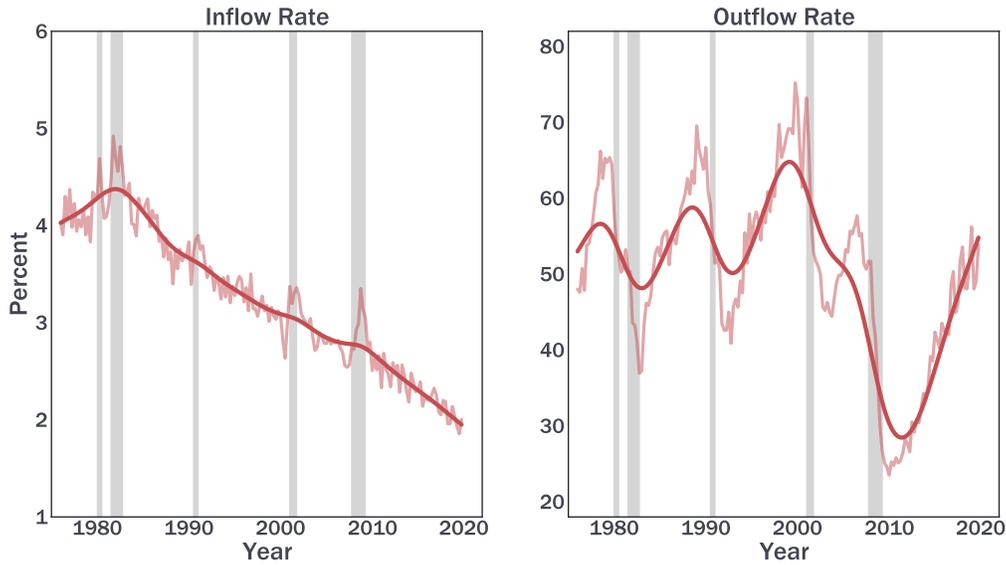
and Pries and Rogerson (2019) show that the exogenous reduction in uncertainty regarding a worker’s fit for a job is key to explaining the decline in worker turnover and job separations over the past four decades. In our paper, while a higher share of informed firms also affects labor market flows, increases in this share are an *endogenous* response to rising worker applications.

Our paper also contributes to the literature on labor search models with multiple applications. Earlier papers in the literature by Albrecht, Gautier, and Vroman (2006), Kircher (2009), and Galenianos and Kircher (2009) focus on the efficiency properties of such models in a directed search environment. Extending the model, Gautier, Moraga-Gonzalez, and Wolthoff (2016) examine the efficiency properties when the number of applications is endogenous. Gautier and Wolthoff (2009) consider a model where workers send at most two applications, and focus on ex-ante heterogeneity on the firm side. To address our question, we extend the framework to incorporate heterogeneity among workers, creating a role for information acquisition in firms’ hiring decisions. Bradley (2020) features a similar setup where firms pay a cost to reveal information about their applicants. Although Bradley (2020) allows firms to receive multiple applications, workers in his model can only send one application. Because our question concerns how rising applications can affect labor market flows, we allow for multiple applications on both sides of the market. Closely related to our work is the seminal paper by Wolthoff (2018), who uses a directed search model with multiple applications to study the business-cycle properties of firms’ recruiting decisions. He finds that the number of applicants interviewed by firms is procyclical when applicants vary by match quality. Our paper instead focuses on long-run trends in the labor market. Specifically, it addresses how an increase in applications strengthens firms’ incentives to acquire information, which in turn affects labor market flows. To our knowledge, this is the first paper to link a rise in applications to long-run trends in labor market flows.

Finally, our paper is related to the literature on firms’ “recruiting intensity”, an activity defined as the extent to which firms actively try to fill their positions. Gavazza, Mongey, and Violante (2018) show that the decline in recruiting intensity in recessions is due to equilibrium effects where increased slack in the labor market allows firms to exert less effort to fill a position. Acharya and Wee (2020) show that with rationally inattentive firms, recruiting intensity declines in recessions because firms reject workers more often when they are unable to acquire accurate information, raising the potential of large losses from hiring an unsuitable worker. While we do not focus on the business cycle, our paper provides a microfoundation to firms’ recruiting intensity as improved search technologies raise the number of applicants per vacancy. This affects the share of firms acquiring information and thus the intensity with which firms fill a position.

The rest of the paper is organized as follows. Section 2 presents our empirical findings on inflow and outflow rates, and application outcomes across education groups. Section 3 discusses our model, and Section 4 provides the calibration strategy. Section 5 presents our results, Section 6 provides a discussion on the robustness of our main results, and Section 7 concludes.

Figure 1: Unemployment inflow and outflow rates



Note: This figure plots the unemployment inflow rate (left panel) and outflow rate (right panel) between 1976:Q1 - 2019:Q4. Quarterly time series are averages of monthly inflow and outflow rates, which are calculated using CPS data as described in Appendix A. Dark-red lines represent the trends, which are HP-filtered quarterly data with smoothing parameter 1600. Gray shaded areas indicate NBER recession periods.

2 Empirical Findings

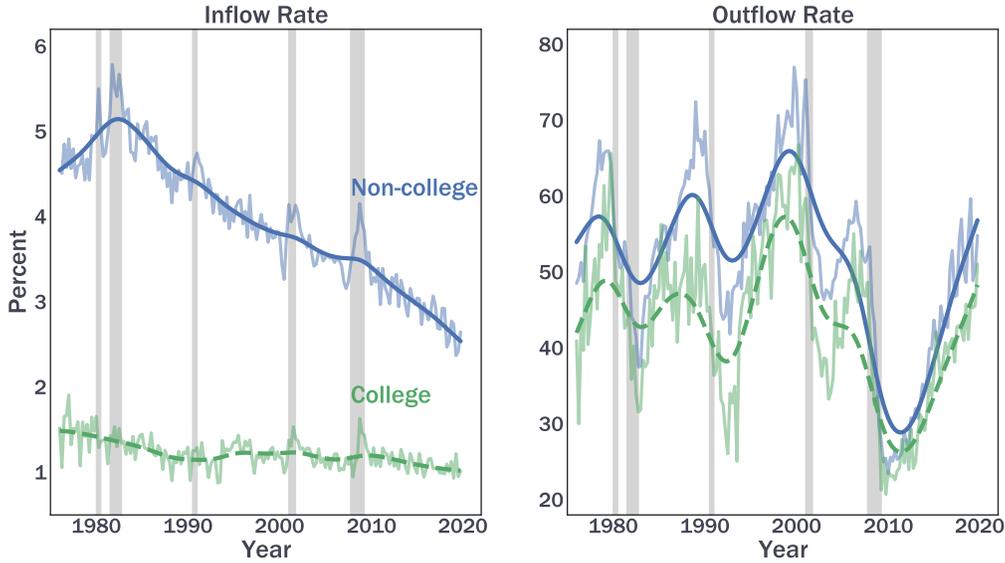
In this section, we discuss our empirical findings that motivate the model and quantitative exercises. In Section 2.1, we show that unemployment inflow rates have declined dramatically, while outflow rates have not exhibited any trend over the past four decades. Importantly, most of the decline in the inflow rate is driven by the fall in the inflow rate of non-college workers. Next, Section 2.2 provides new insights on how the number of applications and application outcomes have changed over time, both in the aggregate and across education groups. Specifically, we find that while the unemployed now submit more applications and report higher reservation wages, they tend to receive fewer offers and are less likely to accept an offer.

2.1 Labor market flow rates

Using monthly data from the CPS on the number of employed, unemployed, and short-term unemployed, defined as respondents who are unemployed for at most five weeks, we calculate the unemployment inflow rate and the unemployment outflow rate over time using standard procedures found in the literature. Appendix A provides details on our data and methodology.

Figure 1 plots quarterly averages of monthly inflow and outflow rates for the period 1976:Q1 - 2019:Q4. It shows that long-run trends in inflow and outflow rates have behaved differently,

Figure 2: Unemployment inflow and outflow rates across education groups



Note: This figure shows the unemployment inflow rate (left panel) and outflow rate (right panel) between 1976:Q1 - 2019:Q4 for individuals without a four-year college (bachelor’s) degree and individuals with at least a four-year college degree separately. Quarterly time series are averages of monthly inflow and outflow rates, which are calculated using CPS data as described in Appendix A. Dark-blue and dashed green lines represent the trends, which are HP-filtered quarterly data with smoothing parameter 1600. Gray shaded areas indicate NBER recession periods.

confirming the findings of earlier studies.³ Since the 1980s, the inflow rate has fallen 50 percent, from 4 percent to 2 percent. In contrast, the outflow rate exhibits no secular change.

We further partition the data into labor market flows for individuals with and without a four-year college degree. For brevity, we refer to these groups as college and non-college workers, respectively. Figure 2 presents two important results. First, over the past four decades, the decline in the inflow rate is much larger for non-college (50 percent) than for college workers (23 percent), indicating that the decline in the aggregate inflow rate is primarily driven by the former. Second, the outflow rates of both groups do not exhibit any discernible long-run trend.

Given that college workers have lower inflow rates compared with non-college workers, a natural question to ask is whether the decline in the aggregate inflow rate is merely due to a rising share of college workers over time or whether the decline reflects a more fundamental change in each group’s labor market experience. To address this question, we implement a shift-share decomposition exercise on the aggregate inflow rate in Appendix A. We find that the within-education group decline explains about 86 percent of the fall in the aggregate inflow rate, while 14 percent can be attributed to compositional differences over time. Hence, group-specific declines in inflow rates (especially for that of non-college workers) explain most of the fall in the aggregate inflow rate over time. Finally, in Appendix A, we perform further cuts of the data by gender and by age, and we continue to find that within these narrower groups, most of the

³See Crump, Eusepi, Giannoni, and Şahin (2019), for example.

decline in inflows can be attributed to the drop in the inflow rates for non-college workers.

In summary, inflow rates have declined substantially over time, with much of the decline being driven by the trend observed for non-college workers. In contrast, outflow rates have not exhibited any long-run trend both in the aggregate and across education groups.

2.2 Job applications, job offers, and job acceptance rates

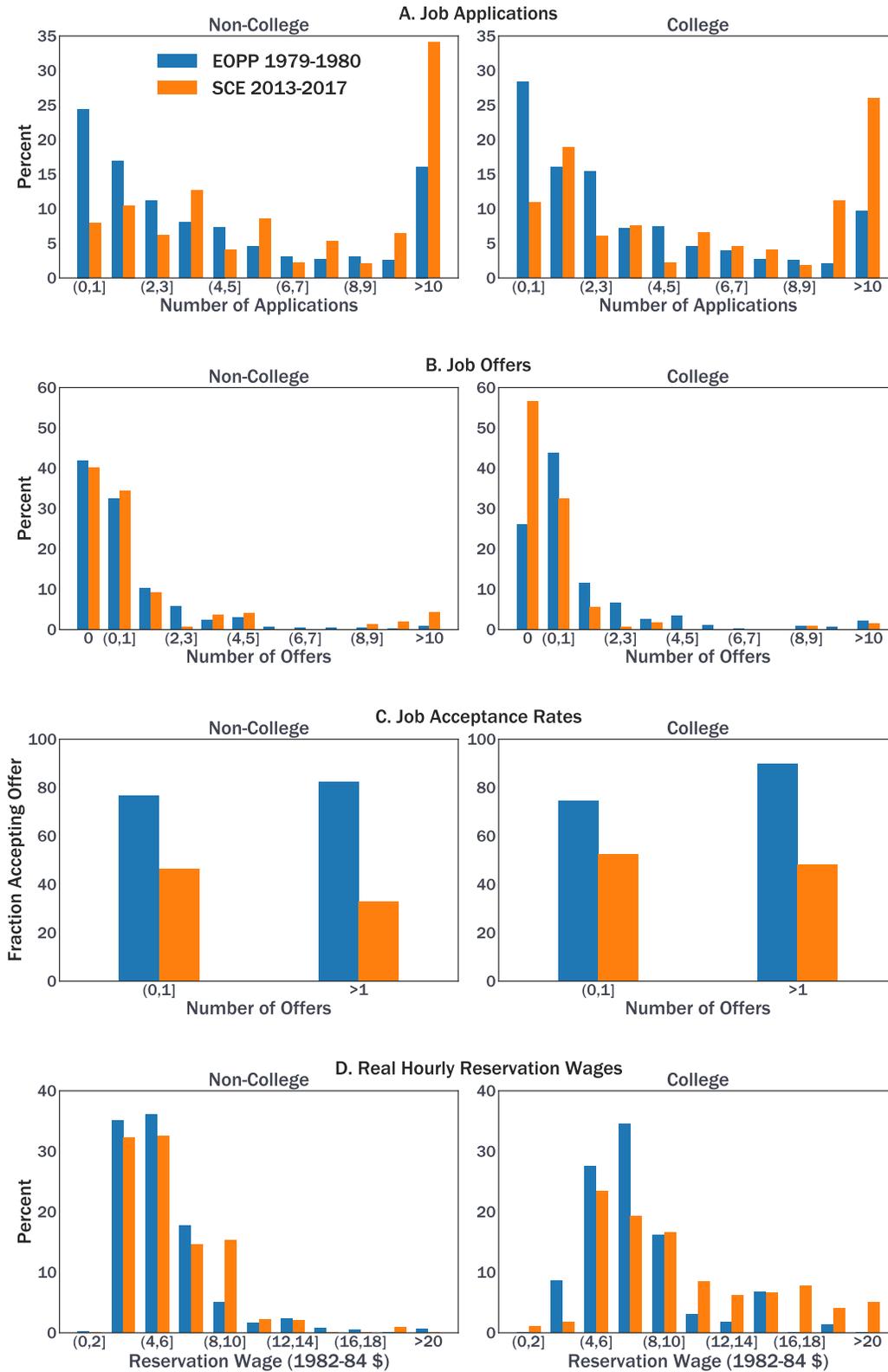
Given that unemployment flows are inextricably tied to how job-seekers contact firms, we use information from two datasets, the EOPP and SCE Labor Market Survey, to provide novel evidence on how the job search experience of workers has evolved over time. A unique feature of both datasets is that they offer insights into job search behavior and, unlike other household surveys, provide detailed information on the job application process such as the number of job applications sent, the number of offers received, and the job offer acceptance decisions of workers. In addition, these datasets offer information about workers' reservation wages.

The EOPP was conducted to analyze the impacts of an intensive job search and a work-and-training program. This household survey took place between February and December 1980 and covers unemployment spells and job search activities occurring between 1979 and 1980. Around 80 percent of the interviews occurred between May and September, and a total of 29,620 families were interviewed. The Federal Reserve Bank of New York's SCE survey is a household survey that is conducted annually with more than 1,000 respondents per year. We use information from the SCE for the years 2013 to 2017. Both datasets also provide individual-level information on demographics, employment, wages, and regular hours of work. Appendix A gives more details on these datasets, provides a list of the variables we use, and explains how we calculate moments using these variables. In order to evaluate the comparability of these datasets with more widely used surveys, Table A1 and Table A2 in Appendix A compare the EOPP and SCE samples to the CPS over the same time period. Overall, the EOPP 1979-1980 and SCE 2013-2017 samples capture well the demographic changes observed in the CPS between both time periods.

We focus on unemployed individuals aged 25-65 with at least one job application during their unemployment spell. Using the EOPP and SCE samples, we calculate the distribution of the number of applications sent, the distribution of job offers received during a month of unemployment, the fraction of unemployed with non-zero offers who accept a job, and the distribution of real hourly reservation wages. We calculate these data moments for 1979-1980 using the EOPP sample and for 2013-2017 using a pooled SCE sample. Finally, we calculate these moments separately for college and non-college workers. Figure 3 summarizes the results.

Our key finding is that the distribution of worker applications submitted per month by the unemployed shifts rightward for both college and non-college workers. Between the two surveys, the median number of applications per month increased from 2.46 to 6 and from 2.82 to 7 for college and non-college workers, respectively, implying that the number of worker applications

Figure 3: Changes in the job search process over time



Note: This figure shows the distributions of the number of job applications and job offers received during a month of unemployment; the fraction of unemployed individuals who accepts a job offer, conditional on having a job offer; and distributions of real hourly reservation wages separately for college and non-college workers. Reservation wages are in 1982-1984 dollars. These moments are calculated from 1979-1980 using the EOPP sample and from 2013-2017 using a pooled SCE sample incorporating unemployed individuals aged 25-65 with at least one job application during their unemployment spell.

more than doubled between 1979-1980 and 2013-2017 for both education groups. To ascertain whether the rise in applications is not simply due to prevailing aggregate economic conditions, Table A3 in Appendix A shows that this result holds even after controlling for business cycle effects. Overall, our findings imply an increase in the average number of worker applications.

In addition, we also document how the change in application behavior has been accompanied by changes in application outcomes. Between the two time periods, college workers observe a significant decline in job offers during a month of unemployment, while non-college workers observe no significant change. The fraction of individuals with no offers increased from 26 percent to 57 percent for college workers, but decreased slightly from 42 percent to 40 percent for non-college workers. Further, among the unemployed who received more than one job offer during a month of unemployment, the fraction of individuals who accept an offer decreased from 90 percent to 48 percent for college workers and from 82 percent to 33 percent for non-college workers. Finally, for both college and non-college workers, the distribution of real hourly reservation wages shifts rightward across these two time periods, with college workers observing a larger increase. The mean real hourly reservation wage (in 1982-1984 dollars) increased from \$7.27 to \$9.75 for college workers and from \$5.59 to \$5.72 for non-college workers. Overall, we conclude that while the unemployed now submit more applications than they used to, they tend to also receive fewer offers, reject these offers more often, and demand higher wages.

We argue that any model that seeks to explain the change in labor market flows with a change in applications, should also jointly account for changes in application outcomes. In what follows, we develop a framework that allows us to examine how a rise in applications can affect labor market flows and application outcomes.

3 Model

In this section, we present the general model and assume that workers are ex-ante identical. Next, we characterize the equilibrium conditions and provide a discussion on the important mechanisms of the model. In Section 4, we segment the economy into two labor markets – non-college and college – and provide details on the differences across these two labor markets.

3.1 Environment

Time is discrete. The economy comprises a unit mass of infinitely-lived workers who are ex-ante identical. Workers are risk neutral and discount the future with factor β . Workers can either be employed or unemployed. Unemployed workers consume home production b . Employed workers consume their wages and are attached to firms that can employ at most one worker. The output from a matched firm-worker pair is equal to its match quality x , which is drawn at the time

of meeting from a time-invariant distribution $\Pi(x)$ with support $[\underline{x}, \bar{x}]$.⁴ Match qualities can evolve over time. In particular, with probability $\rho(x)$, workers re-draw new match quality y from a conditional distribution $\Psi(y|x)$, where $d\Psi(y|x)/dx > 0$, implying that new draws of match quality y are positively correlated with previous values of x . We further assume that $\rho(x)$ is decreasing in x , implying that higher-productivity matches observe a lower frequency of match quality shocks. Employed workers endogenously exit into unemployment whenever their new match quality draw is such that the match is no longer sustainable. Employed workers also exogenously exit into unemployment with probability δ .

Job search Search is random. Only unemployed workers search for jobs. An unemployed worker can costlessly send multiple applications, with number of applications a worker can send each period denoted by a .⁵ A worker sends each application to a separate vacancy. For each vacancy contacted, she observes her match quality x for that particular application. Vacancies can be contacted by multiple applicants, where the number of applicants at a vacancy is a random variable. Unlike workers, firms do not observe their applicants' match qualities. A firm, however, can choose to pay a fixed cost, κ_I , to learn its applicants' qualities. While paying κ_I reveals to the firm information about its applicants' match qualities, it does not inform the firm about the number of offers applicants have nor does it provide information about their match qualities at other jobs.⁶ As such, information is asymmetric as a worker knows her match qualities across all applications and her number of offers received, while a firm that acquires information only knows its applicants' match qualities at its own vacancy. We restrict our attention to symmetric equilibria in pure strategies; that is, all firms with j number of applicants employ the same information acquisition and hiring strategy. Finally, each vacancy costs κ_V to post.

Matching Let u denote the measure of unemployed, v the measure of vacancies, and j the number of applicants for a vacancy. Further let $q(j)$ denote the probability that a firm receives j applicants. Since workers send a applications, the probability that an unemployed worker applies to any one particular vacancy is a/v . Correspondingly, the number of applicants at a vacancy, j , is given by $j \sim \text{bin}(u, a/v)$. The probability that a firm has j applicants is given by:

$$q(j) = \binom{u}{j} \left(\frac{a}{v}\right)^j \left(1 - \frac{a}{v}\right)^{u-j}.$$

In the limit when u and v are measures, the probability the firm has j applicants collapses to:

⁴The support of x can be unbounded. In Section 4, we assume that x is log-normally distributed.

⁵We assume that the number of applications a is exogenous. We could endogenize it by assuming that applications are costly. In Section 6.1, we discuss the implications of this assumption on our main results.

⁶We assume that firms make offers simultaneously. Thus, no worker has an offer prior to firms making offers.

$$q(j) = \frac{1}{j!} \left(\frac{a}{\theta}\right)^j \exp\left(-\frac{a}{\theta}\right), \quad (1)$$

where $\theta = v/u$ is the ratio of vacancies to unemployed job-seekers. Importantly, the rate at which the firm receives applications is not the same as its job-filling probability. In this model, the job-filling probability depends not only on labor market tightness, θ , but also on the acceptance decision of workers, which in turn is affected by the firm's information acquisition problem.

Timing At the beginning of each period, firms post vacancies. Next, existing matches observe both separation and match quality shocks. We assume that newly separated workers cannot immediately search for a new job and must wait one period before searching in the labor market. Following this, unemployed workers submit applications and observe their match quality at each vacancy contacted. Firms receive applications and choose whether to acquire information. Firms then make offers to their chosen applicants, and workers decide whether to accept offers. Once an offer has been accepted, wage bargaining commences and firms that did not acquire information learn about their worker's match quality. Finally, production occurs.

In what follows, we define the worker's and firm's end-of-period value functions, i.e., after search and matching has occurred. We begin with the firm's problem.

3.2 The firm's problem

The value of an operating firm attached to a worker with match quality x is given by:

$$V^F(x) = x - w(x) + \beta(1 - \delta) \left(\rho(x) \int_{\tilde{x}}^{\bar{x}} V^F(y) \psi(y|x) dy + [1 - \rho(x)] V^F(x) \right),$$

where $x - w(x)$ represents the firm's current profits. With probability δ , the job is exogenously destroyed and the firm shuts down. Conditional on no exogenous separation, the match is subject to a match quality shock with probability $\rho(x)$, where the new match quality y is re-drawn from conditional distribution $\Psi(y|x)$, with $\psi(y|x)$ being the associated density. Let \tilde{x} be the reservation match quality – an endogenously determined object to be formally defined below. As long as $y \geq \tilde{x}$, the match is preserved with continuation value $V^F(y)$. With probability $1 - \rho(x)$, the match observes no match quality shock and the firm continues with $V^F(x)$.⁷

3.3 The firm's information acquisition problem

No information acquisition Consider a firm that has j applicants. If the firm chooses not to acquire any information, it is unable to rank any of its applicants and randomly selects

⁷We assume that there is no on-the-job-search. Incorporating this would further heighten the firm's incentive to acquire information as higher quality workers are less likely to search for an alternative job.

a candidate from its pool of j applicants. The expected value of not acquiring information, $V^{NI}(j)$, is then given by:

$$V^{NI}(j) = V^{NI} = \int_{\tilde{x}}^{\bar{x}} V^F(x)\Gamma(x)\pi(x)dx,$$

where $\pi(x)$ is the probability density that the applicant chosen draws match quality x and $\Gamma(x)$ is the acceptance probability of the worker conditional on receiving an offer. Because firms do not know the match quality drawn, the expectation is taken over $x \in [\tilde{x}, \bar{x}]$, as workers reject any job that has a match quality below reservation match quality \tilde{x} . Before we elucidate the derivation of $\Gamma(x)$, it is useful to first consider the value of a firm that chooses to acquire information.

With information acquisition Consider a firm with j applicants that chooses to pay cost κ_I to learn the match qualities of all its applicants. Then, so long as the expected value of a match is increasing in quality x , the firm always makes an offer to the most productive applicant.

Lemma 1 (Firm's hiring choice). *The firm always makes an offer to the applicant with the highest match quality when the surplus of a match is increasing in match quality.*

Proof. See Appendix B. □

Intuitively, by making an offer to the highest-quality applicant, the firm maximizes its expected value since the value of an operating firm, $V^F(x)$ – which itself is a function of surplus – is increasing in match quality x . Further, the firm's probability of having its offer rejected is declining in x , reinforcing the firm's incentive to extend an offer to its highest-quality applicant.⁸ Thus, the expected benefit from acquiring information for a firm with j applicants is:

$$V^I(j) = \int_{\tilde{x}}^{\bar{x}} V^F(x)\Gamma(x)d[\Pi(x)]^j,$$

where $[\Pi(x)]^j$ is the distribution of the maximum order statistic.⁹

Given the expected benefit from acquiring information, the information acquisition problem for a firm with j applicants is:

$$\Xi(j) = \max \left\{ \int_{\tilde{x}}^{\bar{x}} V^F(x)\Gamma(x)d[\Pi(x)]^j - \kappa_I, \int_{\tilde{x}}^{\bar{x}} V^F(x)\Gamma(x)\pi(x)dx \right\}. \quad (2)$$

Proposition 1 (The firm's information acquisition threshold). *For finite κ_I , there exists a threshold $j^* > 1$ above which the firm always chooses to acquire information.*

⁸In Section 3.6, we show that since surplus is increasing in x , employment values are increasing in x and workers always accept the offer with the highest match quality.

⁹ $[\Pi(x)]^j$ is the probability that the highest match quality among j applicants is less than or equal to x .

Proof. See Appendix B. □

As the number of applicants at a firm, j , increases, the likelihood that at least one of its applicants is a high-productivity match also increases. Thus, the expected benefit of information acquisition, $V^I(j)$, is strictly increasing in j , as only firms who acquire information are able to identify the applicant with the highest match quality. In contrast, firms that do not acquire information randomly select a candidate from their applicant pool. Given that each applicant's match quality is independently drawn from the unconditional distribution $\Pi(x)$, the expected value of not acquiring information is invariant to the number of applications received. Although the probability that at least one applicant possesses high match quality is increasing in j , the firm with no information cannot take advantage of this because it makes offers randomly.

Since the expected value of not acquiring information is a constant, the net value of information, $V^I(j) - \kappa_I$, crosses V^{NI} once from below. As such, there exists j^* applications such that $V^I(j) - \kappa_I \geq V^{NI}$ for all $j \geq j^*$. Hence, for any number of applicants $j \geq j^*$, the firm always chooses to acquire information. Finally, it is clear that $j^* > 1$ because $V^I(1) - \kappa_I < V^{NI}$.

Free entry Under free entry, the value of a vacancy is driven to zero and is characterized by:

$$\kappa_V = \sum_{j=1}^{\infty} q(j)\Xi(j). \quad (3)$$

3.4 Employed workers

The value of an employed worker with match quality x at the end of the period is given by:

$$\begin{aligned} V^W(x) = & w(x) + \beta(1 - \delta)(1 - \rho(x))V^W(x) \\ & + \beta[\delta + (1 - \delta)\rho(x)\Psi(\tilde{x} | x)]U + \beta(1 - \delta)\rho(x) \int_{\tilde{x}}^{\bar{x}} V^W(y) \psi(y | x) dy, \end{aligned} \quad (4)$$

where $w(x)$ is the worker's current wage. With probability δ , the match is exogenously destroyed and the worker becomes unemployed. Jobs that are not exogenously destroyed are subject to a match quality shock with probability $\rho(x)$. If the new match quality drawn is above the reservation match productivity, i.e., $y \geq \tilde{x}$, the worker remains employed with continuation value $V^W(y)$. Otherwise, the worker endogenously exits into unemployment. With probability $1 - \rho(x)$, no match quality shock occurs and the worker observes continuation value $V^W(x)$.

3.5 Unemployed workers

To understand the unemployed worker's problem, we first characterize the acceptance decision of a job-seeker. When the employment value, $V^W(x)$, is increasing in match quality, the worker

always prefers to accept her highest match quality drawn so long as that value is above \tilde{x} . Consider a worker who draws match quality $x \geq \tilde{x}$ from one of her a applications and receives an offer for this draw. The worker will accept this offer of quality x if 1) it is her highest match quality, or 2) it is not her highest match quality but other applications with higher match quality failed to yield offers. Thus, the worker's probability of accepting an offer with match quality $x \geq \tilde{x}$ for a particular application is given by:

$$\Gamma(x) = [\Pi(x)]^{a-1} + \sum_{i=1}^{a-1} (a-i)[1 - \Pi(x)]^i [\Pi(x)]^{a-1-i} [1 - Pr(\text{offer} \mid y > x)]^i, \quad (5)$$

and for $x < \tilde{x}$, $\Gamma(x) = 0$. Further note that:

$$Pr(\text{offer} \mid y > x) = \int_x^{\tilde{x}} \sum_{\ell=1}^{\infty} q(\ell) Pr(\text{offer} \mid y, \ell) \frac{\pi(y)}{1 - \Pi(x)} dy, \quad (6)$$

where

$$Pr(\text{offer} \mid y, \ell) = \mathbb{I}[\ell \geq j^*] [\Pi(y)]^{\ell-1} + (1 - \mathbb{I}[\ell \geq j^*]) \frac{1}{\ell}. \quad (7)$$

When $x < \tilde{x}$, the worker rejects the offer since the value of unemployment is larger. When $x \geq \tilde{x}$, the first term on the right-hand-side of Equation (5) depicts the case where the worker accepts an offer of match quality x because it is her highest match quality drawn. This occurs with probability $[\Pi(x)]^{a-1}$. The second term corresponds to the cases where the worker has drawn match quality $y > x$ in her i other applications for $i \in \{1, 2, \dots, a-1\}$, and match qualities less than x for her remaining $(a-1-i)$ applications. This occurs with probability $(a-i)[1 - \Pi(x)]^i [\Pi(x)]^{a-1-i}$. Since her i applications that drew match quality greater than x failed to yield an offer, she accepts her next best outcome which is x . Equation (6) represents the probability that a worker with match quality $y > x$ receives an offer for that application, while Equation (7) represents the offer probability associated with a worker who draws match quality y at a firm with ℓ applicants. The first term on the right-hand-side of Equation (7) depicts the case where the worker meets a firm that chooses to acquire information because it received $\ell \geq j^*$ applicants.¹⁰ Since this firm observes its applicants' match qualities, the worker receives an offer only when she is the best applicant. This occurs with probability $[\Pi(y)]^{\ell-1}$. The second term depicts the case where the worker meets a firm with $\ell < j^*$ applicants. Since the firm does not acquire information and randomly selects an applicant, the worker receives an offer with probability $1/\ell$. Summing across ℓ and conditioning on $y > x$ yields Equation (6).

¹⁰ ℓ is the number of applicants at the firm where the worker has drawn match quality y , and j is the number of applicants at the firm where the worker has drawn match quality x .

The probability that a worker is hired with match quality x , $\phi(x)$, is then given by:

$$\phi(x) = \Gamma(x)Pr(\text{offer} | x) = \Gamma(x) \sum_{j=1}^{\infty} q(j)Pr(\text{offer} | x, j). \quad (8)$$

This shows that $\phi(x)$ is the product of the expected offer probability, $Pr(\text{offer} | x)$, and the acceptance probability, $\Gamma(x)$. Finally, the unemployed worker's value at the end of a period is:

$$U = b + \beta \int_{\tilde{x}}^{\bar{x}} a\phi(x)\pi(x)V^W(x)dx + \beta \left[1 - \int_{\tilde{x}}^{\bar{x}} a\phi(x)\pi(x)dx \right] U. \quad (9)$$

The probability density of match quality x for a single application is given by $\pi(x)$. The worker is hired into this job with probability $\phi(x)$ and receives continuation value $V^W(x)$. Any of the worker's a applications could have yielded this outcome. Thus, the unemployed worker finds a job with probability $a \int_{\tilde{x}}^{\bar{x}} \phi(x)\pi(x)dx$, failing which, she remains unemployed.

3.6 Surplus and wage determination

Wages are determined by Nash bargaining after the worker has accepted an offer. We assume that once a worker accepts an offer, she discards all other offers. At this stage, firms that did not acquire information learn about their worker's match quality. This implies that at the bargaining stage, the outside options of the firm and the worker are equal to their values from remaining unmatched. Further, wages are re-bargained each period. The wage for a job of quality x is:

$$w(x) = \arg \max_w [V^F(x)]^{1-\eta} [V^W(x) - U]^\eta, \quad (10)$$

where $\eta \in [0, 1]$ is the worker's bargaining weight. The surplus of a match with quality x is:

$$S(x) = \frac{x + \beta(1-\delta)\rho(x) \int_{\tilde{x}}^{\bar{x}} S(y)\psi(y|x)dy - (1-\beta)U}{1 - \beta(1-\delta)(1-\rho(x))}, \quad (11)$$

with

$$(1-\beta)U = b + \beta\eta a \int_{\tilde{x}}^{\bar{x}} \phi(y)S(y)\pi(y)dy.$$

The surplus of a match is given by current output plus the expected value from a match quality shock less what the worker gains from remaining unemployed. Equation (11) shows that $S(x)$ is increasing in x , implying that $V^F(x)$ and $V^W(x)$ are also increasing in x . Thus, workers always accept their highest quality offer and firms always extend offers to their best applicant.

3.7 Labor market flows

Unemployed The steady state unemployment rate is implicitly given by:

$$u \int_{\tilde{x}}^{\bar{x}} a\phi(x)\pi(x)dx = (1 - u) \left[\delta + (1 - \delta) \int_{\tilde{x}}^{\bar{x}} \rho(x)\Psi[\tilde{x} | x] g(x) dx \right], \quad (12)$$

where $g(x)$ is the density of employed workers with match quality x , and $G(x)$ is the cdf. The left-hand-side of Equation (12) represents the outflows from unemployment. The right-hand-side represents inflows into unemployment from exogenous and endogenous separations. The latter occurs whenever an employed worker suffers a match quality shock and re-draws values below \tilde{x} .

Employed In steady state, the measure of the employed with match quality x is given by:

$$\begin{aligned} [\delta + (1 - \delta) \rho(x)] g(x) (1 - u) &= (1 - \delta) \int_{\tilde{x}}^{\bar{x}} \rho(y) \psi(x | y) g(y) dy (1 - u) \\ &+ a\phi(x) \pi(x) u. \end{aligned} \quad (13)$$

The left-hand-side denotes outflows among employed workers with match quality x who are exogenously separated from their job or who are subjected to a match quality shock. The first term on the right-hand-side describes the inflows from the pool of employed who experienced a match quality shock and drew new match quality x , while the second term represents the inflows from unemployment.

3.8 Equilibrium

All equilibrium objects defined thus far depend on $\{\tilde{x}, \theta, j^*\}$. The following lemma summarizes the key equations that determine $\{\tilde{x}, \theta, j^*\}$:

Lemma 2 (Key equilibrium conditions). *$\{\tilde{x}, \theta, j^*\}$ are determined by the free entry condition given by Equation (3) and the following conditions:*

$$\tilde{x} = b + \beta\eta \int_{\tilde{x}}^{\bar{x}} a\phi(y) S(y) \pi(y) dy - \beta(1 - \delta) \rho(\tilde{x}) \int_{\tilde{x}}^{\bar{x}} S(y) \psi(y | \tilde{x}) dy, \quad (14)$$

and

$$\begin{cases} V^I(j) - \kappa_I < V^{NI}, & \text{for } j < j^* \\ V^I(j) - \kappa_I \geq V^{NI}, & \text{for } j \geq j^*, \end{cases} \quad (15)$$

where $V^I(j) = (1 - \eta) \int_{\tilde{x}}^{\bar{x}} \Gamma(x) S(x) d[\Pi(x)]^j$ and $V^{NI} = (1 - \eta) \int_{\tilde{x}}^{\bar{x}} \Gamma(x) S(x) d\Pi(x)$.

Equation (14) is derived by evaluating $S(x)$ at the reservation match quality, \tilde{x} , and represents the lowest match quality for which a match can be sustained. Equation (15) determines j^* which is the smallest number of applicants firms must have for them to acquire information. Finally, the free entry condition, Equation (3), provides information on θ .¹¹

3.9 Forces at play

Before turning to our main results, it is useful to understand how the different components in the unemployment inflow and outflow rates respond to changes in a . In what follows, we ask how the factors affecting unemployment outflow and inflow rates would change with a , holding constant our key equilibrium objects, i.e., \tilde{x} , θ , and j^* .

Outflow from unemployment Recall that $\phi(x)$ is the probability that a worker is hired with match quality x . Since $\phi(x) = \Gamma(x) \times Pr(\text{offer} | x)$, we can write the outflow rate as:

$$\text{outflow rate} = \underbrace{a}_{\substack{1) \text{ no. of applications}}} \int_{\tilde{x}}^{\bar{x}} \underbrace{Pr(\text{offer} | x)}_{\substack{2) \text{ probability offer for } x}} \times \underbrace{\Gamma(x)}_{\substack{3) \text{ probability accept } x}} \pi(x) dx. \quad (16)$$

The unemployment outflow rate is a function of three components: 1) the number of applications a worker sends, a ; 2) the probability she receives an offer; and 3) the probability she accepts an offer. The first component in Equation (16) represents the direct effect an increased number of worker applications, a , has on the outflow rate. Holding all else constant, the ability to send out more applications and contact more vacancies raises the likelihood that at least one application returns a high match quality and yields an offer, increasing the outflow rate.

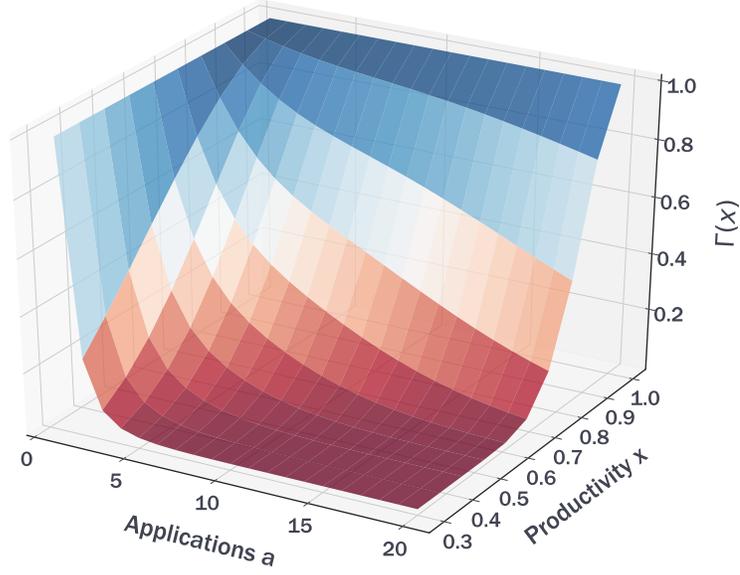
While the direct effect of a contributes positively towards the outflow rate, an increased number of applications also indirectly affects the probability that a single application yields an offer. From Equation (8), the offer probability, $Pr(\text{offer} | x)$, depends on the distribution of applicants across vacancies $q(j)$, which in turn responds to changes in a . Under the Poisson distribution, the mean number of applicants per vacancy is a/θ . For expositional purposes, assume a is a continuous variable. Differentiating $q(j)$ with respect to a , we get:

$$q_a(j) = \left[\frac{j - a/\theta}{a/\theta} \right] \frac{1}{\theta} \frac{1}{j!} \left(\frac{a}{\theta} \right)^j \exp \left(-\frac{a}{\theta} \right).$$

The above derivative shows that for any j applicants less than a/θ , the derivative $q_a(j)$ is negative, while for any j applicants above the mean of a/θ , the derivative is positive. This

¹¹The number of worker applications must equal the number of applications received by firms. In our model, this is trivially satisfied. Under the Poisson distribution: the mean applicants per vacancy is a/θ . Since total applications received by firms is va/θ and total worker applications is au , consistency is satisfied with $au = va/\theta$.

Figure 4: Conditional acceptance probability $\Gamma(x)$ weakly declines in a



Note: This figure plots how $\Gamma(x)$ varies with the number of applications a that an unemployed worker sends and match productivity x . To compute the above, we held constant θ, \tilde{x}, j^* as we increased a .

implies that the distribution of $q(j)$ shifts rightward away from zero applications as a increases. When firms have more applicants on average, the probability that a single application yields an offer falls. To see this, consider a worker who applies to a firm with j applicants and who draws match quality $x > \tilde{x}$. From Equation (7), the probability that a worker receives an offer for this application is weakly declining in j .¹² Thus, as the distribution of applications received by firms, $q(j)$, shifts rightward with higher a , each applicant faces more competition at the same vacancy, reducing the probability that they receive an offer for their match quality x .

The final component in the outflow rate in Equation (16) is the acceptance probability $\Gamma(x)$. Notably, $\Gamma(x)$ is also a function of applications a . Numerically, we show that holding all else constant, acceptance probability $\Gamma(x)$ is weakly decreasing in a , as depicted in Figure 4. Intuitively, as workers submit more applications, they are able to sample more vacancies, raising the probability that one of their *other* applications draws a match quality greater than x .

Overall, whether the unemployment outflow rate rises with increases in a depends on the extent to which the direct effect of a higher contact rate is counteracted by the indirect effects of lower offer and acceptance probabilities.

Inflows into unemployment The unemployment inflow rate can be written as:

$$\text{inflow rate} = \delta + (1 - \delta) \int_{\tilde{x}}^{\bar{x}} \rho(x) \Psi[\tilde{x} | x] g(x) dx.$$

¹² $[\Pi(x)]^{j-1}$ is weakly declining in j and $1/j$ is strictly declining in j .

The first term refers to exogenous separations, while the second term refers to endogenous separations. Holding θ , \tilde{x} , and j^* constant, an increase in applications a raises the share of firms receiving $j \geq j^*$ applications, and thus the share of informed firms. Following from Lemma 1, when more firms acquire information, they identify and hire the most productive applicant within their applicant pool, causing the distribution of realized match quality, $G(x)$, to improve. An economy with a larger concentration of matches at higher match quality x values has lower separation risk because 1) the frequency of match quality shocks $\rho(x)$ declines with x and 2) the persistence in match quality makes individuals with a high x less susceptible to low quality draws in the future. Thus, a larger share of firms acquiring information in response to higher applications a improves the distribution of realized match quality and lowers the inflow rate.

Thus far, we have limited our analysis to a partial equilibrium setting. In general equilibrium, however, \tilde{x} , θ , and j^* can vary in response to changes in a . Changes in these key equilibrium objects in turn affect the acceptance rates of workers, offer probabilities, and the rate at which jobs are endogenously destroyed. As such, we turn to our calibrated model to understand the general equilibrium impact of an increase in applications a on labor market flows.

4 Calibration

In this section, we discuss details of the model’s calibration. Section 4.1 explains how we segment the economy into two labor markets: non-college and college while Section 4.2 discusses our calibration strategy. A summary of internally calibrated parameters can be found in Table 1.

4.1 Segmented labor markets

To account for the differences across education groups, we segment the economy into two labor markets: non-college and college. Each segmented market’s structure follows the general model described in Section 3. We allow workers in each market to draw from a separate time-invariant distribution of match quality denoted by $\Pi_k(x)$ for $k \in \{nc, c\}$, where nc stands for non-college and c represents college. Finally, we denote γ as the share of college workers in the population. We calculate aggregate moments as the weighted sum of moments from each segmented market.¹³

4.2 Calibration strategy

Our model period is a month. We calibrate the initial steady state to the period 1976-1985.¹⁴ Unless otherwise stated, all target moments are calculated from the CPS. We set the discount

¹³For example, the aggregate unemployment rate is simply the population-weighted unemployment rate in both markets: $u = \gamma u_c + (1 - \gamma) u_{nc}$. The same logic applies to other aggregate moments.

¹⁴We choose to calibrate the model to the 10-year period around the 1979-1980 EOPP survey to mitigate the effects of the double-dip recession in the U.S. in the early 1980s.

factor $\beta = 0.993$ and the worker's bargaining power $\eta = 0.5$, as is standard in the literature. The median number of applications per month in the EOPP is 2.7. In our model, the number of applications a takes integer values. As such, we set $a = 3$ for both non-college and college workers. Finally, using the CPS, we find that the average share of the population with at least a four-year college degree between 1976-1985 is 16.7 percent. Hence, we set $\gamma = 0.167$. Next, we discuss our strategy for model parameters that will be calibrated internally.

Evolution of match quality The time-invariant distribution of initial match quality $\Pi_k(x)$ for market $k \in \{nc, c\}$ is assumed to be log normal with parameters (μ_k, σ_k) . We normalize $\mu_{nc} = 0$ and choose μ_c to target a college premium of 0.45.¹⁵ We then use the standard deviation of initial match quality draws σ_{nc} and σ_c to target the fractions of unemployed individuals who receive zero offers per month to be 26 percent and 42 percent among non-college and college workers, respectively, as observed in the EOPP data.

Within each period, a worker is subject to a match quality shock with probability $\rho(x) = \min\{\exp(x_{ref} - x), 1\}$, where $x_{ref} = \gamma \exp(\mu_c + 0.5\sigma_c^2) + (1 - \gamma) \exp(\mu_{nc} + 0.5\sigma_{nc}^2)$ is set to be the weighted sum of the unconditional means from the two initial match quality distributions. The joint distribution of match quality shocks $\Psi(x, x')$ is constructed using Frank's copula:

$$\Psi(x, x') = -\frac{1}{\lambda} \log \left\{ 1 + \frac{[\exp(-\lambda\Pi[x]) - 1][\exp(-\lambda\Pi[x']) - 1]}{\exp(-\lambda) - 1} \right\}.$$

This implies a conditional distribution of match quality re-draws of the form $\Psi(x' | x)$, where the parameter λ controls the degree of dependence between draws. The functional forms of $\rho(x)$ and $\Psi(x' | x)$ for $\lambda > 0$ imply that matches with a higher match quality are less prone to endogenous separations. Matches with high x observe a lower frequency of match quality shocks and, conditional on a shock, they are also more likely to draw a higher new match quality x' .

We target both the average aggregate unemployment inflow rate and college inflow rate in the period 1976-1985 to pin down the exogenous separation probability, δ , and the parameter λ . Observe that as $\lambda \rightarrow 0$, match quality draws become uncorrelated, implying both non-college and college workers have an equal likelihood of separating into unemployment conditional on a shock. Thus, targeting the inflow rate of college workers allows us to match the gap in inflow rates across the two groups when they draw from different initial match quality distributions.

¹⁵Borjas and Ramey (1994) estimate the average log wage differential between college graduates and high-school graduates (high-school dropouts) between 1975-1985 to be 0.4 (0.65) using the CPS. Goldin and Katz (2007) estimate the log wage differential between college and high-school graduates to be 0.45 in 1970 and 0.4 in 1980 using U.S. Census data. Finally, Autor, Katz, and Kearney (2008) estimate the average log wage differential between college graduates and high-school graduates to be between 0.4 and 0.45 using the CPS. We target a log mean wage difference between college and non-college workers of 0.45, which is consistent with these estimates.

Table 1: Internally calibrated parameters

Parameter	Explanation	Value	Target	Model	Data
κ_V	Vacancy posting cost	0.76	Unemployment rate	0.075	0.076
κ_I	Cost of information	0.52	Unemployment rate, college	0.028	0.029
δ	Exog. separation rate	0.002	Inflow rate	0.039	0.043
λ	Persistence of x	19.01	Inflow rate, college	0.017	0.014
b	Home production	0.48	UI replacement rate	0.38	0.40
μ_c	Mean x , college	0.40	College premium	0.38	0.45
σ_c	Std. dev. x , college	0.16	Fraction with no offer, college	0.15	0.26
σ_{nc}	Std. dev. x , non-college	0.19	Fraction with no offer, non-college	0.46	0.42

Note: This table provides a list of model parameters that are calibrated using our model. Moments relating to unemployment levels and flows are obtained from the CPS as averages between 1976 and 1985. The fractions of college and non-college workers with positive offers who accepted an offer are obtained from the EOPP 1979-1980.

Labor market We choose the cost of posting a vacancy, κ_V , to match an aggregate unemployment rate of 7.6 percent, which is the average between 1976-1985. We choose the fixed cost of information acquisition, κ_I , to match an unemployment rate of college workers of 2.9 percent for the same time period. Because we target both the aggregate and college unemployment rates, and thus by construction the non-college unemployment rate as the residual, κ_I partly controls the differential importance of information to the two groups of workers. If firms use less information in hiring workers from one education group than the other, effective expected job creation costs are lower for the group with less information. This in turn influences the observed gap in unemployment rates between the two groups. Finally, the level of home production, b , received by unemployed workers is calibrated to match an average replacement rate of 40 percent.

Table 1 shows that our calibrated model fits the data moments fairly well. In addition, the calibration outcomes suggest that college workers draw from a match quality distribution that first-order-stochastically-dominates (FOSD) that of non-college workers. We now turn to our main exercise of interest: the impact of an increase in applications a on labor market flows.

5 Quantitative Results

In this section, we analyze how an increase in the number of applications, a , affects unemployment flows and job search outcomes. We then analyze how the presence of the information acquisition problem of firms affects these results.

5.1 Equilibrium response to an increase in applications

In the data, the median number of applications roughly doubled from 3 to 6 between the 1979-1980 period and the 2013-2017 period for both education groups. As such, in our main quanti-

Table 2: Impact on key equilibrium variables from increase in applications

Equilibrium objects	Non-college		College	
	$a = 3$	$a = 6$	$a = 3$	$a = 6$
Reservation match quality \tilde{x}	0.98	1.00	1.48	1.53
Labor market tightness θ	0.54	0.51	1.29	1.02
Application cutoff to acquire information j^*	4	5	3	4
Percent firms informed	80.40	99.13	45.47	83.86

Note: This table summarizes the changes in equilibrium variables when the number of worker applications, a , increases from 3 to 6.

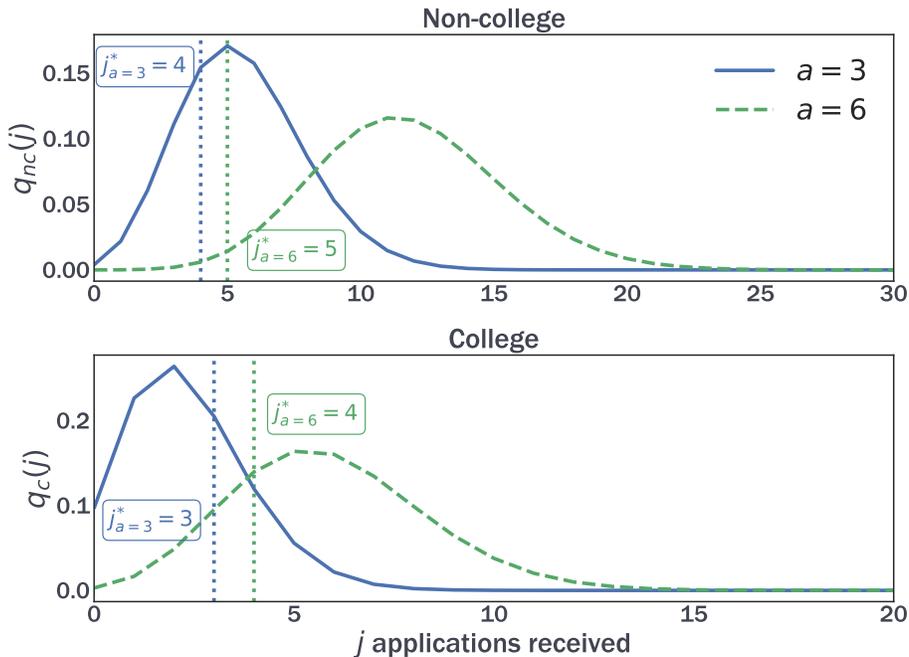
tative exercise, we ask how a doubling in the number of applications from 3 to 6 affects labor market moments in our calibrated model, holding all other parameters fixed.

To build intuition for our results, we start by documenting the changes in the equilibrium objects $\{\tilde{x}, \theta, j^*\}$. Table 2 highlights three main results. First, an increase in the number of worker applications results in a modest rise in the reservation match quality \tilde{x} of workers. Intuitively, when workers submit more applications, they sample more job opportunities, raising the probability that at least one application draws a high match quality and yields an offer. This raises the worker’s outside option, increasing her selectivity over the minimum match quality job she is willing to accept. At the same time, a greater number of worker applications increases the average number of applicants at a vacancy, depressing the worker’s ability to find a job and thus her outside option. This counteracting force causes the rise in \tilde{x} to be muted.

Second, labor market tightness, θ , declines in both markets despite firms receiving more applicants when a rises. Figure 5 shows that the distribution of applicants at a vacancy, $q(j)$, shifts rightward as a increases. Although the firm is more likely to be contacted by applicants, the acceptance rate of workers also declines with higher a , as we discuss later. This lower acceptance rate reduces the value from posting a vacancy, mitigating the benefits of a higher contact rate.

Finally, the rise in the average number of applicants per vacancy leads to a larger share of informed firms. Although the information acquisition threshold j^* increases, the share of firms acquiring information significantly increases in our model. When workers send more applications, there is a higher probability that at least one of a firm’s applicants is a high-productivity match. This, together with the fact that workers’ rejection probabilities are declining in match quality, reinforces the firm’s incentive to acquire information about its applicants. An increase in the share of firms acquiring information, however, raises the expected cost of job creation. Higher expected job creation costs and higher offer rejection incidence counteract the benefits of an increased contact rate, causing a decline in vacancy posting and a fall in labor market tightness θ . Importantly, θ falls not because there are more unemployed individuals, but rather because fewer vacancies are created.

Figure 5: Firms receive more applications as a increases



Note: The top panel shows how the probability that a firm in the non-college labor market receives j applications; i.e., $q_{nc}(j)$ changes with a doubling in the number of applications a . The bottom panel shows the equivalent for the college labor market, i.e., $q_c(j)$. Dashed vertical lines represent the equilibrium j^* cutoffs above which firms acquire information.

5.2 The response of inflow and outflow rates

We now examine how inflow and outflow rates of non-college and college workers are affected by a rise in applications a . Importantly, we compare our model predictions and *validate* underlying changes on job offer and acceptance rates as well as reservation wages with available data for the periods 1976-1985 and 2010-2019. These two time periods cover the periods when the EOPP (1979-1980) and the SCE (2013-2017) were conducted. For unemployment inflow and outflow rates, we take 10-year averages of the trend components as we are interested in long-run differences. We emphasize, however, that for the period 2010-2019, the U.S. economy underwent a slow recovery after the Great Recession. As a result, the reported outflow rates in the data are below the average observed in Figure 2. We detail the results of our exercise in Table 3.

5.2.1 Inflow rates

For non-college individuals, our model predicts a substantial decline in the unemployment inflow rate, from 4.33 percent to 2.41 percent. This stark 59 percent decline in the inflow rate is close to the observed 50 percent reported in the data.¹⁶ Similar to the data, the model generates differential movements in inflow rates between non-college and college workers. However, our

¹⁶We report percent change as $100 \times (\ln(2.41) - \ln(4.33)) = 59$.

Table 3: Impact on labor market flows from increase in applications

Panel A: Non-college						
	$a = 3$		$a = 6$		Log difference	
	Model	Data	Model	Data	Model	Data
Unemployment rate	8.46	8.49	5.31	7.56	-46	-12
Inflow rate	4.33	4.91	2.41	2.98	-59	-50
Outflow rate	46.8	53.1	42.9	39.7	-9	-29
direct a effect	3.00		6.00		69	
indirect a effect	0.16		0.07		-78	

Panel B: College						
	$a = 3$		$a = 6$		Log difference	
	Model	Data	Model	Data	Model	Data
Unemployment rate	2.80	2.97	3.00	3.27	7	10
Inflow rate	1.73	1.39	1.95	1.10	12	-23
Outflow rate	60.0	45.4	63.2	34.6	5	-27
direct a effect	3.00		6.00		69	
indirect a effect	0.20		0.11		-64	

Note: This table summarizes the model-predicted average flow outcomes when the number of worker applications a increases from 3 to 6 and compares it against the data. Data moments are obtained as averages from the CPS for the periods 1976-1985 and 2010-2019, where the former period corresponds to the period with the lower average number of applications $a = 3$ and the latter period corresponds to the period with the higher average number of applications $a = 6$. The log difference is multiplied by 100.

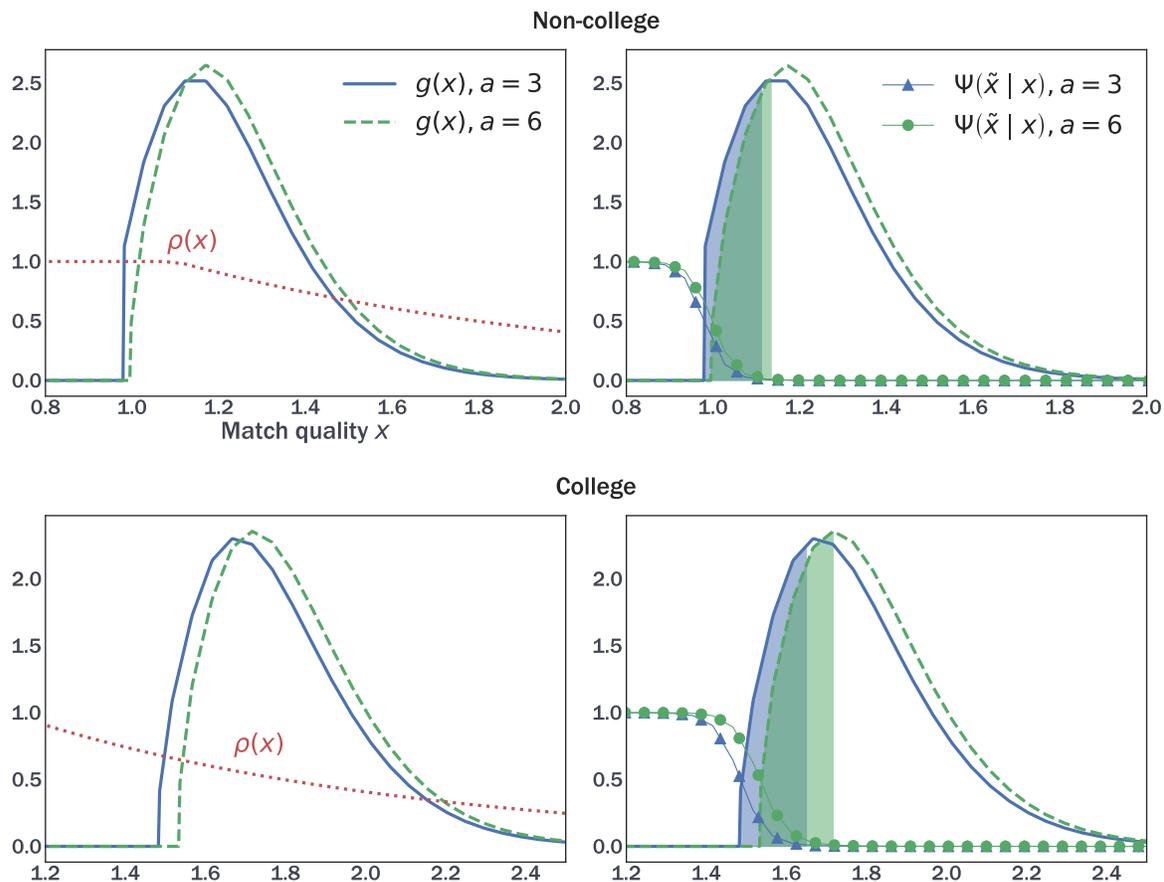
model predicts a small rise in the inflow rates of college workers from 1.73 percent to 1.95 percent, compared with a decline from 1.39 percent to 1.10 percent in the data.

What gives rise to the differential results in the inflow rates of non-college and college workers? In our model, a higher number of applications results in two opposing forces: 1) a larger share of firms acquiring information leads to higher quality matches that are longer-lived (match quality effect) but 2) increased worker selectivity results in more separations, as new re-draws of match quality must exceed an even higher reservation quality threshold for a match to be sustained (selectivity effect). In our model, non-college workers experience a larger improvement in average match quality due to increased information acquisition by firms, while observing a smaller rise in worker selectivity. Because increased competition at each vacancy reduces the probability that a non-college worker attains a job, the rise in their outside option is more subdued.¹⁷ Consequently, the match quality effect dominates and the inflow rate of non-college workers declines sharply.

While the match quality effect for college workers is slightly lower than that observed for non-college workers, the selectivity effect among college workers is larger. Since college workers draw higher match qualities than non-college workers on average, an increase in worker applications

¹⁷We discuss in greater detail how job-finding probabilities are affected when we discuss our results on outflows.

Figure 6: Realized match quality distribution improves as applications increase



Note: The top panels show the distribution of employed workers across match quality x in the non-college labor market, i.e., $g(x)$, under when the number of applications $a = 3$ (blue solid lines) and $a = 6$ (green dashed lines), respectively. The bottom panel shows the equivalent for the college labor market. The dotted red line represents arrival rates of match quality shocks, while the lines with triangles and circles represent the probability of the job being destroyed conditional on a match quality shock, i.e., $\Psi(\tilde{x}|x)$, for the number of applications $a = 3$ and $a = 6$, respectively, both for the non-college and college markets.

further increases their likelihood of drawing high-productivity matches and attaining a job. This in turn strengthens the rise in their unemployment value, causing the worker selectivity effect to dominate. As such, the model predicts a slight increase in the inflow rate of college workers. We elaborate on these mechanisms formally below.

To explain how the effect of improved firm selection can lead to a decline in separations, we focus our discussion on how a rise in applications affects the frequency of match quality shocks and the probability that a match becomes unsustainable given a shock. In our baseline model with $a = 3$ applications, college workers draw on average higher match qualities than their non-college counterparts, as depicted in Figure 6 by the blue solid lines. Consequently, non-college workers are more likely than college workers to experience a match quality shock, as depicted by the area under the dotted red lines in Figure 6. A doubling in applications, a , induces a larger fraction of firms to acquire information, causing the distribution of realized

match quality to shift rightward as more firms extend offers to their highest quality applicant. Figure 6 depicts this shift with the green dashed lines for both non-college and college individuals. Average match quality improves by 3 percent and 2 percent for non-college and college workers, respectively. While the shifts in both distributions are comparable, the improvement in realized match quality, has a much larger effect for non-college workers. In particular, an improvement in the distribution of realized match quality implies that fewer non-college individuals experience a match quality shock with probability 1 each period. As such, exits into unemployment among non-college workers fall with the lower frequency of match quality shocks.

While non-college workers are less likely to experience a match quality shock in the second time period, conditional on such a shock, they are also less likely to separate from their job. Figure 6 displays the probability that a worker with match quality x has her job destroyed conditional on receiving a shock, i.e., $\Psi(\tilde{x}|x)$. The lines with blue triangles and green circles indicate $\Psi(\tilde{x}|x)$ for $a = 3$ and $a = 6$ applications, respectively. The negligible increase in reservation match quality and the shift towards higher x values imply that a smaller share of non-college workers draw a new match quality below the reservation match value (as depicted by the smaller shaded green region relative to the shaded blue region). Conditional on a shock, the share of non-college workers who draw a new match quality $y < \tilde{x}$ and separate into unemployment falls from 4.2 percent to 2.2 percent when a doubles.¹⁸ Overall, the lower frequency of match quality shocks and a smaller propensity to re-draw match qualities below \tilde{x} are the key factors behind the sharp decline in the non-college inflow rate. These forces dominate the weak worker selectivity effect for non-college workers.

Conversely, while college individuals observe a lower frequency of match quality shocks, the lines with green circles in the bottom-right panel of Figure 6 show that conditional on receiving such a shock, a larger fraction of employed college individuals separate into unemployment when $a = 6$. This is because improvements in the distribution of realized match quality are small relative to the increase in reservation match quality \tilde{x} . The improvement in realized match quality is small because college workers already draw on-average higher match quality values. On the other hand, conditional on experiencing a match quality shock, the increase in \tilde{x} for college individuals causes the probability that a current match becomes unsustainable to rise from 2.4 percent when $a = 3$ to 3.0 percent when $a = 6$. As such, the inflow rate for college workers rises in our model. Notably, these results reveal that a rise in applications and an improvement in realized match quality does not necessarily dictate that inflow rates must fall. Whether inflow rates fall depend on how much improved selection by informed firms (concentration at higher match quality values) outweighs increased selectivity by workers (higher \tilde{x}).

¹⁸Conditional on a shock, the share of individuals who endogenously exit into unemployment is given by $\int_{\underline{x}}^{\tilde{x}} \Psi(\tilde{x}|x)g(x)dx$.

Validation The worker selectivity effect manifests through changes in the reservation wage. As such, we validate the model-predicted reservation wages against empirical findings from the EOPP and SCE. Consistent with the data, Table 4 shows that our model predicts stagnant reservation wage growth for non-college workers. Alongside a small increase in inflow rates among college workers, Table 4 shows that the increased worker selectivity for college workers has not been accompanied by a large increase in their reservation wages. How does the model reconcile both the decline in inflow rates and increase in reservation wages observed in the data for college workers? In part, our parsimonious exercise of varying only applications misses out on other trends in the data such as a rising college premium. Increases in the college premium affect the distribution of realized match quality by 1) strengthening college workers' outside options and their reservation wage, and by 2) raising overall match quality not only at the bottom but across the distribution. The former works to raise unemployment inflows, while the latter lowers it. In Section 5.3, we show that jointly matching the rise in applications with the rise in the college premium over time allows the model to generate both a rise in reservation wages among college workers and a small decline in their inflow rate, as in the data. Meanwhile, improved firm selectivity (match quality effect) is reflected through changes in expected hiring cost per vacancy. While the EOPP provides information on hours spent recruiting per week, such information is absent from the SCE. As such, we calculate the average recruiting effort to average monthly wages in the model and contrast this to estimates provided by the literature. Overall, the ratio of recruiting costs to monthly wages increased from 0.20 to about 0.60-0.93 over time.¹⁹ Qualitatively, our model captures this rise in hiring costs per vacancy. In our model, the ratio of expected information costs per vacancy to average monthly wages rises by 28 percent upon a doubling in the number of worker applications.

Taking stock In sum, the model is capable of generating the differential decline of inflow rates across education groups seen in the data. The steep decline in the non-college inflow rate arises from better matches due to greater information acquisition and a weak worker selectivity effect. Meanwhile, when both applications and the college premium rise, the model captures the relatively weaker decline in inflow rates observed for college workers. The differential response of the worker selectivity effect to applications manifests through an empirically-consistent prediction: a smaller increase in reservation wages for non-college workers. Finally, improved firm selection leading to improved match quality is consistent with increased recruiting effort in the data.

¹⁹Faberman and Menzio (2018) report an average recruiting effort per week of 8.2 hours. Assuming a 40 hour work-week, we find a ratio of $8.2/40 = 0.20$. In 2016, the ratio of recruiting costs to average monthly wages is 0.60 according to Society for Human Resource Management (2016) and 0.93 according to Gavazza, Mongey, and Violante (2018).

5.2.2 Outflow rates

Focusing on unemployment outflows, a doubling in the number of applications a causes the outflow rate in our model to decline a modest 9 percent and rise a modest 5 percent for non-college and college workers, respectively. While outflow rates in the data are lower in the period 2010-2019 due to the slow labor market recovery following the Great Recession, Figure 2 shows that outflow rates were back to pre-recession levels by 2019, suggesting no trend decline. As such, we view the modest changes in outflow rates predicted by our model to be largely successful in generating the absence of long-run changes in empirical outflow rates.

Our model’s predicted differential outcomes for college and non-college workers highlight how a rise in applications can have an ambiguous effect on outflow rates. Recall from Section 3.9 that the manner by which outflow rates vary with applications depends on whether the direct effect of a higher number of applications outweighs its indirect effects on offer and acceptance probabilities. Specifically, we decompose the percent change in the outflow rate between two time periods t_1 and t_2 as:

$$\ln(\text{outflow}_{t_2}) - \ln(\text{outflow}_{t_1}) = \overbrace{\ln(a_{t_2}) - \ln(a_{t_1})}^{\text{direct effect}} + \underbrace{\ln\left(\int_{\bar{x}_{t_2}}^{\bar{x}} \phi_{t_2}(x) \pi(x) dx\right) - \ln\left(\int_{\bar{x}_{t_1}}^{\bar{x}} \phi_{t_1}(x) \pi(x) dx\right)}_{\text{indirect effect}}.$$

Why does the model predict smaller changes in outflow rates in the aggregate and across education groups? For both college and non-college workers, the effects of a rise in applications on job offer and acceptance probabilities are sizeable, as seen in Table 3. These indirect effects stemming from endogenous changes in household job search decisions and firms’ hiring decisions mitigate the direct effect of a sheer increase in the number of applications. In fact, for non-college workers, the indirect effects of lower offer and acceptance probabilities dominate the direct effect of a higher number of applications, causing non-college outflow rates to be slightly lower. For college workers, the opposite holds true. Importantly, for both groups, the changes in the outflow rates are relatively muted and in line with what we observe in the data over the long-run.

Validation The model’s ability to reproduce observed trends in unemployment outflows originates from its predicted declines in both job offer and acceptance rates. In order to validate the mechanism underlying the model-predicted changes in the outflows, we compare the changes in job offer and acceptance probabilities in the model to those observed in the data. Table 4 details the result of this comparison.

Focusing on offer probabilities, in our model, the distribution of offers unambiguously shifts to the left with the rise in applications for both types of workers. The fraction of non-college

Table 4: Testable implications on the impact of rise in applications on applications outcomes

Panel A: Non-college						
	$a = 3$		$a = 6$		Log difference	
	Model	Data	Model	Data	Model	Data
Fraction > 0 offer	54.1	58.1	44.5	59.7	-19	3
Fraction > 1 offer	13.3	25.5	10.2	25.3	-27	-1
Acceptance rate	44.8	40.0	28.4	32.8	-46	-20
Reservation wage	1.06	5.59	1.08	5.72	2	2

Panel B: College						
	$a = 3$		$a = 6$		Log difference	
	Model	Data	Model	Data	Model	Data
Fraction > 0 offer	85.4	73.8	76.2	43.3	-11	-53
Fraction > 1 offer	46.00	29.90	37.7	10.7	-20	-103
Acceptance rate	33.91	80.60	22.6	51.4	-41	-45
Reservation wage	1.58	7.27	1.62	9.75	3	29

Note: This table summarizes the average application outcomes when the number of worker applications a increases from 3 to 6. Data moments are obtained as averages from the EOPP for the period 1979-1980 and from the SCE for the period 2013-2017, where the former period corresponds to the period with the lower average number of worker applications $a = 3$ and the latter period corresponds to the period with the higher average number of worker applications $a = 6$. Reservation wages are average hourly reservation wages in 1982-1984 dollars. The log difference is multiplied by 100.

workers with positive offers (greater than zero) declines 19 percent, while the fraction with multiple offers (greater than one) declines 27 percent. For college workers, the same statistics fall by 11 percent and 20 percent, respectively. In the model, offer probabilities fall because there is less vacancy creation and more applicants per vacancy. Empirically, we observe the fraction of college individuals with positive offers declining by 53 percent, while the fraction of non-college individuals with positive offers barely changes. We caution that because the time period for which the SCE survey is conducted spans the years following the Great Recession, overall lower vacancy creation and less competition amongst non-college individuals due to a higher fraction of discouraged workers could have contributed to the observed data outcomes. In the absence of the slow recovery, the offer rate for non-college workers could have been lower than observed.²⁰ Given the context of the Great Recession, we view our model's prediction that offer probabilities decline with the rise in applications to be reasonable, with the estimated decline within the range of the two observed outcomes for college and non-college workers.

Turning to acceptance rates, Table 4 also shows how changes in our model-implied acceptance rates compare to the data. We calculate the model's average acceptance rate as the expected probability of accepting an offer for a particular application, $\int_{\tilde{x}}^{\bar{x}} \Gamma(x) \pi(x) dx$. In our model,

²⁰According to the CPS, the ratio of discouraged workers to the unemployed was 0.041 between 2013-2017, about 14 percent higher than its average value between 1994-2019.

which does not feature business cycles, a higher number of applications results in workers becoming more selective over the minimum job they are willing to accept – as depicted by the increase in \tilde{x} . Besides this, workers also experience a higher probability that at least one of their applications draws a higher match quality. As foreshadowed in Section 3.9, the increased probability of drawing a higher match quality from another application leads to the worker to more frequently reject a job offer of given quality x . As such, acceptance rates in our model decline by 46 percent and 41 percent for non-college and college workers, respectively, while the same empirical counterparts decline by 20 percent and 45 percent respectively. Since the period 2010-2019 covers the aftermath of the Great Recession, workers’ weaker outside options may have partially tempered the decline in the empirical acceptance rate for non-college workers who experienced higher unemployment rates during this period. Overall, our model’s predicted acceptance rates are largely validated by the data.

We emphasize that the decline in acceptance rates in our model does not stem from a sharp increase in reservation wages. Across the two time periods, our model-implied reservation wages rise by 2 percent and 3 percent for non-college and college workers, respectively. This muted increase stems from the fact that job-finding rates do not necessarily dramatically improve with a rise in applications in our model, as workers face increased competition at a vacancy. Rather, acceptance rates decline in our model with higher applications because workers are more likely to have drawn a higher match quality offer in at least one of their other applications, reducing their need to accept the first offer they receive.

Taking stock Overall, our model explains why an improvement in search technology through a rise in applications need not lead to a trend increase or decline in unemployment outflow rates. Consistent with the data, the declines in the offer and acceptance probabilities mitigate the direct benefits of increased applications, causing little change in outflow rates. Further, our model explains how a higher number of applications can result in differential declines in unemployment inflow rates for non-college and college workers. A higher number of applicants per vacancy raises a firm’s incentives to acquire information. More informed firms imply a greater formation of high quality matches and, consequently, fewer endogenous job separations. For college workers, this effect is weaker and offset by higher worker selectivity.

5.3 Matching the increase in college premium

While our baseline exercise predicts a rise in the unemployment inflow rate for college workers, calibrating the model to also match the rise in the college premium reverses this result and brings it closer to the data. Table 5 summarizes the model results when 1) only the number of worker applications, a , increases from 3 to 6 and when 2) the number of worker applications, a , increases from 3 to 6 *together* with an increase in the mean level of productivity of college

Table 5: Matching the increase in college premium together with the increase in applications

Panel A: Non-college						
	Model			Percent change		
	$a = 3$	$a = 6$	$a = 6$ and high μ_c	Data	$a = 6$	$a = 6$ and high μ_c
Reservation match quality \tilde{x}	0.98	1.00	0.99		2	1
Labor market tightness θ	0.54	0.51	0.50		-6	-7
Percent firms informed	80.4	99.1	99.2		21	21
Inflow rate	4.33	2.41	2.23	-50	-59	-66
Outflow rate	46.8	42.9	42.5	-29	-9	-10
Reservation wage	1.06	1.08	1.07	2	2	1
Mean wage	1.18	1.21	1.20	7	2	2

Panel B: College						
	Model			Percent change		
	$a = 3$	$a = 6$	$a = 6$ and high μ_c	Data	$a = 6$	$a = 6$ and high μ_c
Reservation match quality \tilde{x}	1.48	1.53	2.02		3	31
Labor market tightness θ	1.29	1.02	1.53		-23	17
Percent firms informed	45.5	83.9	76.7		61	52
Inflow rate	1.73	1.95	1.70	-23	12	-2
Outflow rate	60.0	63.2	69.7	-27	5	15
Reservation wage	1.58	1.62	2.13	29	3	30
Mean wage	1.73	1.77	2.30	26	2	28

Note: This table summarizes the model results when 1) only the number of worker applications a increases from 3 to 6 and 2) the number of worker applications a increases from 3 to 6 together with an increase in the mean level of productivity of college workers μ_c to match the increase in the college premium in the data. These results are compared against the data. Data moments on labor market flows are obtained as averages from the CPS. Reservation wages are obtained as averages from the EOPP for the period 1979-1980 and from the SCE for the period 2013-2017, where the former time period corresponds to the period with lower average number of applications $a = 3$ and the latter time period corresponds to the period with higher average number of applications $a = 6$. Changes in wages in the data are obtained from CPS 1980 and 2015 samples. The log difference is multiplied by 100.

workers μ_c such that the model-implied college premium rises from 0.38 to 0.65 as in the data.²¹ We focus much of our discussion on the results for college workers since markets are segmented by education and a rise in μ_c preserves the benchmark predictions for non-college workers' flows, as it only affects the frequency of match quality shocks, $\rho(x)$, for non-college workers.²²

For college workers, when both a and μ_c increase, the higher productivity of college workers

²¹Autor, Katz, and Kearney (2008) document that the average log wage differential between college graduates and high-school graduates increased from 0.45 to 0.65 between 1985 and 2005.

²²Recall that $\rho(x) = \min\{\exp(x_{ref} - x), 1\}$, where $x_{ref} = \gamma \exp(\mu_c + 0.5\sigma_c^2) + (1 - \gamma) \exp(\mu_{nc} + 0.5\sigma_{nc}^2)$. Hence, changes in μ_c affect $\rho(x)$ for non-college workers through x_{ref} .

encourages more vacancy creation and further elevates college workers' unemployment values. As such, both θ and \tilde{x} rise for college workers. The fraction of informed firms is lower relative to our baseline model where only a increases. Since college workers are now even more productive, firms have less incentive to acquire information, as the risk of matching with a low-productivity worker is reduced. As such, expected job creation costs are lower relative to the baseline model, and this raises vacancy creation and labor market tightness.

How unemployment inflow rates respond to a rise in applications depends on the strength of the worker selectivity effect relative to the match quality effect. While our baseline model predicts a slight increase in the inflow rate of college workers when only a rises, matching the college premium leads our model to predict a 2 percent decline when a doubles *and* μ_c increases. In this case, the substantial rightward shift in the distribution of realized match quality dominates the effect of a higher reservation match quality. Importantly, jointly matching the rise in applications and increase in the college premium also allows us to better explain the change in reservation wages for college workers. In an economy where only a increases, the college reservation wage rises by 3 percent, as the increase in worker selectivity and reservation match quality is partially mitigated by a decline in vacancy creation and increased competition amongst workers. Conversely, vacancy creation increases when both a and μ_c rise. As a result, reservation match quality increases significantly and college workers' reservation wage rises a sizeable 30 percent, close to the 29 percent increase observed in the data.

Thus, our model's predictions on the changes in the inflow rate and reservation wages of college workers come closer to the data once we account for the joint increase in the college premium and the number of applications. If we had instead only matched the rise in the college premium and left applications constant, our model would predict counterfactual changes in the inflow rates for both education groups. For non-college workers, we have shown that accounting for the increase in applications is key to generating the observed changes in labor market flows. For college workers, matching the rise in the college premium alone would have resulted in an excessively large decline in inflow rates, as further improvements in worker selectivity brought about by increased applications are absent. Thus, raising μ_c without increasing a prevents us from capturing the differential declines in inflow rates between college and non-college workers.

Finally, we compare how our results line up against [Martellini and Menzio \(2020\)](#) who also investigate the effects of improvements in search technology on labor market flows. Our model's predictions on wages and labor market flows diverges from theirs in the following manner. First, [Martellini and Menzio \(2020\)](#) predict that for *all* workers, match productivity and wages grow with improvements in search technology. We arrive at a similar result but *only* for college workers when we allow both the number of applications and the college premium to increase over time. Table 5 shows that the average reservation wage and wage of college workers increase by 30 percent and 28 percent in the model, respectively, and by 29 percent and 26 percent in

the data.²³ However, for non-college workers, our model predicts that a rising college premium and a higher number of applications marginally improve wages. Our findings are supported by the data; the reservation wage and average wage of non-college workers increase by 1 percent and 2 percent in the model, respectively, while the same data counterparts increase by 2 percent and 7 percent. Thus, an interpretation of [Martellini and Menzio \(2020\)](#) is that their model is better equipped to explain the experience of college workers, while our model can rationalize the differential wage growth between college and non-college workers over time. Incorporating ex-ante heterogeneity of workers in our model allows us to capture the stagnant wage growth at the bottom of the wage distribution and the resulting increase in wage inequality over time across groups. Second, in [Martellini and Menzio \(2020\)](#), *both* unemployment inflow and outflow rates remain unchanged over the long-run even if search technology improves. Conversely, our model predicts a sharp decline in inflow rates since the 1980s, and little change in outflow rates, as in the data. Our model generates these asymmetric changes in inflow and outflow rates as the decline in acceptance rates are not pegged to changes in reservation wages. In [Martellini and Menzio \(2020\)](#), the decline in acceptance rates is driven by the increase in reservation match quality and wages. In contrast, acceptance rates can decline in our model without an accompanying rise in reservation wages, as workers reject jobs more often when they can choose from more options. Thus, our model can generate sizeable declines in inflow rates – especially for non-college workers – while still maintaining small changes in outflow rates. An important implication of this result is that improvements in search technology need not translate into secular changes in implied matching efficiency in our model. To see this, we apply a standard Cobb-Douglas matching function to our model-simulated data and derive matching efficiency, ζ , as the residual component of matches, M , that is unexplained by vacancies v and the level of unemployment u , i.e., $M = \zeta u^\alpha v^{1-\alpha}$. Assuming as standard in the literature, that the elasticity of the matching function with respect to unemployment, α , is equal to 0.5, our model predicts that implied matching efficiency would have declined by 4 percent over time despite the improvements in search technology. This minute change in our model-implied matching efficiency is consistent with the lack of a secular trend in the Beveridge curve over the long-run, as highlighted by [Martellini and Menzio \(2020\)](#).

5.4 The Role of Information

We now consider two thought experiments to uncover how information acquisition interacts with an increase in applications to affect labor market flows. In the first experiment, we set $\kappa_I = 0$, and label this the “Full Information” (FI) model. While we use the term “Full information”,

²³Figure 3 shows the distributions of real hourly reservation wages for college and non-college workers over time. Similarly, Figure A4 in Appendix A presents the distributions of real hourly wages for college and non-college workers over time.

Table 6: The role of firms’ investment on information upon an increase in applications

Panel A: Non-college									
	FI		NI		Log difference				
	$a = 3$	$a = 6$	$a = 3$	$a = 6$	Data	Model	FI	NI	
Reservation match quality \tilde{x}	0.80	0.84	0.91	0.87		2	5	-4	
Labor market tightness θ	0.78	0.83	0.71	0.76		-7	6	7	
Inflow rate	5.38	5.88	4.80	5.34	-50	-59	9	10	
Outflow rate	68.5	62.7	43.3	34.4	-29	-9	-9	-23	
direct a effect	3.00	6.00	3.00	6.00		69	69	69	
indirect a effect	0.14	0.08	0.14	0.06		-78	-78	-92	

Panel B: College									
	FI		NI		Log difference				
	$a = 3$	$a = 6$	$a = 3$	$a = 6$	Data	Model	FI	NI	
Reservation match quality \tilde{x}	0.90	1.60	2.03	2.26		3	58	11	
Labor market tightness θ	5.59	3.24	5.21	2.18		-23	-55	-87	
Inflow rate	1.42	6.89	1.40	2.72	-23	12	158	67	
Outflow rate	39.7	75.1	36.9	62.8	-27	5	64	53	
direct a effect	3.00	6.00	3.00	6.00		69	69	69	
indirect a effect	0.18	0.10	0.12	0.10		-64	-5	-16	

Note: This table summarizes the equilibrium variables, average labor market flows, and worker application outcomes when the number of applications a increases from 3 to 6. Model refers to the baseline scenario in which there is a fixed cost κ_I of acquiring information on the applicants’ match quality for firms. FI is the “Full information” model in which $\kappa_I = 0$, and NI is the “No information” model in which $\kappa_I \rightarrow \infty$. Data moments on labor market flows are obtained as averages from the CPS, and data moments on application outcomes are obtained as averages from the EOPP for the period 1979-1980 and from the SCE for the period 2013-2017, where the former time period corresponds to the period with lower average number of applications $a = 3$ and the latter time period corresponds to the period with higher average number of applications $a = 6$. The log difference is multiplied by 100.

it should be noted that firms only observe the match qualities of applicants at their vacancy. They cannot observe the applicants’ match qualities at other jobs or the applicants’ number and quality of competing offers. In our second experiment, we consider the other extreme and set $\kappa_I \rightarrow \infty$. We label this the “No Information” (NI) model. We fully re-calibrate the FI and NI models to match the same targets as our baseline model. Details of our calibration strategy and model fit can be found in Appendix C.1. Throughout, we compare the results of the FI and NI model against our baseline model where only applications a increased. In both of these models, the firm’s investment in information acquisition does not vary with the number of applications. Hence, these experiments allow us to demonstrate how ignoring changes in the firm’s information decision in response to more applications would affect predictions of our model.

Non-college workers Table 6 Panel A details the results for non-college workers. Unlike our baseline model, both the FI and NI models observe an increase in labor market tightness,

θ with the rise in applications. While firms in our baseline model face higher expected job creation costs whenever more firms anticipate that they will acquire information, job creation costs remain constant in the FI and NI economies, as firms either attain information for free or never acquire it. This together with a higher contact rate promotes more vacancy creation, causing θ to increase with the rise in applications in the FI and NI economies.

Focusing on reservation match quality \tilde{x} , the FI model predicts a rise in \tilde{x} , while the NI model predicts a decline in \tilde{x} as applications increase. These differences stem from how workers' outside options vary across the two models. In the FI model, firms always identify the highest quality applicant. When workers submit more applications, the probability that at least one application draws a high match quality and yields an offer increases. This strengthens the worker's outside option, encouraging a rise in \tilde{x} . Conversely, in the NI model, firms always extend offers to randomly selected candidates from their applicant pool. Thus, workers' outside options weaken and \tilde{x} falls as the increased probability of drawing a high match quality does not translate into more offers and competition instead increases among workers with more applicants per vacancy.

These equilibrium outcomes have implications for labor market flows. In contrast to our baseline model, both the FI and NI models predict a counterfactual increase in the inflow rate for non-college workers as applications rise, albeit for different reasons. In the FI model, inflows increase as the effects from higher worker selectivity far outweigh the effects from an improved distribution of realized match quality; \tilde{x} rises by 5 percent while average match quality increases by 4 percent. As such, the inflow rate rises 9 percent, contrary to the 50 percent decline in the data. Conversely, in the NI model, firms' inability to identify good matches and the decline in \tilde{x} actually causes average realized match quality to decline 3 percent. The larger concentration of low quality matches which are more susceptible to job destruction raises the inflow rate for non-college workers in the NI model. In terms of outflow rates for non-college workers, all models predict declines as the indirect effects of a rise in applications counteract its direct benefits. The NI model predicts the largest decline in outflow rates as a rise in applications mainly serves to increase competition amongst workers, as such the outflow rate declines by 23 percent. Overall, we find that unlike our baseline model, neither the FI nor the NI model is capable of capturing the stark decline in the inflow rate for non-college workers. Our results suggest that an endogenous change in the share of informed firms is necessary to temper the rise in non-college workers' outside options and to generate a decline in their inflow rate.

College workers For college workers, Panel B of Table 6 shows that reservation match quality increases in all models. As will be discussed below, the direct effect of a higher applications outweighs the indirect effects for college workers in both the FI and NI model, raising job-finding probabilities and outside options of college workers. The improvement in college workers' outside options is the main factor driving the larger increase in \tilde{x} in the FI and NI models. At the same

time, labor market tightness, θ , falls in all models. Although job creation costs are constant in the FI and NI models, vacancy posting declines in both models with a rise in applications. Since the sharp increase in \tilde{x} reflects the improvement in workers' outside options, the value of a filled vacancy is diminished when workers are able to extract more from a match.

In terms of labor market flows, both the FI and NI models predict empirically-inconsistent large increases in the inflow and outflow rates of college workers. For inflows, the large increases occur because the rise in worker selectivity swamps the effects from an improved distribution of realized match quality. Consequently, the sharp rise in \tilde{x} raises the share of employed workers displaced into unemployment, as workers must now re-draw values above this higher threshold for matches to be sustained. Why are the effects from an improved distribution of realized match quality more muted relative to the rise in worker selectivity in the FI and NI models? For the NI model, the inability of firms to identify high quality applicants and the resultant randomness in hiring cause the distribution of realized match quality to improve marginally; average match quality rises by 3 percent while \tilde{x} increases by a larger 11 percent. In the FI model, the worker selectivity effect dominates because the increased propensity of workers to draw even higher match values raises their average probability of obtaining an offer from firms that can perfectly identify their best applicant. Even though average match quality increases by 21 percent in the FI model, the ability of workers to draw high match qualities in *more than one* application causes the worker selectivity effect to overturn the benefits from an improved distribution.

Turning to unemployment outflows, the large increases in the outflow rates occur because both models predict a rise in expected offers when a doubles. Although workers face increased competition at a vacancy, the increase in the number of vacancies contacted more than counteracts the former effect in the NI model.²⁴ Similarly, in the FI model, the average number of applicants per vacancy rises from 0.5 to 1.9 when a doubles. Since workers on average face at most one other competitor at a vacancy but observe an increased likelihood of drawing high match qualities at more than one application, expected offers increase on average for workers in the FI model with the rise in applications. In contrast, our baseline model features the mean number of applicants per vacancy rising from 2.3 to 5.9 and the share of informed firms almost doubling with the increase in applications. Thus, increased competition at a vacancy and a larger share of informed firms who are more selective cause expected offers to be lower in our baseline model. Overall, our results highlight that the interaction between a firm's information acquisition decision and the number of worker applications is important for capturing the decline in offer probabilities and expected offers. Thus, we view the endogenously changing share of informed firms as a necessary ingredient to replicating the trends in unemployment flows.

²⁴The average number of applicants per vacancy rises from 0.6 to 2.7 in the NI model. This implies that a worker on average faces no other competitors at a vacancy when $a = 3$, and that she competes on average with 2 other applicants at a vacancy when $a = 6$. Since hiring is random in the NI model, the fall in her average offer probability from 1 to 0.33 is smaller relative to the direct effect of a has on increase vacancies contacted.

6 Discussion

In this section, we provide a discussion on alternative formulations of our framework and its implications for our results.

6.1 Endogenizing the number of applications

In our model, we assume that the number of applications is exogenously given. An alternative is to endogenize the number of applications by assuming that a worker must exert costly search effort to contact more vacancies. Following [Kaas \(2010\)](#), a worker who exerts search effort ξ at cost $k(\xi)$ samples n vacancies from a Poisson distribution with parameter ξ . Then, the number of vacancies contacted by the worker would also be a random variable. Rather than allowing a to exogenously increase from 3 to 6, an equivalent exercise would be to exogenously reduce the cost $k(\xi)$ such that the mean number of applications rises from 3 to 6. Qualitatively, our model's predictions would continue to hold if one were to endogenize the number of applications. However, we view our current exercise of exogenously varying a as a more direct way of analyzing the role a rising number of applications has on labor market flows.

6.2 Assuming a marginal cost of information acquisition

While our model nests both the FI and NI models, a natural question arises as to whether our model mechanisms would differ if we were to instead assume a marginal cost of information. Incorporating such a cost structure would limit how much the benefits of information can increase with the number of applicants at a vacancy. Consider an economy where firms pay a cost κ_I for *each* applicant it screens. Denote \hat{j} as the level such that for any $j > \hat{j}$, the firm observes that the marginal cost of information exceeds its marginal benefit; i.e., $\kappa_I > V^I(j+1) - V^I(j)$ for any $j > \hat{j}$. There still exists a lower bound $j^* > 1$ where for any $j < j^*$, the value of not acquiring information exceeds the net benefit of acquiring information; i.e., $V^{NI} > V^I(j) - \kappa_I j$ for $j < j^*$. Thus, for any $j^* \leq j \leq \hat{j}$, the firm acquires information on all of its applicants, and for any $j > \hat{j} \geq j^*$, the firm acquires information on a subset \hat{j} of its applicants. [Appendix C.2](#) provides greater detail on such a setup.

Holding all else constant, an increase in applications would still raise the average number of applicants per vacancy in this marginal cost environment. So long as the mean applicants per vacancy is not far above \hat{j} in the initial steady state, the increase in applications would still raise the share of informed firms in the economy and improve the distribution of realized match quality, contributing towards a lower unemployment inflow rate.

6.3 Wage protocols

The Nash bargaining protocol in our model ensures that firms always extend offers to their highest quality applicant and workers always accept the offer with the highest match quality. This result would continue to hold even if one were to allow workers to use counteroffers in the bargaining process, as in [Postel-Vinay and Robin \(2002\)](#). In that case, workers use their second-best offer (if any) to bargain up the value they received in their preferred job. Suppose a worker receives an offer for an application that draws match quality y and an offer for a separate application that draws match quality x where $y < x$. When firms engage in Bertrand competition for the worker, the worker always chooses to accept the job with the higher match quality – in this case x – because she can attain the entire surplus of her second-best match, $S(y)$. Since workers always accept an offer with the highest match quality, firms still strictly prefer to extend an offer to their highest quality applicant since this minimizes their rejection probability. Thus, all we require in our model for firms and workers to prefer their highest quality match is for surplus and acceptance probabilities to be increasing in match quality.

7 Conclusion

We develop a search model with multiple applications and costly information to rationalize how an increase in worker applications can lead to a decline in unemployment inflow rates without precipitating any significant long-run changes in unemployment outflow rates. In our model, the counteracting forces of improved firm selection and increased worker selectivity are key to understanding how much inflow rates can decline in response to a rise in worker applications. Similarly, the extent to which outflow rates change in response to a rise in worker applications depends on how much the direct effect from an increased ability to contact more vacancies is mitigated by the endogenous declines in offer and acceptance probabilities.

Quantitatively, our model correctly predicts the small observed changes in the outflow rates both for non-college and college workers. Focusing on inflows, we find that the effect from improved firm selection dominates for non-college workers and accounts for the sharp decline in their inflow rate. Extending the model to also match the rise in the college premium, our model also predicts a decline in the inflow rate of college workers. Importantly, we use data from the EOPP and SCE to validate our model’s predictions on the changes in the number of job offers, job acceptance rates, and reservation wages, all of which are application outcomes that affect how inflow and outflow rates vary in response to an increase in applications. Overall, our model’s predictions largely align with the observed changes in application outcomes in the data.

Finally, we show that the endogenous response in the firm’s information acquisition decision to an increase in applications is critical for replicating the observed empirical patterns. When the firm’s investment in information is unvarying, either because information is free or infinitely

costly, these alternative models fail to generate the observed trends in labor market flows and job application outcomes in the data.

Our model can be extended in several dimensions. First, the number of applications that unemployed individuals submit can vary over the business cycle. This, together with the fact that applications have increased over time could have implications for firms' hiring behavior and the emergence of slow labor market recoveries following economic downturns. Second, incorporating ex-ante worker and firm heterogeneity into our model would be useful to understand why some firms receive relatively more applications and how this affects labor market power and earnings inequality over time. We leave these considerations for future research.

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Appendix

A Data

In this data appendix, we discuss more details on the CPS, EOPP, and SCE, explain our calculations from these datasets, and provide additional results that complement the main text.

A.1 CPS

Calculating inflow and outflow rates In this section, we first provide details on the measurement of unemployment inflow and outflow rates over time using the CPS. In doing so, we follow Shimer (2005), Elsby, Michaels, and Solon (2009), Elsby, Hobijn, and Şahin (2010), Shimer (2012), and Crump, Eusepi, Giannoni, and Şahin (2019), among many others.

The CPS provides monthly data on the number employed, the number unemployed, and the number unemployed with at most five weeks of unemployment duration (which we define as the short-term unemployed).²⁵ Let U_t , U_t^S , and L_t be the number of unemployed individuals, the number of short-term unemployed individuals, and the number of individuals in the labor force at time t , respectively. Also, let s_t and f_t denote the unemployment inflow (job separation) rate and unemployment outflow (job-finding) rate at time t , respectively. Then, we can define the change in the number of unemployed individuals between time t and $t + 1$ as follows:

$$dU/dt = -f_t U_t + s_t (L_t - U_t). \quad (17)$$

Moreover, we can write

$$U_{t+1} = U_{t+1}^S + (1 - F_t) U_t,$$

where F_t is the unemployment outflow (job-finding) probability. This equation implies that the number of unemployed at time $t + 1$ is equal to the number of short-term unemployed at time $t + 1$ plus the number of unemployed at time t who do not find a job. Then, we have

$$F_t = 1 - \frac{U_{t+1} - U_{t+1}^S}{U_t}.$$

Assuming a Poisson process for arrival rate $f_t \equiv -\log(1 - F_t)$, we obtain the unemployment outflow rate $f_t = -\log\left(\frac{U_{t+1} - U_{t+1}^S}{U_t}\right)$.

²⁵Importantly, the redesign of the CPS in 1994 caused a discontinuity in the time series for the number of short-term unemployed because of a change in the way unemployment duration was recorded, as discussed by Polivka and Miller (1998) and Shimer and Abraham (2002). We correct this by multiplying the standard series for short-term unemployment by a constant of 1.16 in every time period after 1994, as in Elsby, Hobijn, and Şahin (2010). Shimer (2012) finds similar results with alternative ways of correcting the data.

Next, we solve the differential Equation (17) forward and obtain

$$U_{t+1} = \frac{(1 - e^{-(s_t+f_t)})}{s_t + f_t} s_t L_t + e^{-(s_t+f_t)} U_t.$$

Finally, we repeat these calculations separately for college and non-college workers. Following these steps, we generate Figures 1 and 2 in Section 2.

Shift share decomposition of the aggregate inflow rate Here, we conduct a shift share decomposition analysis of the aggregate inflow rate to show that the decline in inflow rates is not simply a byproduct of a significant rise in the share of college workers over time.

Let s_t^k be the inflow rate of education group $k \in \{nc, c\}$ at time t , where nc represents the non-college and c represents the college. Let ω_t^k be the average share (weight) of group k at time t . Finally, let \bar{s}_t be the economy-wide average inflow rate at time t ; i.e., $\bar{s}_t = \sum_k \omega_t^k s_t^k$. Then, the change in the average inflow rate over two time periods t_1 and t_2 is given by:

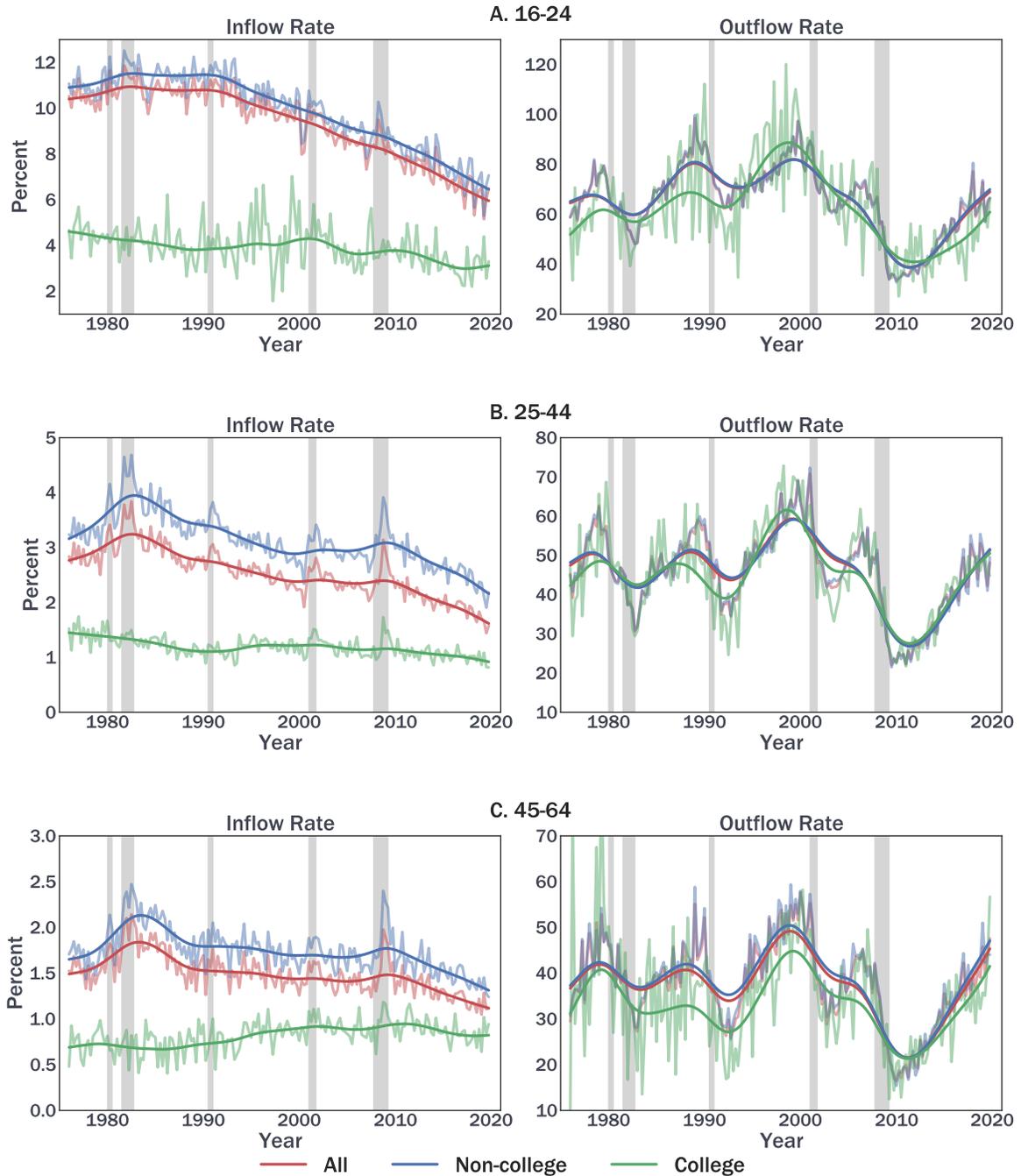
$$\begin{aligned} \Delta \bar{s} &= \bar{s}_{t_2} - \bar{s}_{t_1} \\ &= \sum_k \omega_{t_2}^k s_{t_2}^k - \sum_k \omega_{t_1}^k s_{t_1}^k \\ &= \underbrace{\sum_k (\omega_{t_2}^k - \omega_{t_1}^k) s_{t_2}^k}_{\text{between-group}} + \underbrace{\sum_k \omega_{t_1}^k (s_{t_2}^k - s_{t_1}^k)}_{\text{within-group}}, \end{aligned}$$

where the between-group measure holds the inflow rates within each group constant and measures how much of the total change in the average inflow rate is due to compositional changes. Conversely, the within-group measure holds the weights constant and measures how much of the total change in the average inflow rate can be attributed to the changes in the group-specific inflow rates. As in Section 5, if we define t_1 as the period 1976-1985 and t_2 as the period 2010-2019, we find that the within-group measure accounts for 86 percent of the total change in the average inflow rate, while the between-groups measure accounts for the remaining 14 percent.

Inflow and outflow rates across age and gender groups During the past four decades, the U.S. labor market experienced a significant rise in female labor force participation and a change in the age composition of workers as Baby Boomers participated in the labor force and aged over time. In this section, we present unemployment inflow and outflow rates by age and gender groups for all individuals and education groups separately. This helps us to examine whether our main results presented in Figures 1 and 2 hold across age and gender groups.

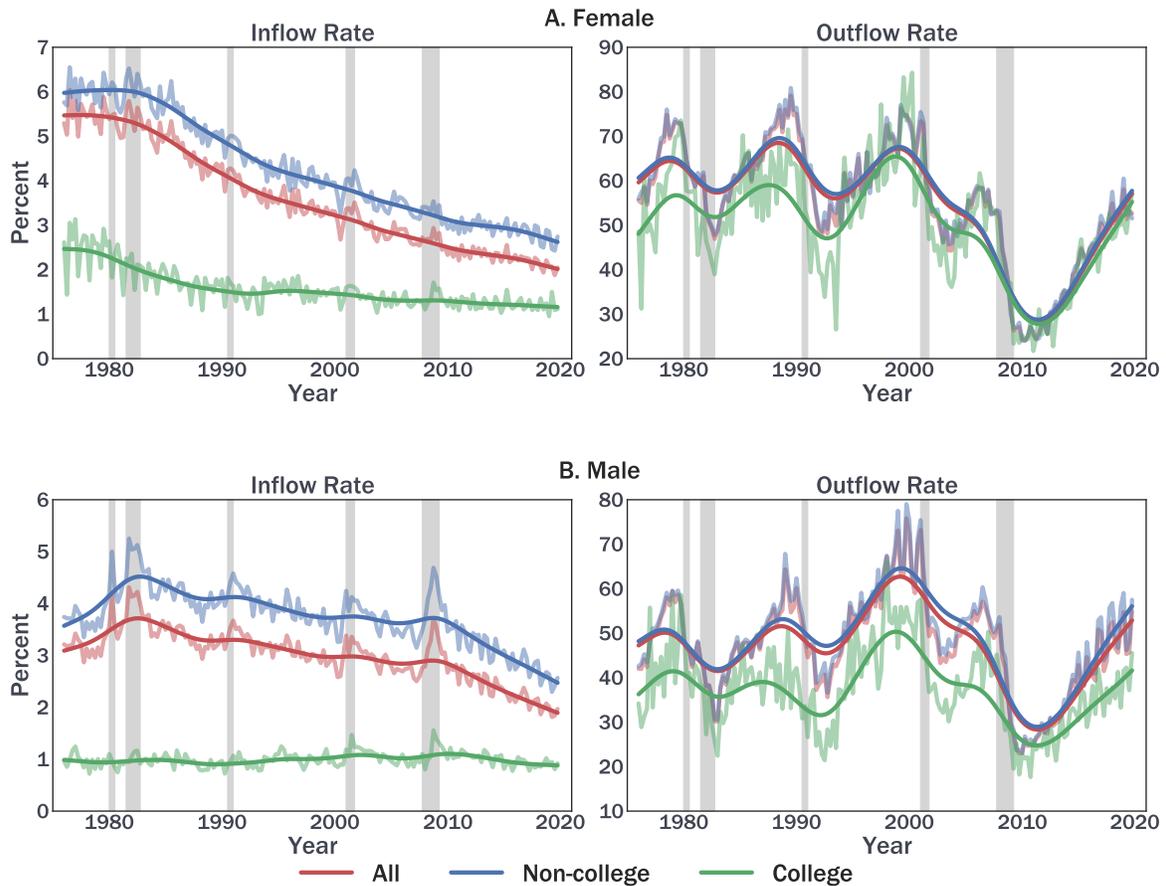
Figure A1 shows that young individuals (age group 16-24) have higher inflow and outflow rates than relatively older individuals (age groups 25-44 and 45-64). Moreover, the inflow rates

Figure A1: Unemployment inflow and outflow rates across age and education groups



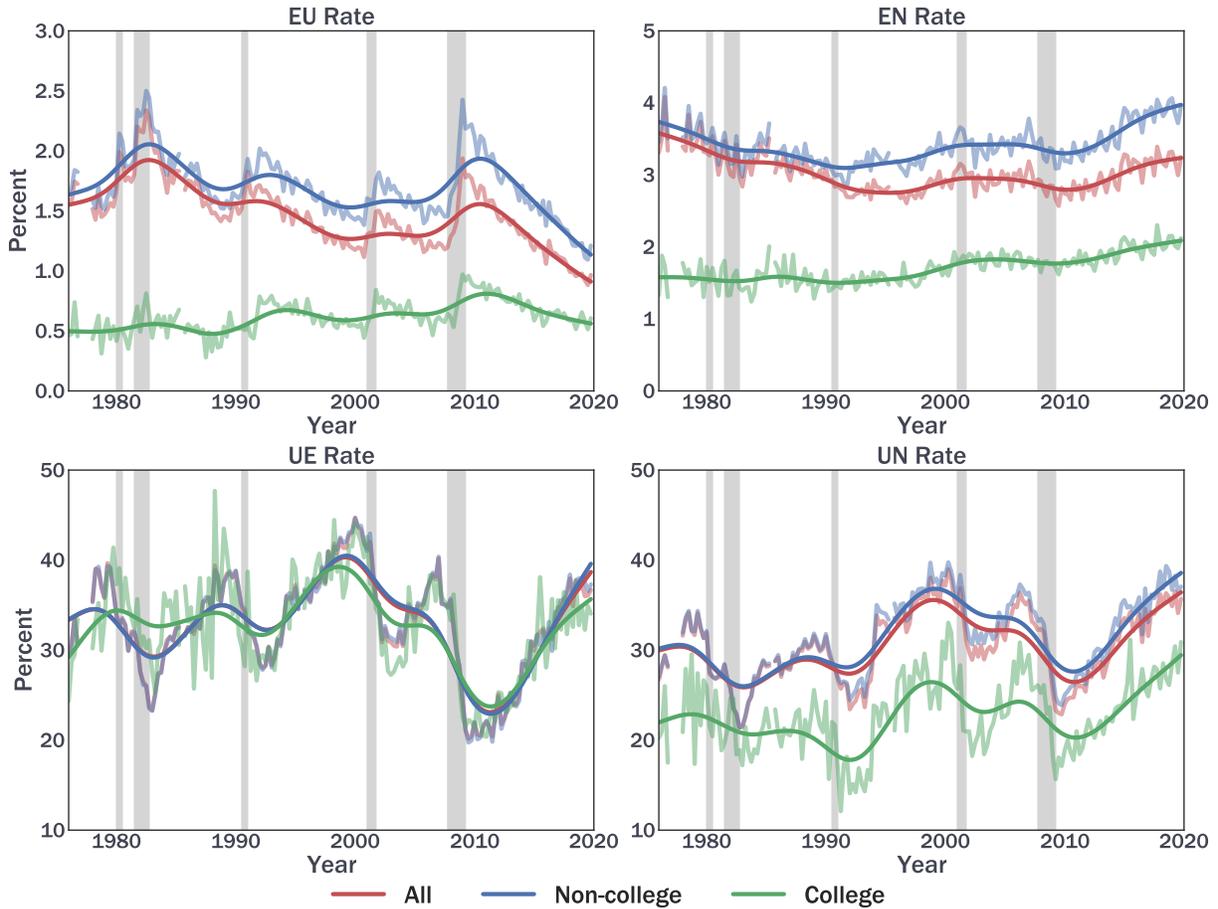
Note: This figure shows the unemployment inflow rate (left panels) and outflow rate (right panels) between 1976:Q1 - 2019:Q4 for all individuals (red lines), individuals without a four-year college (bachelor's) degree (blue lines), and individuals with at least a four-year college degree (green lines) under various age bins separately. Quarterly time series are averages of monthly inflow and outflow rates, which are calculated using CPS data as described in Appendix A. Dark solid lines represent the trends, which are HP-filtered quarterly data with smoothing parameter 1600. Gray shaded areas indicate NBER recession periods.

Figure A2: Unemployment inflow and outflow rates across gender and education groups



Note: This figure shows the unemployment inflow rate (left panels) and outflow rate (right panels) between 1976:Q1 - 2019:Q4 for all individuals (red lines), for individuals without a four-year college (bachelor's) degree (blue lines), and individuals with at least a four-year college degree (green lines), for males and females separately. Quarterly time series are averages of monthly inflow and outflow rates, which are calculated using CPS data as described in Appendix A. Dark solid lines represent the trends, which are HP-filtered quarterly data with smoothing parameter 1600. Gray shaded areas indicate NBER recession periods.

Figure A3: Transition rates using CPS panels



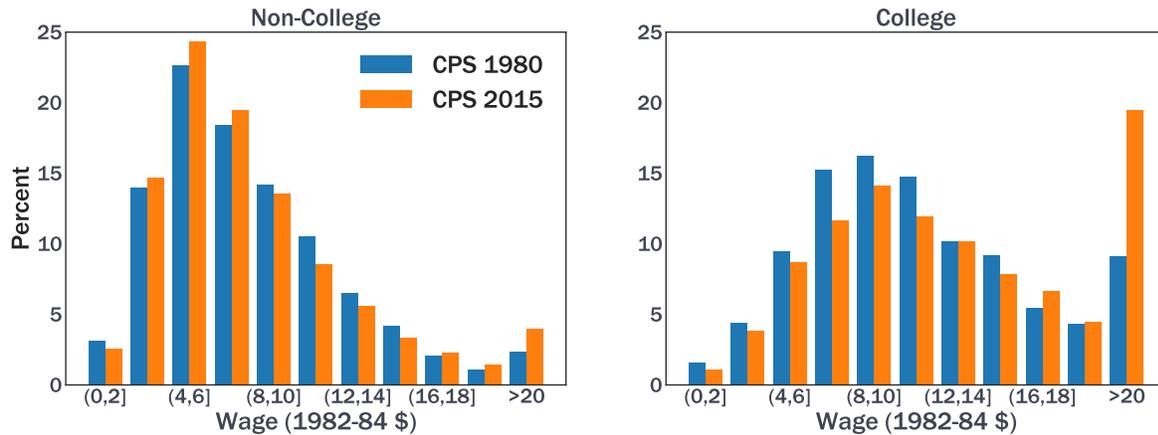
Note: This figure shows the unemployment inflow rate (EU) and outflow rate (UE) as well as employment-to-out-of-labor-force rate (EN) and unemployment-to-out-of-labor-force rate (UN) between 1976:Q1 - 2019:Q4 for all individuals (red lines), for individuals without a four-year college (bachelor's) degree (blue lines), and individuals with at least a four-year college degree (green lines). Quarterly time series are averages of monthly inflow and outflow rates, which are calculated using CPS panels. Dark solid lines represent the trends, which are HP-filtered quarterly data with smoothing parameter 1600. Gray shaded areas indicate NBER recession periods.

decreased the most for young individuals over time compared with those for other age groups. Importantly, for all age groups, the inflow rates of non-college workers exhibit sizable declines over time, while the inflow rates of college workers exhibit smaller changes. On the other hand, for all age and education groups, the outflow rates do not exhibit any long-run trends.

Next, Figure A2 shows that the inflow rates of females were double those of males during 1980s. However, this gap has narrowed over time as the inflow rates of females declined more rapidly. Furthermore, for both males and females, these declines in the inflow rates have been driven mostly by non-college workers. Again, the outflow rates of individuals across gender and education groups do not exhibit any long-run trend.

Hence, these results show that, across various age and gender groups, most of the decline in the inflow rate over time is driven by non-college workers.

Figure A4: Real Hourly Wages



Note: This figure shows the distribution of real hourly wages in 1982-1984 dollars in 1980 and 2015 separately for non-college and college workers. These results are obtained from the CPS using a sample of individuals aged 25-65 who are not self-employed.

Calculating inflow and outflow rates from CPS panels The CPS measure of short-term unemployed workers is underestimated given that some workers who enter unemployment exit unemployment within the same month. However, the methodology outlined above accounts for this bias, which is referred to as time aggregation bias by [Shimer \(2012\)](#). Hence, following the literature, we take this method as our preferred method in calculating inflow and outflow rates.

We now calculate monthly transition rates following individuals in CPS panels. The results are summarized in [Figure A3](#). We highlight several findings. First, the aggregate inflow (EU) and outflow (UE) rates obtained from CPS panels, shown in [Figure A3](#), are lower than their counterparts in [Figure 2](#). Second, according to [Figure A3](#), the decline in the aggregate inflow rate over time is still driven by the decline of the inflow rate for non-college workers. Third, the decline in inflow rate of non-college workers over time is not driven by an increase in their employment-to-out-of-the-labor-force (EN) flows given that their EN rate is roughly U-shaped. Finally, the outflow rate (UE) here also does not exhibit a secular trend either in the aggregate or across education groups.

Distribution of real hourly wages over time [Figure 3](#) in [Section 2](#) shows the distributions of real hourly reservation wages for college and non-college workers over time. We now present the equivalent distributions for real hourly wages. [Figure A4](#) shows that while there is a significant rightward shift in the distribution of real hourly wages of college workers, the distribution of real hourly wages of non-college workers remain mostly unchanged between 1980 and 2015. This finding corroborates with the stagnant wage growth at the bottom of the wage distribution and the resulting increase in wage inequality over time. This also implies that both reservation wages and wages experienced limited growth among non-college workers.

A.2 EOPP

The goal of the EOPP was to help participants to find a job in the private sector during an intensive job search assistance program. Individuals had to be unemployed and meet income eligibility requirements to be able to participate in this program. The survey was created to analyze the effects of the program on the labor market outcomes of the participants. As a result, by design, the survey oversampled low-income families, but this did not greatly weaken moments pertaining to the aggregate economy, as also shown by Table A2.

The survey incorporates both household-level and individual-level variables, which can be linked by household and individual identifiers. The individual-level dataset, which is the dataset we use, contains main record, training, job, unemployment insurance (UI), looking for work, disability, and activity spell modules. These modules provide data on demographics, earnings and hours information for each job held, unemployment spells and durations, job search activities and methods during each unemployment spell, UI receipt, and reservation wages.

In our study, we analyze a sample of unemployed individuals aged 25-65 who are not self-employed and who submitted at least one job application during each unemployment spell that occurred in 1979 and 1980. This gives us 5410 unique individual-spell observations.²⁶ For each of these individual-spell observations, we first calculate the monthly unemployment duration.²⁷ Using data on the number of job applications for each type of job search (e.g., private employment agencies, newspapers, labor unions, friends and relatives, etc), we obtain the total number of job applications for each spell. Then, we divide the total number of job applications in a spell by the duration of that spell to obtain the average monthly number of job applications for that spell. Similarly, using information on the number of job offers received through each type of job search, we calculate the total number of job offers received and the monthly number of job offers received for each spell. The data also provide an indicator variable on whether the individual accepted any of the job offers received. Using this variable, we also calculate the fraction of individuals who receive a certain number of job offers and accept an offer. Last, the survey also asked the lowest hourly wage rate that the individual would accept during the unemployment spell. We use this information to measure the reservation wage of the individual. We separately report all of these moments across education groups.²⁸

²⁶There are 78 observations in which the recorded beginning date of an unemployment spell happens to appear after the recorded end date of the same unemployment spell. We drop these observations from our sample.

²⁷To do so, we use variables named STLOOK16, ENDLOK16, STLOOK26, and ENDLOK26, which provide beginning and end dates (in mm/dd/yy format) of the first and second looking-for-work spells, respectively.

²⁸APLYJOBS and OFERJOBS provide the number of job applications and job offers received through various job search methods, respectively. The indicator variable on offer acceptance is given by variable ACPTJOBS. The variable WAGEACPT provides reservation wage information. Finally, DEGREE and GRADE provide information on the highest degree received and the highest grade of school completed, respectively, which we use to classify individuals into education groups.

A.3 SCE

The SCE Labor Market Survey was developed by the Federal Reserve Bank of New York.²⁹ The data provide the respondent’s demographics, job information if employed (i.e., earnings, hours, industry, employer size, etc), job search activities, and reservation wages.

We use the annual survey between 2013-2017. Because of the small sample size relative to the EOPP data, we pool the SCE observations across these years, as in Faberman, Mueller, Şahin, and Topa (2020). For the SCE, as for the EOPP, we study a sample of unemployed individuals aged 25-65 who are not self-employed and who submitted at least one job application during each unemployment spell. This includes individuals who are unemployed at the time of the survey and employed individuals who had an unemployment spell previously and started their new job less than four months prior to the time of the survey. For both of these groups, we analyze their job search activities during each unemployment spell. For currently unemployed individuals, the survey provides the total number of job applications during the past four weeks, the total number of job offers received during the past four weeks; and, if no job offers were received in the past four weeks, the total number of job offers received in the last six months, where we use the unemployment spell duration information to convert the latter to the average monthly number of job offers received. Moreover, the survey also provides information on whether the individual accepted or will accept a job offer. For currently employed individuals with a previous unemployment spell, the survey also provides the total number of job applications and the total number of job offers received during the unemployment spell. Again, we use information on the duration of the unemployment spell to convert these numbers to the average monthly number of job applications and job offers received. For these individuals, given that they are currently employed after an unemployment spell, we infer that they accepted a job offer. Then, using information about the offers and offer acceptance decisions for all individuals in the sample, we calculate the fraction of individuals accepting job offers the same as for the EOPP. Moreover, the SCE also asks the lowest wage the individual would accept, which we use to measure the reservation wage. We separately report all of these moments across education groups.³⁰

²⁹Source: Survey of Consumer Expectations, 2013-2019 Federal Reserve Bank of New York (FRBNY). The SCE data are available without charge at <http://www.newyorkfed.org/microeconomics/sce> and may be used subject to the license terms posted there. FRBNY disclaims any responsibility or legal liability for this analysis and interpretation of Survey of Consumer Expectations data.

³⁰For currently unemployed individuals, variables JS14, JS19, JS19b, JS23, and L7 give the total number of job applications during the past four weeks, the total number of job offers received during the past four weeks, the number of job offers received during the past six months, whether the individual accepted or will accept the job offer, and the duration of unemployment spells, respectively. For currently employed individuals who had an unemployment spell previously, JH13, JH14, and JH16 provide information on the duration of the unemployment spell, the total number of job applications, and the total number of job offers received during the unemployment spell, respectively. The variable RW2h_rc provides the reservation wage information. Finally, variables Q36 and _EDU_CAT (categorical) provide information on the highest grade of school completed.

Table A1: Comparison of EOPP, SCE, and CPS Samples: Demographics

Share (%)	EOPP 1980	CPS 1980	SCE 2015	CPS 2015
College degree	17.9	17.0	34.8	34.2
No college degree	82.1	83.0	65.2	65.8
Age 25-44	58.2	58.8	43.4	50.6
Age 45-54	21.4	21.0	29.5	25.3
Age 55-64	20.4	20.2	27.1	24.1
Female	51.5	53.8	52.1	52.5
Married	76.8	74.0	68.1	59.2
White	83.3	86.9	77.7	78.5
Number of observations	35,864	904,791	756	772,922

Note: This table compares demographics across EOPP, SCE, and CPS samples. In all datasets, the sample consists of individuals aged 25-65 who are not self-employed. College degree indicates the group of individuals with at least a four-year college degree. Married indicates the group of individuals who are married or cohabiting.

A.4 Comparison of EOPP, SCE, and CPS samples

In this section, we compare the EOPP and the SCE samples to the CPS samples over time. This is important, as the comparison reveals that the EOPP and the SCE samples mostly capture the changes in educational attainment, marital status, labor force participation of females, the age decomposition of the labor force, as well as earnings and hours over time.³¹

Table A1 compares demographics from samples across these three datasets. We highlight several results. First, the EOPP sample captures education and age composition of the CPS sample almost exactly. Second, there has been a steady increase in the fraction of individuals with a college degree over time, as shown by the comparison between the CPS 1980 and the CPS 2015. Importantly, the SCE sample has almost the same fraction of individuals with a college degree. This implies that the EOPP 1980 and the SCE 2015 samples capture this increase in educational attainment quite well. Third, the SCE sample slightly overestimates the increase in older workers (age groups 45-54 and 55-64) in the labor force relative to those in the CPS sample. Finally, when compared to the CPS 1980 and the CPS 2015 samples, the EOPP 1980 and the SCE 2015 samples slightly underestimate the decline in the fraction of married individuals.

Next, Table A2 compares labor market moments from samples across these three datasets. Importantly, when compared to the CPS 1980 and the CPS 2015 samples, the EOPP 1980 and the SCE 2015 samples generate the rise in the labor force share of females over time, although the magnitude of the increase is larger between the EOPP and the SCE samples than between

³¹We also compared SCE and CPS samples for each year between 2013 and 2017. The results are very similar to the ones for 2015.

Table A2: Comparison of EOPP, SCE, and CPS samples: Labor market moments

	EOPP 1980	CPS 1980	SCE 2015	CPS 2015
Unemployment rate (%)	4.7	5.6	4.9	4.5
Female - share of employed (%)	70.2	54.5	71.0	64.7
Male - share of employed (%)	85.2	84.1	77.9	77.4
Labor force share of females (%)	38.6	43.1	59.0	48.0
Average weekly hours	38.1	39.2	40.9	36.9
Median weekly hours	40.0	40.0	40.0	40.0
Std. dev. of weekly hours	10.6	9.5	9.6	8.9
Average annual earnings (\$)	16,373	17,290	85,298	97,074
Median annual earnings (\$)	14,040	15,600	68,000	77,777
Std. dev. of annual earnings (\$)	14,901	10,305	77,660	67,130
Number of observations	35,864	904,791	756	772,922

Note: This table compares labor market moments across EOPP, SCE, and CPS samples. In all datasets, the sample consists of individuals aged 25-65 who are not self-employed. Earnings are calculated for employed sample and values are in nominal terms.

the CPS samples. The remaining labor markets moments in relation to employment, weekly hours, and annual earnings are mostly comparable between the EOPP 1980 and the SCE 2015 and the CPS 1980 and the CPS 2015 samples, with the exception that the share of employed females is overstated in the EOPP 1980 sample relative to that in CPS 1980 sample.

A.5 Eliminating the business cycle effects

In Section 2.2, we use data from the EOPP and SCE samples and show that the unemployed are now sending more applications than they used to in the 1980s. One concern may be that there are some aggregate labor market differences between the 1979-1980 period and the 2013-2017 period, which may have some effect on this conclusion. For example, unemployed individuals may send more applications during an expansion than during a recession. In order to ensure that this change is not driven by cyclical changes in the labor market, we now control for aggregate moments to eliminate these business cycle effects. In particular, we use the EOPP and the SCE samples to estimate the following regression equation:

$$y_{it} = \alpha + \beta_1 X_{it} + \beta_2 d_{t2} + \beta_3 \text{Unemp. rate}_t + \beta_4 \text{Real GDP}_t + \epsilon_{it},$$

where i indexes individuals with at least one job application during an unemployment spell, t indexes years, y is the number of monthly job applications, X is a vector of demographic characteristics of the individual, d_{t2} is an indicator variable that takes a value of 1 if the year

Table A3: Eliminating the business cycle effects

Dependent variable: Number of job applications per month								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d_{t2}	7.29 (2.02)	5.07 (1.54)	8.95 (3.35)	4.36 (1.95)	8.90 (3.14)	4.76 (1.83)	7.88 (2.21)	5.29 (1.72)
Unemp. rate			-12.30 (14.93)	5.26 (10.17)			-26.71 (39.91)	23.30 (29.21)
Real GDP					71.44 (79.90)	-12.70 (55.11)	-133.73 (241.41)	158.41 (181.57)
Constant	6.82 (0.59)	7.65 (1.19)	5.28 (1.91)	8.27 (1.96)	5.65 (1.33)	7.85 (1.67)	5.65 (1.33)	7.90 (1.69)
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: This table provides results on the differential number of job applications between the 1979-1980 period and the 2013-2017 period, controlling for the cyclical components of the aggregate unemployment rate and real GDP, as well as individual characteristics including gender and education. Values in parenthesis denote the standard errors.

is between 2013 and 2017 and 0 otherwise, the Unemp. rate and Real GDP are the cyclical components of HP-filtered series of the unemployment rate and real GDP. Table A3 summarizes the results. We find that, from the 1979-80 period to the 2013-2017 period, the average monthly number of job applications significantly increased (between 4.36 and 8.95 depending on the specification) even after we control for changes in aggregate economic conditions.

B Model

In this appendix, we provide proofs for the propositions in the main text.

Proof for Lemma 1 Consider a firm who has acquired information and who has j applicants. Suppose that the applicant with the highest match quality has match productivity x . Further suppose that the firm also has another applicant with match quality $y < x$. For the firm to make an offer to applicant y as opposed to applicant x , it must be that $V^F(y)\Gamma(y) > V^F(x)\Gamma(x)$.

Under Nash-bargaining, we have $V^F(x) = \eta S(x)$ and $V^W(x) - U = (1 - \eta)S(x)$. Thus, if surplus, $S(x)$, is increasing in match quality, x , then both $V^F(x)$ and $V^W(x) - U$ are also increasing in x . Since the worker's gain from matching, $V^W(x) - U$, is increasing in x , the worker is always strictly better off accepting the offer that brings her the highest match quality, implying that $d\Gamma(x)/dx > 0$. Finally, since both $\Gamma(x)$ and $V^F(x)$ are increasing in x , we have $V^F(x)\Gamma(x) > V^F(y)\Gamma(y)$ for $x > y$. This implies that the firm would never make an offer to a lower-ranked candidate.

Proof for Proposition 1 Consider a firm with j applicants. Suppose the firm chooses to acquire information, allowing it to rank its applicants by match quality. The probability that the highest match quality observed is less than or equal to x is given by $[\Pi(x)]^j$, where $[\Pi(x)]^j$ represents the distribution of the maximum order statistic. Denote $F_j(x) = [\Pi(x)]^j$. It is then clear that for a given x , $[\Pi(x)]^j$ is weakly declining as j increases, implying that:

$$[\Pi(x)]^{j+1} \leq [\Pi(x)]^j \implies F_{j+1}(x) \text{ FOSD } F_j(x).$$

In other words, the distribution $F_{j+1}(x)$ has more concentration at higher x values than the distribution $F_j(x)$. Since both $\Gamma(x)$ and $V^F(x)$ are increasing in x but independent of j , this implies that the only term in the value of acquiring information $V^I(j)$ that changes with j is the distribution of the maximum order statistic, $F_j(x) = [\Pi(x)]^j$. Since the distribution $F_{j+t}(x)$ FOSD $F_j(x)$ for $t > 0$, it must be that

$$V^I(j+1) - V^I(j) = \int_{\bar{x}}^{\bar{x}} \Gamma(x)V^F(x)d[\Pi(x)]^{j+1} - \int_{\bar{x}}^{\bar{x}} \Gamma(x)V^F(x)d[\Pi(x)]^j > 0, \quad \forall j > 0.$$

Thus, the benefit of acquiring information is strictly increasing in j . Finally, the benefit of acquiring information when the firm has only one applicant is equal to the value of not acquiring information; i.e., $V^I(1) = V^{NI}$. Given that the constant fixed cost of acquiring information κ_I is finite and that $V^I(j)$ is increasing in j , it is then straightforward to show that the net value of acquiring information must cut the value of not acquiring information once from below at j^* .

Ruling out other pure-strategy equilibria It is trivial to show that all firms acquiring information regardless of their applicant size, j , cannot be an equilibrium. To see this, suppose all firms choose to acquire information no matter the number of applications received. While the acceptance probability, $\Gamma(x)$, will endogenously change when all firms acquire information, it is still the case that for a firm with a single applicant, $V^I(1) = V^{NI}$. Thus, the firm that has a single applicant always has a profitable deviation to not acquire information when $\kappa_I > 0$ and all other firms are acquiring information. Hence, an equilibrium where all firms acquire information cannot exist, since firms with $j = 1$ applicants are always better off acquiring no information.

Can a pure strategy equilibrium where no firms acquire information exist? Suppose instead that all firms choose not to acquire information. So long as surplus is increasing in x , the worker always accepts the highest match quality offer. Thus, a firm who is able to make an offer to its highest quality applicant lowers its probability of being rejected. Since the likelihood of a firm having a high quality applicant is increasing in j , the expected benefit of information is strictly increasing in j . This together with finite information cost, κ_I , implies that a single firm with high enough j applicants has a profitable deviation and would choose to acquire information. Thus, an equilibrium where no firm acquires information is not possible for a finite κ_I .

Table A4: Calibration of FI and NI models

Parameter	Value		Target	Model		Data
	FI Model	NI Model		FI Model	NI Model	
κ_V	0.51	0.70	Unemployment rate	0.066	0.090	0.076
δ	0.0003	0.001	Inflow rate	0.047	0.043	0.043
λ	5.51	9.76	Inflow rate, college	0.014	0.014	0.014
b	0.59	0.70	UI replacement rate	0.49	0.43	0.40
μ_c	0.43	0.78	College premium	0.54	0.59	0.45
σ_c	0.28	0.37	Frac. with no offer, college	0.26	0.24	0.26
σ_{nc}	0.19	0.20	Frac. with no offer, non-college	0.29	0.33	0.42

Note: This table provides a list of calibrated parameters in the “Full Information” (FI) and “No Information” (NI) models. Moments relating to unemployment levels and flows are obtained from the CPS as averages between 1976 and 1985. Fractions of individuals who accept the offer, conditional on having an offer, among non-college and college workers are obtained from the EOPP 1979-1980.

C Extensions

In this appendix, we provide details of calibration outcomes for the “Full Information” (FI) and “No Information” (NI) models and elaborate on our discussion for the model with a marginal cost of information acquisition.

C.1 Calibration details of FI and NI models

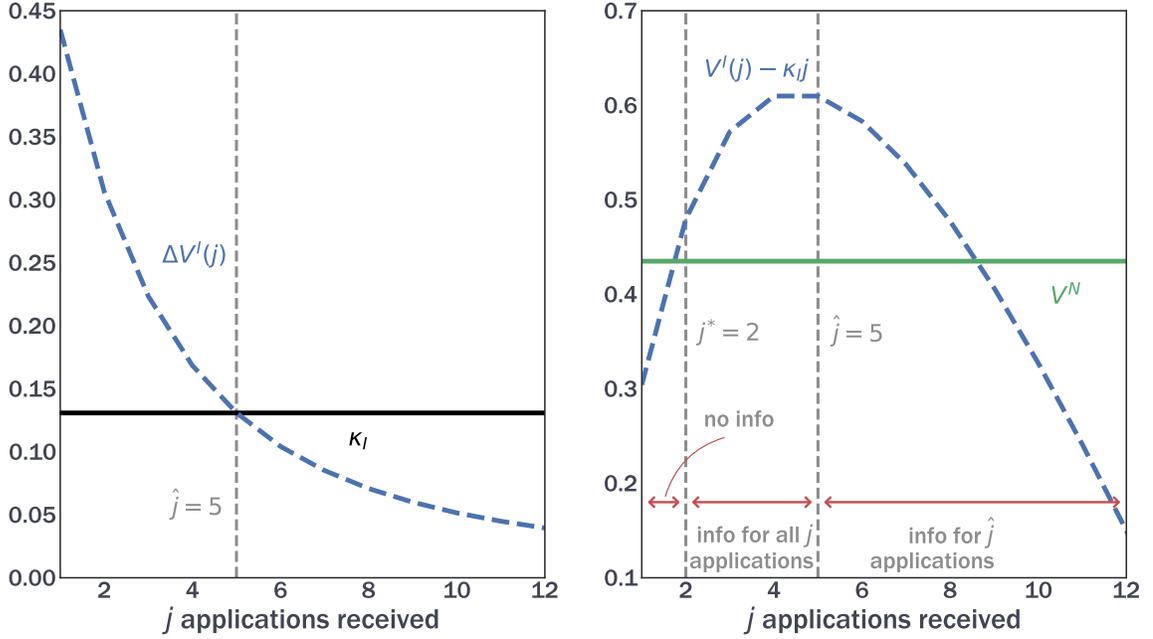
Recall that we set $\kappa_I = 0$ in the FI model and $\kappa_I \rightarrow \infty$ in the NI model in Section 5.4. Given that κ_I is already set, we leave out the unemployment rate of college individuals, which was used as a calibration target for κ_I in our calibration of the baseline model. For the rest of the parameters, we target the same moments as in the baseline model given in Table 1. Table A4 summarizes the calibration outcomes of the FI and NI models.

C.2 Marginal cost of information

We now elaborate on our discussion for the model with a marginal cost of information acquisition in Section 6.2. Suppose that κ_I is instead a marginal cost the firm pays for each applicant it acquires information on. Denote \hat{j} as the level such that for any $j > \hat{j}$, the firm observes that the marginal cost of information exceeds the marginal benefit of information; i.e., $\kappa_I > V^I(j+1) - V^I(j)$ for any $j > \hat{j}$. The left panel of Figure A5 shows a numerical example where beyond \hat{j} applicants the marginal cost of information, κ_I , exceeds the marginal benefit of information, $\Delta V^I(j)$. Since the marginal cost of information exceeds the marginal benefit, the firm optimally only acquires information on a subset $\hat{j} < j$ of its applicants.

In this environment, the firm’s problem can be characterized by the following two cases. First, for any $j > \hat{j}$, the firm solves the problem: $\max\{V^I(\hat{j}) - \kappa_I \hat{j}, V^I(j) - \kappa_I j, V^{NI}\}$. Second,

Figure A5: Upper bound on benefits of information rises with j with marginal cost of information



Note: In this numerical example, we treat κ_I as the marginal cost of information. The left panel shows the change in the benefit of acquiring information, $\Delta V^I(j)$, against the constant marginal cost, κ_I , of acquiring information for each additional applicant. The right panel shows how the net benefit of acquiring information, $V^I(j) - \kappa_I j$, varies with the number of applicants if the firm was to acquire information on all applicants against the constant value of not acquiring information, V^N . For $j > \hat{j}$, firms only acquire information on \hat{j} applicants.

for any $j \leq \hat{j}$, the firm instead solves: $\max\{V^I(j) - \kappa_I j, V^{NI}\}$.

It is still the case that for any $\kappa_I > 0$, the firm would not acquire any information for $j = 1$ applicants since the firm is always better off acquiring no information; i.e., $V^I(1) - \kappa_I = V^{NI} - \kappa_I < V^{NI}$. More generally, the minimum number of applicants the firm requires before it acquires information, j^* , must still satisfy $V^I(j) - \kappa_I j > V^{NI}$. Thus, the firm's information acquisition strategy can be characterized as:

$$\begin{cases} \text{Acquire no information,} & \text{for } j < j^* \\ \text{Acquire information on } j \text{ applicants,} & \text{for } j^* \leq j \leq \hat{j} \\ \text{Acquire information on } \hat{j} \text{ applicants only,} & \text{for } j > \hat{j}. \end{cases}$$

The right panel of Figure A5 shows how the firm would not acquire information for $j < j^*$ applicants since the value of not acquiring information is strictly greater. Given a choice of acquiring information on a subset of applicants vs. not acquiring information at all, the firm's value is maximized when it only acquires information on a subset $\hat{j} < j$ applicants for any applicant pool size j such that $j^* \leq \hat{j} < j$.