Job Applications and Labor Market Flows*

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August 2021

Abstract

Job applications have risen over time yet job-finding rates remain unchanged. Meanwhile, separations have declined. We argue that increased applications raise the probability of a good match rather than the probability of job-finding. Using a search model with multiple applications and costly information, we show that when applications increase, firms invest in identifying good matches, reducing separations. Concurrently, increased congestion and selectivity over which offer to accept temper increases in job-finding rates. Our framework contains testable implications for changes in offers, acceptances, reservation wages, applicants per vacancy, and tenure, objects that enable it to generate the 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 have led to an increase in the number of job applications over time. Despite a large increase in the number of applications, the unemployment outflow (job finding) rate in the U.S. has not observed any long-run change. Conversely, the unemployment inflow (job separation) rate has undergone a steady decline since the 1980s. Given that unemployment flows are inextricably tied to job-search behavior, a natural question arises as to why an increase in applications has not led to any sustained increase in the outflow rate. We argue that the main benefit of increased applications has not been to increase the probability of finding a job, but rather to increase the probability of finding a good match, as evidenced by the decline in the separation rate.

To address this question, we make two contributions. First, we empirically study the trends in job applications and unemployment flows. Using information from the Employment Opportunity Pilot Project (EOPP) and the Survey of Consumer Expectations (SCE), we document novel facts on how applications have changed over time. We find that the median number of applications submitted by unemployed workers per month has doubled since the 1980s. Using data from the Current Population Survey (CPS), we show that the inflow rate has declined sharply since the 1980s while the outflow rate remains relatively unchanged. Notably, compositional changes only account for a small share of the variations in inflow and outflow rates. Second, we build a tractable equilibrium labor search model to quantitatively analyze how an increase in applications can drive a decline in the inflow rate without precipitating any trend increase or decrease in the outflow rate. Our model departs from the standard 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. Notably, the endogenous change in firms' hiring behavior is a key channel through which increased applications can replicate the observed changes in unemployment flows over time. Finally, our model has several testable implications on the changes in applications outcomes such as offer and acceptance probabilities and reservation wages. Using the EOPP and SCE, we provide novel empirical results on how these application outcomes have changed over time and show how our model's predictions align with these trends.

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. Employment relationships endogenously dissolve if match quality falls below a reservation threshold. 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 applications, as a higher number of applicants per vacancy increases the probability that a firm has at least one high productivity candidate. Firms, however, can only exploit this benefit if they acquire information and are able to rank applicants. Because wages are increasing in match quality, acquiring information also confers an additional benefit to firms. In particular, firms minimize their rejection probabilities whenever they extend offers to their highest quality applicants.

Having developed our model, we apply our framework to the data. We calibrate our model to match labor market moments and application outcomes for the period 1976-1985. We use our calibrated model to analyze how unemployment inflow and outflow rates change when *only* the number of applications that workers can send increases. Importantly, our model has testable implications for labor market outcomes that underlie the predicted changes in unemployment flows. We demonstrate that the model's predictions on application outcomes such as offer and acceptance rates, reservation wages, the tenure distribution, and the number of applicants per vacancy largely mimic patterns observed in the data. Overall, we argue that any model that analyzes changes in inflow and outflow rates must also account for changes in such factors that have a first order effect on unemployment flows.

Under our calibrated model, the inflow rate declines by 20 percent when applications increase, about one-third of the decline in data.[1] Why does the model predict that an increase in applications leads to a decline in the inflow rate? 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 which – because of the persistence in match quality – are less susceptible to job destruction, reducing inflows. On the other hand, the ability to contact more vacancies 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. As such, the inflow rate declines with the rise in applications.

The decline in the inflow rate in the model is largely driven by a sharp fall in the share of individuals employed in low-quality and high-turnover jobs, consistent with observed patterns in the data. When more firms acquire information in response to a rise in applications, fewer low-quality matches are formed. Consequently, the share of short duration jobs declines. At the same time, our model replicates the empirical finding that median tenure has remained unchanged despite the decline in short duration jobs. Because each high-quality match now

[1]These 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.

observes a marginally higher separation probability due to increased worker selectivity, median tenure remains unchanged despite the lower concentration of short duration jobs.

Turning to outflows, our model predicts that a rise in applications causes the outflow rate to decline by a marginal 5 percent. These results are consistent with the fact that the outflow rate has remained relatively unchanged over time in the data. Why does the model generate a muted response in the outflow rate despite a rise in applications? Similar to inflows, an increase in applications has an ambiguous effect on outflows. While an increased contact between job-seekers and vacancies contributes toward a higher outflow rate, whether the job-finding rate actually increases 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. A fall in either of these probabilities contributes toward depressing outflow rates. In our calibrated model, and as in the data, the decline in offer and acceptance rates is sizable, and more than counteracts the direct effect of contacting more vacancies when applications increase. The decline in offer probabilities partially stems from the fact that the rise in applications in our model leads to an overall higher number of applicants per vacancy, consistent with the data.[2] The decline in acceptance rates in our model is not solely driven by an increase in reservation match quality and hence, reservation wages. In the model, holding fixed reservation match quality, acceptance rates still decline substantially as workers reject jobs more often when they submit more applications and can choose from more offers. This result concurs with our empirical findings that while acceptance rates have fallen by a large margin in the data, the coincident rise in reservation wages has not been to the same magnitude. In summary, our model predicts that the rise in applications has been accompanied by a decline in offer probabilities and acceptance rates.

Finally, we demonstrate why endogenizing the firm's information acquisition problem is necessary to understand how a rise in applications affects trends in unemployment flows. To do so, we consider two thought experiments: a case where information about a firm's applicants is free (full information) and a case where information is infinitely costly (no information). We find that both models predict changes in unemployment flows that are inconsistent with the data. Intuitively, the effective cost of job creation is invariant to the number of applications in either of these models as information is either free or no firm pays for information. Since the cost is constant but the benefit of a vacancy is increasing when the probability of zero applicants is lower, vacancy creation rises. This higher vacancy creation does not occur in our baseline model as the effective cost of job creation is rising with the share of informed firms. Thus, in the full information environment, the outflow rate rises by a non-trivial amount as higher vacancy

[2] Faberman and Menzio (2018) find an average of 24 applicants per vacancy in 1980 using the EOPP, while Marinescu and Wolthoff (2020) find an average of 59 applicants per vacancy in 2011 using data from CareerBuilder.

creation mitigates some of the congestion arising from an increase in applications. Furthermore, firms in this environment always observe their applicants' qualities, while workers have a larger probability of drawing at least one high quality match when they submit more applications. Since both acceptance and offer probabilities are increasing in match quality, the probability a worker finds a job rises with the number of applications submitted. In contrast, the outflow rate declines substantially in the no information environment because the benefits of additional applications are negated when firms cannot identify high-quality matches. Although vacancy creation rises, it does not rise enough to keep the number of applicants per vacancy constant. As such, increased applications result in lower offer probabilities and a large decline in the outflow rate. In terms of inflows, while both counterfactuals predict declines in the inflow rate, the magnitudes are much smaller relative to our baseline model's predictions and the data. Overall, our results suggest that the interaction between the firms' information decision and the workers' application behavior is necessary to explain the joint dynamics in unemployment flows.

Related literature We are not the first paper to consider a labor search model with multiple applications. Earlier papers in the literature by Albrecht, Gautier, and Vroman (2006), Kircher (2009), Galenianos and Kircher (2009), Gautier, Moraga-Gonzalez, and Wolthoff (2016) and Albrecht, Cai, Gautier, and Vroman (2020) focus on the efficiency properties of such models. Gautier, Muller, van der Klaauw, Rosholm, and Svarer (2018) use Danish data and show how a rise in applications can lead to negative congestion effects. Separately, Gautier and Wolthoff (2009) consider a model where workers send at most two applications, and focus on ex-ante heterogeneity on the firm side. In contrast, we 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 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. Our paper instead focuses on long-run trends in the labor market. To our knowledge, this is the first paper to link a rise in applications to long-run trends in unemployment flows.

Our work also contributes to the literature that studies secular changes in labor market flows. Crump, Eusepi, Giannoni, and Şahin (2019) document a secular decline in inflow rates alongside no long-run change in outflow rates. Across different datasets, Hyatt and Spletzer (2016), Pries and Rogerson (2019) and Molloy, Smith, and Wozniak (2020) report evidence of a decline in separation rates and the change in the tenure distribution. Despite a sharp decline in the share of short-duration jobs, Molloy, Smith, and Wozniak (2020) report that median tenure remains unchanged. Our paper shows how increased applications can replicate these findings.

On the theoretical side, 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 affect labor market flows through their effects on household search and firm hiring decisions. Mercan (2017) and Pries and Rogerson (2019) show that an 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, an improvement in information via a higher share of informed firms also affects labor market flows. However, the increase in the share of informed firms in our model is an *endogenous* response to rising applications. Separately, 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 since the 1950s even if search technology improves. While our starting point is that improvements in search technology have led to an increase in applications, our paper's focus is to explain how this rise since the 1980s can enable workers to find better matches and observe fewer separations, without triggering a simultaneous rise in their job-finding probabilities. By focusing on the effects of increased applications, our model also has testable implications for the changes in application outcomes such as offer probabilities, acceptance rates, reservation wages, tenure, and the number of applicants per vacancy – factors which have a first order effect on unemployment 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 a higher number of applicants per vacancy affects the share of firms investing in information and thus the rate at which firms fill a position.

The rest of the paper is organized as follows. Section 2 presents our empirical findings on job applications, inflow and outflow rates, and application outcomes. 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.

2 Empirical Findings

In this section, we discuss our empirical findings that motivate the model and quantitative exercises. In Section 2.1, we provide evidence on how the number of applications has changed over time. Next, in Section 2.2, we outline the trends in unemployment flows. Finally, in Section

2.3, we document how application outcomes have changed over time.

2.1 Job applications

Using information from the EOPP and SCE Labor Market Survey, we provide novel evidence on how the application behavior of unemployed workers has evolved over time. A unique feature of these datasets is that they offer insights into job search behavior and, unlike other household surveys, provide information on the application process such as the number of applications sent, the number of offers received, and the acceptance decisions of unemployed workers. In addition, these datasets contain information about workers' reservation wages.

The EOPP was designed 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 of unemployed workers 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 provide individual-level information on demographics, employment, wages, and regular hours of work. Appendix A provides a list of the variables we use, and explains how we calculate moments using these variables. 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 the two time periods.

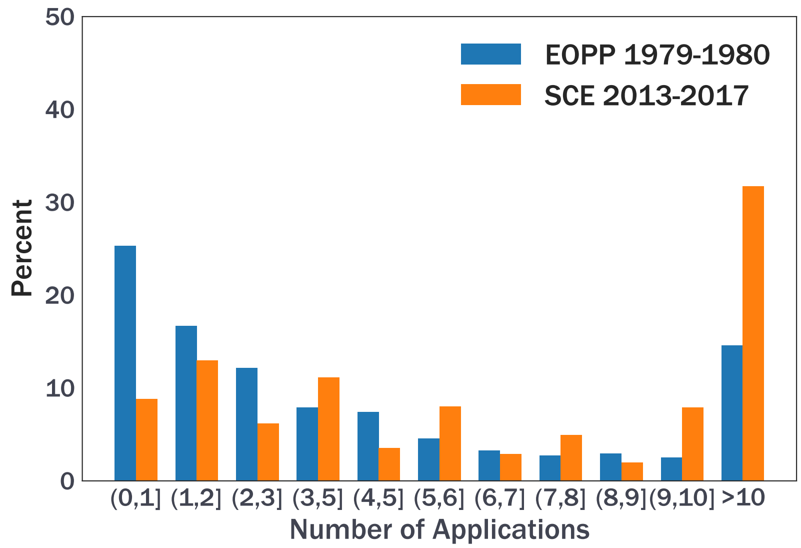
In both datasets, we consider a sample of unemployed individuals aged 25-65 who sent at least one job application during their unemployment spell.[3] Figure 1 highlights how the distribution of applications submitted per month by the unemployed has shifted rightward over time. Between the two surveys, the median number of applications per month increased from 2.7 to 6, implying that the median number of applications more than doubled between 1979-1980 and 2013-2017. To ascertain whether the rise in applications is due to prevailing aggregate economic conditions, Table A3 in Appendix A shows that this result continues to hold even after controlling for business cycle effects. Finally, Table A4 in Appendix A documents that the rise in applications is a common pattern across various demographic groups. Overall, our findings imply that the number of applications has increased over the past four decades.

2.2 Labor market flow rates

Turning now to unemployment flows, we use monthly data from the CPS on the total employed, unemployed, and short-term unemployed, i.e., respondents who are unemployed for at

[3]While the SCE provides information on the number of job applications submitted by employed workers, the EOPP does not. For this reason, we focus only on applications submitted by unemployed workers.

Figure 1: Change in number of job applications over time



Note: This figure shows the distributions of applications submitted by unemployed job-seekers in a given month in 1979-1980 using the EOPP data, and in 2013-2017 using the SCE data. In both datasets, our sample consists of unemployed individuals aged 25-65 with at least one job application during their unemployment spell.

most five weeks, and calculate the outflow and the inflow rates over time using standard procedures found in the literature. Appendix A provides details on our data and methodology.[4] Echoing previous studies, Figure 2 shows that the outflow rate exhibits almost no secular change since the 1980s, while the inflow rate has fallen by 58 percent, from 4.1 to 2.3 percent.

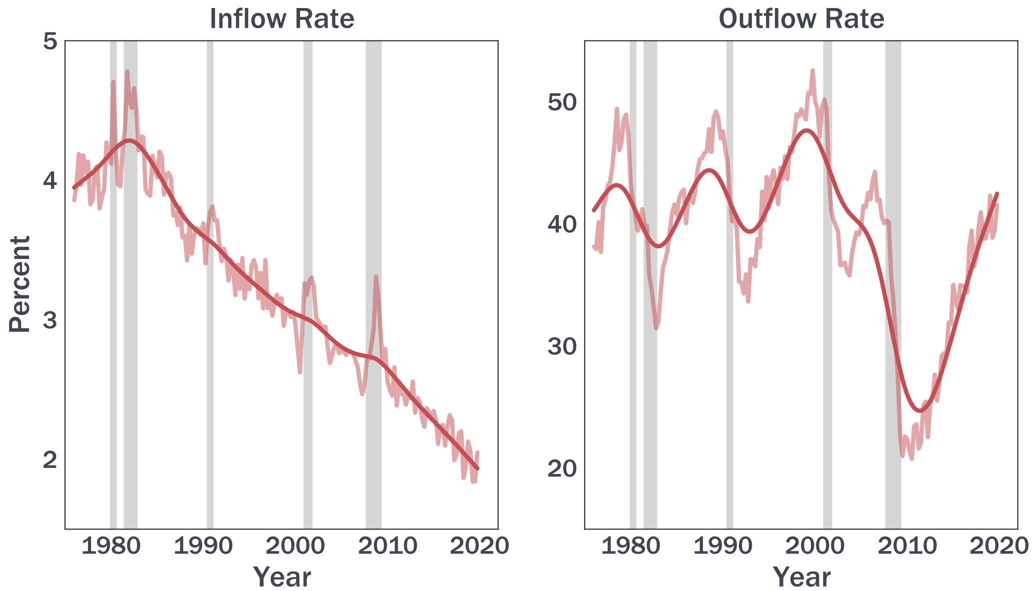
Since the U.S. labor force underwent significant demographic changes over this period of time, a natural question arises as to whether the decline in the unemployment inflow rate is due to changes in worker demographics or whether the decline reflects a more fundamental change in each group's labor market experience. Similarly, we ask whether demographic changes somehow contributed to the lack of trend in the aggregate outflow rate. To answer these questions, we conduct a shift-share analysis on aggregate outflow and inflow rates in Appendix A. Table A5 summarizes the results of this exercise. We find that the within-group decline explains the predominant share (71 percent) of the decline in the inflow rate. For the outflow rate, the lack of trend remains true even after controlling for compositional changes. Overall, we find that changes in demographics explain very little of the trends observed in unemployment flows.

2.3 Offer arrival and acceptance rates and reservation wages

Flows out of unemployment are inextricably tied to job search behavior. As our goal is to understand why a rise in applications has not led to a trend increase in unemployment outflow rates, we use the EOPP and SCE data to shed further light on how application outcomes such as

[4] The CPS measure of short-term unemployed workers is underestimated since some workers enter and exit unemployment within the same month. We follow Shimer (2012) to account for this bias. In Figure A1 of Appendix A, we exploit the panel nature of the CPS and present results based on monthly transition rates.

Figure 2: Unemployment outflow and inflow 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.

offer probabilities, acceptance rates, and reservation wages have changed since the 1980s. Intuitively, an increase in applications allows workers to contact more vacancies. Higher competition among workers, however, can lower the probability of receiving an offer. Increased applications can also affect workers' acceptance decisions and reservation wages. Since these factors affect job-finding rates, we document how these variables have changed over time. In Section 5.1, we show how these findings serve as testable implications for our model.

We calculate 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 moments for 1979-1980 using the EOPP sample and for 2013-2017 using a pooled SCE sample. Figure 3 summarizes the results.

We highlight several results. Between the two time periods, unemployed workers observed a decline in the number of offers received during a month of unemployment. The fraction of individuals with no offers increased from 38 percent to 45 percent. Among those who received more than one offer during a month of unemployment, the fraction of individuals who accept an offer decreased from 84 percent to 35 percent. Finally, the distribution of real hourly reservation wages shifted rightward across these two time periods. The mean real hourly reservation wage (in 1982-1984 dollars) increased from \$5.83 to \$6.94.[5] While acceptance rates have fallen by a large margin, the coincident rise in reservation wages has not been to the same magnitude,

[5]We use seasonally adjusted Consumer Price Index for All Urban Consumers: All Items (CPIAUCSL) where the unit is set to 100 between 1982 and 1984.

Figure 3: Changes in job offers, acceptance rates, and reservation wages over time

Note: This figure shows the distributions of job offers received during a month by the unemployed; the fraction of unemployed individuals who accepts a job offer (conditional on having non-zero offers); and distributions of real hourly reservation wages over time. Reservation wages are in 1982-1984 dollars. These moments are calculated for 1979-1980 using the EOPP sample and for 2013-2017 using a pooled SCE sample. For both datasets, we use a sample of unemployed individuals aged 25-65 with at least one job application during their unemployment spell.

suggesting that the increase in the latter only partially explains the sharp decline in the former.[6]

We conclude that while the unemployed now submit more applications, they also tend to receive and accept fewer offers, and demand higher wages. Since such application outcomes have a first order impact on unemployment outflows, we argue that any model that seeks to explain the impact of the rise in applications on labor flows should also jointly account for changes in application outcomes. In what follows, we develop a framework to examine how a rise in applications can affect labor flows and application outcomes.

3 Model

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 $[\underline{x}, \overline{x}]$. Match qualities can evolve over time. In particular, with probability $\rho(x)$, workers re-draw new match quality y from a conditional distribution $\Psi(y \mid x)$, where $d\Psi(y \mid x)/dx > 0$, 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

[6] In fact, the reservation wage grew less than the mean wage as shown in Appendix A.

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 the exogenous number of applications a worker sends each period denoted by a.[7] A worker sends each application to a separate vacancy. For each vacancy contacted, they observe their 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.[8] 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.[9] As such, information is asymmetric as a worker knows their match qualities across all applications and the number of offers received, but 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 hiring strategy. Finally, each vacancy costs κ_V to post.[10]

Matching Let u denote the measure of unemployed, v the measure of vacancies, and j the number of applicants at 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. The probability the firm has j applicants collapses to:

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

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. The job-filling probability depends not only on its rate of contacting applicants, 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. Newly separated workers must wait one period before searching 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

[7] In Section 6.1, we study an alternative framework that allows for a variable number of applications.
[8] In Section 6.2, we discuss how our model would change if we instead assume a marginal cost of information.
[9] We assume that firms make offers simultaneously. Thus, no worker has an offer prior to firms making offers.
[10] In Section 6.3, we provide a sketch of how our model would vary with on-the-job-search.

decide whether to accept offers. Firms can only make an offer to one candidate and there is no recall. Once an offer has been accepted, firms that did not acquire information learn about their worker's match quality and wage bargaining commences. Wages are re-bargained every period. We assume that once a worker accepts an offer, they discard all other offers, implying that at the bargaining stage, the worker's unemployment value forms their outside option. Finally, production occurs. Having described the environment, we proceed to defining the worker's and firm's end-of-period value functions. 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:

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

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 observes a match quality shock with probability $\rho(x)$, where the new match quality y is re-drawn from conditional distribution $\Psi(y \mid x)$, and $\psi(y \mid x)$ is the associated density. Let $\widetilde{x}$ be the reservation match quality – an endogenously determined object to be formally defined below. As long as $y \geq \widetilde{x}$, 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 $V^F(x)$.

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

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

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 $x \in [\widetilde{x}, \overline{x}]$, as workers reject any job that has a match quality below reservation match quality $\widetilde{x}$. 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. As we show in Section 3.6, wages are determined via surplus splitting and surplus is increasing in quality x. Since the firm's gain to matching is a share of surplus, 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.*

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, $V^F(x)$ is increasing in match quality x. Because wages are determined by surplus-splitting, the firm's probability of having its offer rejected is also declining in x, reinforcing the firm's incentive to extend an offer to its highest-quality applicant. Thus, the expected benefit from acquiring information for a firm with j applicants is:

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

where $[\Pi(x)]^j$ is the distribution of the maximum order statistic and is equal to the probability that the highest match quality among j applicants is less than or equal to x.

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

$$\Xi(j) = \max\left\{V^I(j) - \kappa_I, V^{NI}\right\}.$$

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.*

Proof. See Appendix B. □

As the number of applicants, j, at a firm increases, the likelihood that at least one of the applicants is a high-quality 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:

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

3.4 Employed workers

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

$$\begin{aligned} V^W(x) &= w(x) + \beta(1-\delta)(1-\rho(x))V^W(x) \\ &\quad + \beta\left[\delta + (1-\delta)\rho(x)\Psi(\widetilde{x} \mid x)\right]U + \beta(1-\delta)\rho(x)\int_{\widetilde{x}}^{\overline{x}} V^W(y)\,\psi(y \mid x)\,dy, \end{aligned}$$

where $w(x)$ is the worker's 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., $y \geq \widetilde{x}$, 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. Since the employment value, $V^W(x)$, is increasing in match quality, the worker always prefers to accept their highest match quality drawn so long as that value is above $\widetilde{x}$. Consider a worker who draws match quality $x \geq \widetilde{x}$ from one of their a applications and receives an offer for this draw. The worker will accept this offer of quality x if 1) it is their highest match quality, or 2) it is not their 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 $x \geq \widetilde{x}$ for a particular application is given by:

$$\Gamma(x) = [\Pi(x)]^{a-1} + \sum_{i=1}^{a-1}(a-i)[1-\Pi(x)]^i[\Pi(x)]^{a-1-i}[1-Pr(\text{offer} \mid y > x)]^i. \tag{2}$$

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

$$Pr(\text{offer} \mid y > x) = \int_x^{\overline{x}} \sum_{\ell=1}^{\infty} \widehat{q}(\ell)\,Pr(\text{offer} \mid y, \ell)\frac{\pi(y)}{1-\Pi(x)}dy, \tag{3}$$

where

$$Pr(\text{offer} \mid y, \ell) = \mathbb{I}[\ell \geq j^*]\,[\Pi(y)]^{\ell-1} + (1-\mathbb{I}[\ell \geq j^*])\,\frac{1}{\ell}, \tag{4}$$

and $\widehat{q}(\ell) = q(\ell)/(1-q(0))$.[11] When $x < \widetilde{x}$, the worker rejects the offer since the value of unemployment is larger. When $x \geq \widetilde{x}$, the first term on the right-hand-side of Equation (2) depicts the case where the worker accepts an offer of match quality x because it is their 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 their i other applications for $i \in \{1, 2, \ldots, a-1\}$, and match qualities less than x for their remaining $(a-1-i)$ applications. This occurs with probability $(a-i)[1-\Pi(x)]^i[\Pi(x)]^{a-1-i}$. Since their i applications that drew match quality greater than x failed to yield an offer, they accept their next best outcome which is x. Denote ℓ as the number of applicants at the firm where the worker has drawn match quality y, and j as the number of applicants at the firm where the worker has drawn match quality x. Then, Equation (3) represents the probability that a worker with match quality $y > x$ receives an offer for that application, while Equation (4) 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 (4) depicts the case where the worker meets a firm that chooses to acquire information as it received $\ell \geq j^*$ applicants. Since this firm can rank its applicants, the worker receives an offer only when they are 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 no information is acquired, the firm randomly selects an applicant and the worker receives an offer with probability $1/\ell$. Summing across ℓ and conditioning on $y > x$ yields Equation (3).

The probability that a worker is hired with match quality x, $\phi(x)$, is simply the product of the expected offer probability and acceptance probabiliity for a given x:

$$\phi(x) = \Gamma(x) Pr(\text{offer} \mid x) = \Gamma(x) \sum_{j=1}^{\infty} \widehat{q}(j) Pr\left(\text{offer} \mid x, j\right). \tag{5}$$

Thus, the unemployed worker's value at the end of a period is:

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

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 $a \int_{\widetilde{x}}^{\overline{x}} \phi(x)\pi(x)dx$; otherwise, they remain unemployed.

[11] The weights are given by $\widehat{q}(\ell)$ as opposed to $q(\ell)$ since by construction, the probability that a worker visits a firm with zero applicants is zero. The expectation is thus taken only over the subset of firms who have applicants.

3.6 Surplus and wage determination

Wages are determined by Nash bargaining only after the worker has accepted an offer.[12] In accepting an offer, the worker discards all other offers prior to bargaining. Similarly, we assume that there is no recall: firms who have made an offer to a particular candidate, have rejected all their other applicants.[13] Further, firms that did not acquire information learn about their worker's match quality at this stage. 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:

$$w(x) = \arg\max_{w} \left[V^F(x)\right]^{1-\eta} \left[V^W(x) - U\right]^{\eta}, \tag{6}$$

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

$$S(x) = \frac{x + \beta(1-\delta)\rho(x)\int_{\widetilde{x}}^{\overline{x}} S(y)\psi(y \mid x)\,dy - (1-\beta)U}{1-\beta(1-\delta)(1-\rho(x))}, \tag{7}$$

with

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

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 (7) 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:

$$u\int_{\widetilde{x}}^{\overline{x}} a\phi(x)\pi(x)dx = (1-u)\left[\delta + (1-\delta)\int_{\widetilde{x}}^{\overline{x}} \rho(x)\Psi\left[\widetilde{x} \mid x\right] g(x)\,dx\right], \tag{8}$$

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 (8) represents the outflows from unemployment. The right-hand-side represents inflows into unemployment from exogenous and endogenous separations.

[12] In Section 6.4, we discuss the implications of alternative wage protocols on our main results.

[13] The assumption of no recall is standard in the literature (e.g. Albrecht, Gautier, and Vroman, 2006; Galenianos and Kircher, 2009; Gautier and Wolthoff, 2009; Gautier and Moraga-Gonzalez, 2018; and Albrecht, Cai, Gautier, and Vroman, 2020). While allowing for recall can raise the firm's probability of filling a vacancy by allowing them to contact other applicants when their chosen candidate rejects their offer, it can also lower the worker's acceptance rate, $\Gamma(x)$ as workers are less likely to accept an offer of any match quality x when other applications have drawn higher match qualities. These two competing forces suggest that a rise in applications under full recall need not lead to more vacancy creation and a rise in job-finding rates.

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

$$[\delta + (1-\delta)\rho(x)]\, g(x)(1-u) = (1-\delta)\int_{\widetilde{x}}^{\overline{x}} \rho(y)\,\psi(x \mid y)\, g(y)\, dy(1-u) + a\phi(x)\,\pi(x)\, u.$$

The left-hand-side denotes outflows from exogenous separations and from workers who observe 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 $\{\widetilde{x}, \theta, j^*\}$. The following lemma summarizes the key equations that determine $\{\widetilde{x}, \theta, j^*\}$:

Lemma 2 (Key equilibrium conditions)**.** $\{\widetilde{x}, \theta, j^*\}$ *are determined by the free entry condition given by Equation* (1) *and the following conditions:*

$$\widetilde{x} = b + \beta\eta \int_{\widetilde{x}}^{\overline{x}} a\phi(y)\, S(y)\, \pi(y)\, dy - \beta(1-\delta)\,\rho(\widetilde{x}) \int_{\widetilde{x}}^{\overline{x}} S(y)\, \psi(y \mid \widetilde{x})\, dy, \tag{9}$$

and

$$\begin{cases} V^I(j) - \kappa_I < V^{NI}, & \text{for } j < j^* \\ V^I(j) - \kappa_I \geq V^{NI}, & \text{for } j \geq j^*, \end{cases} \tag{10}$$

where $V^I(j) = (1-\eta)\int_{\widetilde{x}}^{\overline{x}} \Gamma(x)\, S(x)\, d\left[\Pi(x)\right]^j$ *and* $V^{NI} = (1-\eta)\int_{\widetilde{x}}^{\overline{x}} \Gamma(x)\, S(x)\, d\Pi(x)$.

Equation (9) is derived by evaluating $S(x)$ at the reservation match quality, $\widetilde{x}$, and represents the lowest match quality for which a match can be sustained. Equation (10) determines j^* which is the smallest number of applicants firms must have for them to acquire information.[14] Finally, the free entry condition, Equation (1), provides information on θ.[15]

3.9 Forces at play

Before turning to our main results, it is useful to understand how the different components of the unemployment inflow and outflow rates respond to changes in applications 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., $\widetilde{x}, \theta$, and j^*.

[14] In Appendix B, we show that all firms acquiring information regardless of their applicant size or no firms acquiring information cannot be an equilibrium of this model for a finite $\kappa_I > 0$.

[15] While the firm's decision to acquire information may be weakly increasing in the share of firms who acquire information, we find that under our calibration as shown in Section 4, a unique equilibrium exists.

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

$$\text{outflow rate} = \underbrace{a}_{\text{1) no. of applications}} \int_{\tilde{x}}^{\bar{x}} \underbrace{Pr(\text{offer} \mid x)}_{\text{2) probability offer for } x} \times \underbrace{\Gamma(x)}_{\text{3) probability accept } x} \pi(x)\, dx. \tag{11}$$

The unemployment outflow rate is a function of three components: 1) the number of applications a worker sends, a; 2) the probability they receive an offer; and 3) the probability they accept an offer. The first component in Equation (11) 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 (5), the offer probability, $Pr(\text{offer} \mid x)$, depends on the distribution of applicants across vacancies $q(j)$, which in turn responds to changes in a. For expositional purposes, assume a is a continuous variable. Differentiating $q(0)$ with respect to a, we get:

$$q_a(0) = -\frac{1}{\theta} \exp\left(-\frac{a}{\theta}\right).$$

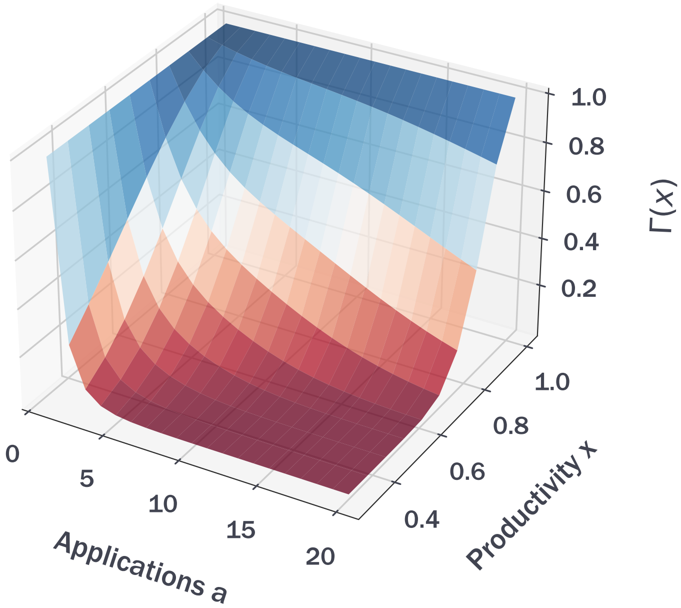
The above derivative shows that the probability that a firm is visited by zero applicants, $q(0)$, is strictly declining in the number of applications a, implying that the distribution, $q(j)$, shifts rightward away from zero applications with an increase in a. When firms have more applicants on average, 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 $x > \widetilde{x}$. From Equation (4), the probability that a worker receives an offer for this application is weakly declining in j.[16] 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 (11) is the acceptance probability $\Gamma(x)$. Notably, $\Gamma(x)$ is also a function of applications a. Numerically, we show that holding all else constant, $\Gamma(x)$ 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. This in turn reduces the probability of accepting an offer with match quality 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

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

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 $\theta, \widetilde{x}, j^*$ as we increased a.

of lower offer and acceptance probabilities.

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

$$\text{inflow rate} = \delta + (1-\delta) \int_{\widetilde{x}}^{\overline{x}} \rho(x) \Psi \left[\widetilde{x} \mid x \right] g\left(x\right) dx.$$

The first term refers to exogenous separations, while the second term refers to endogenous separations. Holding $\theta, \widetilde{x}$, and j^* constant, an increase in applications a raises the share of firms receiving $j \geq j^*$ applicants, and thus the share of informed firms. 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, $\widetilde{x}, \theta$, 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

A period in our model is a month. We calibrate the initial steady state to the period 1976-1985. We choose this interval of time as it covers the period of the EOPP survey that provides information for the period 1979-1980. Because we are interested in long-term trends, we treat the 10-year period around 1979-1980 as a steady-state. We set the discount 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 $a = 3$. We now proceed to discuss our strategy for model parameters that will be calibrated internally.

Evolution of match quality We assume that the unconditional distribution of initial match quality $\Pi(x)$ follows a beta distribution with shape parameters (A, B) and with support $x \in [0, 1]$. Because the shape and skewness of the unconditional distribution of match qualities affects the expected benefit of a creating a job and consequently, the number of vacancies created, it has an impact on the individual's probability of receiving an offer. The shape of the unconditional distribution of match qualities also affects the likelihood of drawing a high value of x. As such, to pin down parameters (A, B), we target the fraction of job-seekers with zero offers and the fraction of individuals accepting a job conditional on having received more than 1 offer. In our model, the fraction of job-seekers with zero offers is given by $\left(\int_{\underline{x}}^{\overline{x}} [1 - Pr(\text{offer} \mid x)\pi(x)dx]\right)^a$, while the fraction of job-seekers who accept given more than 1 offer is given by the joint probability of accept and more than 1 offer divided by the probability of more than 1 offer.[17] In our model, the probability an individual accepts a job given more than 1 offer is affected by the reservation match quality. Clearly, if all offers are for match qualities below $\widetilde{x}$, the worker rejects all offers. The level of $\widetilde{x}$ in turn is affected by the likelihood of drawing high match quality values.

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} is set equal to the mean of the unconditional distribution of match qualities, i.e. $x_{ref} = A/(A + B)$. This implies that workers who draw and accept job offers with match qualities below the mean of the distribution observe a match quality shock with probability 1. In contrast, the frequency of match quality shocks for workers who draw match qualities above the mean is strictly declining in x. This formulation allows us to reflect the fact that low wage jobs observe higher unemployment risk.[18] Conditional on receiving a match quality shock, we assume that individuals draw their new match qualities from the joint

[17] To calculate the joint probability of accept and more than 1 offer in our model, we first compute the joint probability of accept and exactly 1 offer: $(a-1)\int_{\widetilde{x}}^{\overline{x}}\left[1 - \int_{\underline{x}}^{\overline{x}} Pr(\text{offer} \mid y)\pi(y)dy\right] Pr(\text{offer} \mid x)\pi(x)dx$. Since the joint probability of accept and have offers is just the job-finding rate, the joint probability of accept and more than 1 offer is equal to the job-finding rate less the joint probability of accept and exactly 1 offer. We then divide this by the probability of more than 1 offer to get the conditional probability of accept given more than 1 offer.

[18] Using social security data, Karahan, Ozkan, and Song (2019) estimate that workers with low lifetime earnings observe a higher risk of job loss than the median worker.

Table 1: Internally calibrated parameters

Parameter	Description	Value	Target	Model	Data
κ_V	Vacancy posting cost	0.49	Outflow rate	0.43	0.41
κ_I	Cost of information	0.71	Recruiting cost/mean wage	0.97	0.93
δ	Exog. separation rate	0.025	Inflow rate	0.043	0.041
λ	Persistence of x	6.99	EU_{20}/EU_{80}	4.41	4.05
A	Beta distribution	1.66	Fraction with no offers	0.34	0.38
B	Beta distribution	1.17	Fraction accept given >1 offer	0.82	0.84
b	Home production	0.22	Reservation wage/mean wage	0.86	0.66

Note: This table provides a list of model parameters that are calibrated using our model. Moments relating to unemployment flows are obtained from the CPS as averages between 1976 and 1985. The fractions of workers with no offers and the fraction who accept given more than one offer are obtained from the EOPP 1979-1980. Finally, reservation wage to mean wage ratio is obtained from using reservation wage data for the unemployed in the EOPP and mean wage data for the employed in the CPS.

distribution $\Psi(x, x')$ which is constructed using a Gumbel copula:

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

This implies a conditional distribution of match quality re-draws of the form $\Psi(x' \mid x)$, where the parameter $\lambda \in [1, \infty)$ controls the degree of dependence between draws. When $\lambda = 1$, x and x' are independent, and when $\lambda \to \infty$ there is perfect positive dependence between x and x'. The functional forms of $\rho(x)$ and $\Psi(x' \mid x)$ for $\lambda > 1$ imply that matches with high x are less likely to observe an endogenous separation. Thus, we use λ to match the ratio of unemployment inflow rates of the bottom 20th percentile (EU_{20}) in real hourly wage earnings to the inflow rates of the top 20th percentile (EU_{80}) in the data. Using data from the CPS between 1976-1985, we find this ratio to be 4.05, suggesting that individuals at the bottom quintile of the wage distribution are around 4 times more likely to separate from their job than individuals at the top quintile.

Labor market While the unemployment inflow rate is a function of both endogenous and exogenous separations, we target the average unemployment inflow rate over the period 1976-1985 to pin down the exogenous separation probability δ. We choose the vacancy posting cost, κ_V, to match an average outflow rate of 0.41.[19] Since the fixed cost of information, κ_I, affects recruiting costs, we follow Gavazza, Mongey, and Violante (2018) and set κ_I to match a ratio of recruiting costs to average wages of 0.928. In our model, the expected recruiting cost takes the form of $\kappa_V + \sum_{j \geq j^*}^{\infty} q(j)\kappa_I$. This is the recruiting cost a firm can expect to pay when choosing whether to create a vacancy. Finally, the level of home production, b, is set to match the ratio of the unemployed workers' reservation wage to the mean wage. In the data, we calculate the average hourly reservation wage of the unemployed in the EOPP and the average hourly wage

[19]In the CPS, we calculate HP-filtered time series of average outflow and inflow rates. We target the average of the trend component between 1976 and 1985.

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

	$a = 3$	$a = 6$	Log difference
Information threshold j^*	5	7	-
Percent firms informed	44.1	95.3	79
Labor market tightness θ	0.69	0.50	-32
Reservation match quality $\widetilde{x}$	0.67	0.74	10

Note: This table summarizes the changes in equilibrium variables when the number of worker applications, a, increases from 3 to 6. The log difference is multiplied by 100.

of the employed in the CPS and find a ratio of 0.66. Table 1 shows that our calibrated model fits the data moments fairly well.

5 Quantitative Results

5.1 Equilibrium response to an increase in applications

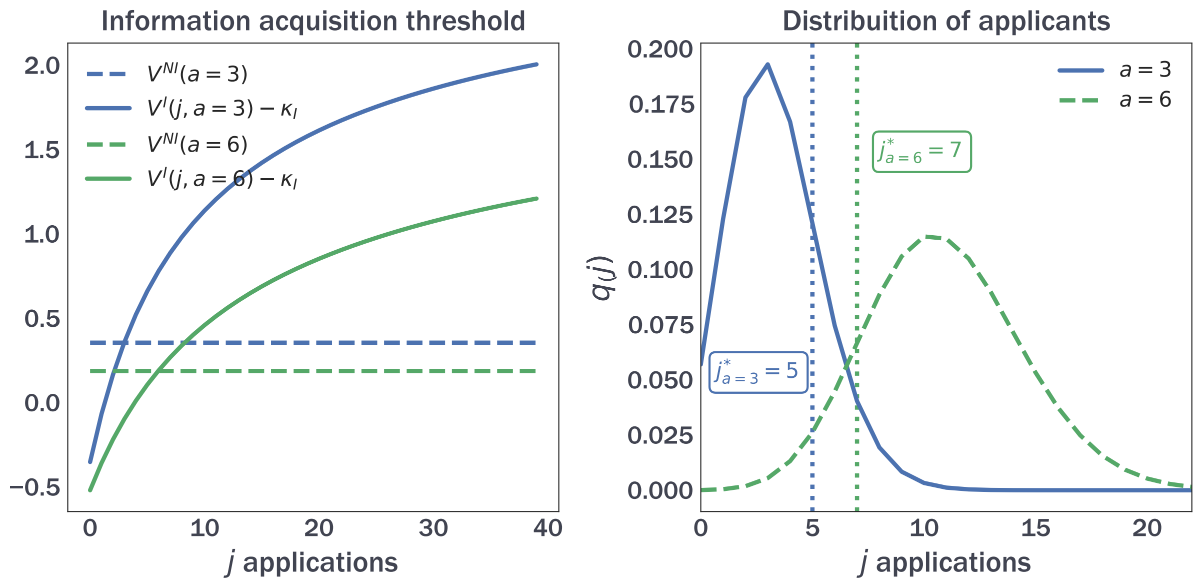
Using our calibrated model, we now analyze how an increase in the number of applications, a, affects unemployment flows and application outcomes. In the data, the median number of applications roughly doubled from 3 to 6 between the 1979-1980 period and the 2013-2017 period. Thus, for our main quantitative exercise, we ask how doubling 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 first document the changes in the equilibrium objects $\{\widetilde{x}, \theta, j^*\}$. Table 2 highlights our results. First, an increase in applications, a, raises the share of firms acquiring information. This is despite an increase in the information threshold, j^*. The latter occurs because the expected value of acquiring information, $V^I(j)$, falls by more when acceptance probabilities decline with a rise in a. The left panel of Figure 5 shows how $V^I(j)$ and V^{NI} vary with a. Intuitively, for a given number of applicants j, information is less valuable if workers are more likely to reject an offer. Nonetheless, the right panel of Figure 5 shows that the increase in a causes the distribution of applicants per vacancy, $q(j)$, to shift right, resulting in a larger share of firms with $j > j^*$ applicants. Consequently, more firms acquire information when a is higher, with the share of informed firms increasing from 44.1 percent to 95.3 percent.

Second, an increase in a causes labor market tightness, θ, to fall. Because more firms are acquiring information on average, this raises the expected cost of recruiting. At the same time, a larger mass of informed firms lowers workers' acceptance rates as workers who draw high match qualities are now more likely to be identified by the firm and receive offers. Consequently, workers are less likely to accept an offer of any match quality x if they receive an offer with match quality $y > x$. Both a higher recruiting cost and a lower acceptance rate contribute towards lowering vacancy creation. Thus, θ declines despite firms contacting applicants at a higher rate.

Finally, reservation match quality, $\widetilde{x}$, rises by a moderate amount when applications double.

Figure 5: Firms raise information acquisition threshold but receive more applications as a rises



Note: The left panel shows how the information acquisition threshold j^* is determined from the value of acquiring information $V^I(j)$ and the value of not acquiring information V^{NI} under $a = 3$ and $a = 6$. The right panel shows how the probability that a firm receives j applications; i.e., $q(j)$ changes with a doubling in the number of applications a. The dashed vertical line represents the equilibrium j^* cutoff below which firms do not acquire information.

The rise in $\widetilde{x}$ is modest as there exists counteracting forces that mitigate the extent to which a rise in applications improves the worker's outside option. On the one hand, the ability to send more applications and contact more vacancies raises the probability that at least one application draws a high match quality and yields an offer. This higher probability of finding a good match raises the worker's outside option and their selectivity over the minimum acceptable job quality. On the other hand, a greater number of applications and the decline in vacancy creation implies that the average number of applicants at a vacancy is larger. This increased congestion depresses the worker's ability to find a job and thus their outside option. Consequently, the rise in $\widetilde{x}$ is modest.

5.2 The response of inflow and outflow rates

We now examine how inflow and outflow rates are affected by a rise in applications a. Importantly, we compare our model predictions on unemployment flows and job search outcomes against available data for the periods 1976-1985 and 2010-2019. These two time intervals cover the EOPP (1979-1980) and the SCE (2013-2017). For 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 the U.S. economy underwent a slow recovery after the Great Recession. As a result, the reported outflow rates between 2010 and 2019 in the data are below the long-run average observed in Figure 2. By 2019, however, outflow rates had recovered to their long-run average of around 0.41. We detail the results of our exercise in Table 3.

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

	Impact on unemployment flows					
	$a = 3$		$a = 6$		Log difference	
	Model	Data	Model	Data	Model	Data
Inflow rate	0.043	0.041	0.035	0.023	-20	-58
Outflow rate	0.426	0.408	0.404	0.318	-5	-25
direct a effect	3		6		69	
indirect a effect	0.142		0.067		-74	

Note: This table summarizes the model-predicted inflow and outflow rates when the number of worker applications a increases from 3 to 6 and compares them to 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.

5.2.1 Inflow rates

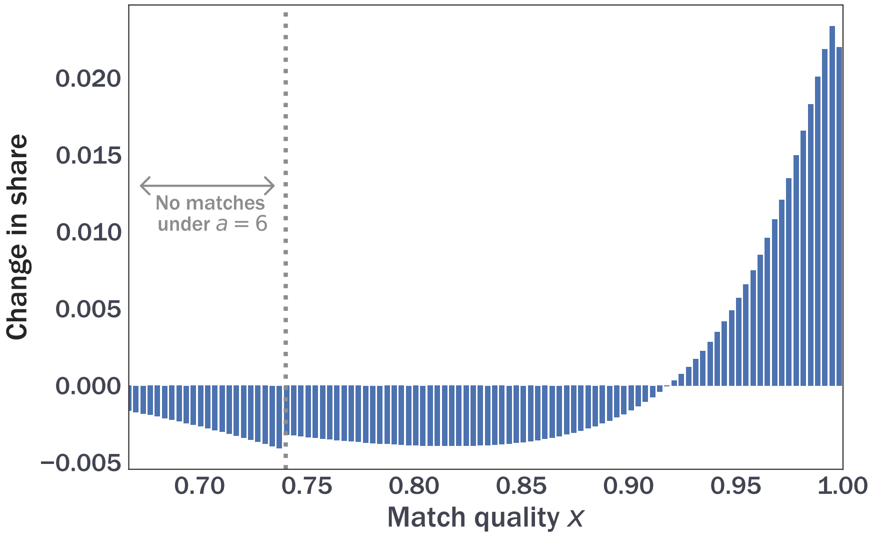
Table 3 highlights that a rise in applications alone causes inflow rates to decline by 20 percent, accounting for one-third of the decline in the data. This is despite an increase in reservation match quality. To explain how the effect of improved firm selection – i.e., a greater formation of high quality matches – causes a decline in separations, we show how the distribution of employed workers across match quality changes with a rise in a, and how the change in this distribution affects the frequency of shocks and the likelihood that a match is severed given a shock.

Figure 6 highlights how the distribution of employed over match quality changes with the rise in applications a. Because more firms acquire information when a increases, a larger share of firms are able to identify and hire high productivity applicants, giving rise to a greater formation of high quality matches and a decline in the share of low-to-middling quality jobs. In our model, the frequency of match quality shocks, $\rho(x)$, is decreasing in x. The larger share of high quality matches thus leads to a 4.5 percent fall in the frequency of match quality shocks, implying greater job stability as jobs remain at their current productivity levels for longer. In addition, workers are also less likely to separate from their job in the event of a match quality shock when the distribution of employed is concentrated amongst high quality matches. Conditional on a shock, the share of employed who draw a new match quality $x' < \widetilde{x}$ and separate into unemployment falls by 51 percent when a doubles.[20] The combined effects of a lower frequency of match quality shocks and a large decline in the likelihood of drawing new qualities below the reservation match level outweigh the effect of a higher reservation match quality $\widetilde{x}$ on separation rates. Consequently, the inflow rate in our model declines substantially as the effects from improved firm selection dominate the effects from increased worker selectivity.

Our model also produces testable implications for the changes in the tenure distribution, especially for the share of short duration jobs. As the realized distribution of match quality

[20]Conditional on a shock, the share of employed who draw match quality $x' < \widetilde{x}$ is $\int_{\widetilde{x}}^{\overline{x}} \Psi(\widetilde{x} \mid x) g(x) dx$.

Figure 6: Realized match quality distribution improves as applications increase



Note: The figure shows how the share of employed workers across match quality x changes when a increases from 3 to 6. Specifically, for each bin, the figure shows the difference in the pmf $[G(x_2)_{a=3} - G(x_1)_{a=3}] - [G(x_2)_{a=6} - G(x_1)_{a=6}]$.

shifts rightward and towards high quality matches, the share of low quality jobs with high turnover declines. Thus, the share of short duration jobs declines significantly in our model while the share of jobs with long duration falls by less. Table 4 shows that the share of workers employed in jobs lasting less than a quarter falls by 70 percent when a increases, while the share employed in jobs lasting more than a year and less than three years falls by a smaller 36 percent.

Our results concur with empirical findings on how the tenure distribution has changed over time. Empirically, short tenure employment relationships have observed the sharpest decline. Molloy, Smith, and Wozniak (2020) use data from the CPS and show that the median tenure has remained relatively unchanged over the last four decades, while the share of employed in jobs lasting more than a year and less than three years has declined 12 percent. Using data from the Quarterly Workforce Indicators (QWI), Pries and Rogerson (2019) find that the share of employed in jobs lasting less than a quarter has fallen by 49 percent between 1999 and 2015. Importantly, these empirical findings are inconsistent with the predictions of an alternative model that posits a decline in exogenous separation rates over time. In such a model, the decline in exogenous separation rates would imply a uniform decline in the separation rates of all jobs, an increase in all tenure lengths, and a rise in median tenure. In contrast, our model would not only suggest a sharp decline in jobs of very short tenure length, but also that jobs of high match quality now observe slightly larger separation rates stemming from the increase in reservation match quality. To see this, note that the probability a match endogenously dissolves for a given x is given by $\rho(x)\Psi(\widetilde{x} \mid x)$. Since $\widetilde{x}$ is higher under $a = 6$, this raises $\Psi(\widetilde{x} \mid x)$, implying that a match of given x quality is now more prone to separation.[21] As such, our model predicts median tenure rising by a negligible 0.07 percent, a finding consistent with the data.

Taking stock In sum, the rise in applications in our model accounts for one-third of the empirical decline in inflow rates. The decline in our model-predicted inflow rate stems from a sharp drop in the formation of low-quality jobs. Median tenure, however, remains relatively unchanged in our model. Overall, our model's predictions align with the empirical changes in the tenure distribution over time.

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 5 percent. While the outflow rate in the data is lower in the period 2010-2019, this is largely due to the fact that the economy experienced a slow labor market recovery following the Great Recession. By 2019, the outflow rate had returned back to its long-run average of about 0.41. As such, we view the modest decline in our model-predicted outflow rate to be largely consistent with the lack of long-run change in the empirical outflow rate.

Why does our model predict relatively small changes in the outflow rate despite a doubling in the number of applications? Recall from Section 3.9 that the extent to which the outflow rate varies with applications depends on whether the direct effect of submitting more 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:

$$\begin{aligned}\ln\left(\text{outflow}_{t_2}\right)-\ln\left(\text{outflow}_{t_1}\right) &= \overbrace{\ln\left(a_{t_2}\right)-\ln\left(a_{t_1}\right)}^{\text{direct effect}} \\ &\quad + \underbrace{\ln\left(\int_{\widetilde{x}_{t_2}}^{\overline{x}}\phi_{t_2}\left(x\right)\pi\left(x\right)dx\right)-\ln\left(\int_{\widetilde{x}_{t_1}}^{\overline{x}}\phi_{t_1}\left(x\right)\pi\left(x\right)dx\right)}_{\text{indirect effect}}.\end{aligned}$$

Table 3 shows that the indirect effects stemming from endogenous changes in individuals' job search decisions and firms' hiring decisions mitigate the direct effect from a sheer increase in the number of applications. In fact, the indirect effects of lower offer and acceptance probabilities dominate the direct effect of a higher a, causing the outflow rate to be slightly lower.

Crucially, the model's ability to reproduce the lack of long-run trend in the outflow rate in the data originates from its predicted declines in offer and acceptance rates. Table 4 compares the changes in offer and acceptance probabilities in the model relative to those observed in the data. In our model, the fraction of applicants with offers declines by 41 percent. The

[21] Trivially, $d\Psi(\widetilde{x} \mid x)/d\widetilde{x} = \psi(\widetilde{x} \mid x) > 0$. Thus, a larger $\widetilde{x}$ leads to a greater probability of drawing match qualities below this new higher threshold.

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

Panel A: Tenure distribution

	$a = 3$		$a = 6$		Log difference	
	Model	Data	Model	Data	Model	Data
Share employed $t < 1$ quarter	0.014	0.080	0.007	0.049	-70	-49
Share employed $1 \leq t < 3$ years	0.16	0.18	0.11	0.16	-36	-12
Median tenure (years)	3.28	4	3.28	4	0	0

Panel B: Outflow rate components

	$a = 3$		$a = 6$		Log difference	
	Model	Data	Model	Data	Model	Data
Mean applicants per vacancy a/θ	4.35	24.0	11.9	59.0	103	90
Fraction > 0 offer	0.66	0.62	0.44	0.55	-41	-12
Acceptance rate	0.35	0.80	0.22	0.43	-45	-62
Reservation wage	0.71	5.83	0.78	6.92	8	17

Note: This table summarizes the changes in the employment tenure distribution and outflow rate components (the average fraction > 0 offer, the average acceptance rate, and the average reservation wage) when the number of worker applications a increases from 3 to 6. Data moment on the share of jobs that last $t < 1$ quarter is taken from Pries and Rogerson (2019) who use data from the QWI. Data moments on the share employed in jobs lasting $1 \leq t < 3$ years and median tenure are taken from Molloy, Smith, and Wozniak (2020) who use CPS data. Data moments on the mean number of applicants per vacancy is taken from Faberman and Menzio (2018) for 1980 and Marinescu and Wolthoff (2020) for 2011. Data moments on outflow rate components 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 in the data are average hourly reservation wages in 1982-1984 dollars. The log difference is multiplied by 100.

fraction with offers also declines in the data, albeit by less. The larger decline in our model stems from the fact that both the fall in vacancy creation and a higher number of applications contributes to increased congestion amongst workers. Notably, labor market tightness, θ, is only one component that affects the amount of competition amongst job-seekers when workers can submit multiple applications. A more relevant measure in this setting is the average number of applicants per vacancy, a/θ. In our model, a/θ rises by 103 percent. Using data from the EOPP, Faberman and Menzio (2018) report an average of 24 applicants per vacancy in 1980 while Marinescu and Wolthoff (2020) find an average of 59 applicants per vacancy in 2011 using data from CareerBuilder. Overall, our model's increase in the average number of applicants per vacancy is close to the 90 percent rise observed in the data.[22]

The decline in the fraction receiving offers is one of the outcomes serving to counteract the positive direct effect of a higher a on outflow rates. The other key variable that affects the outflow rate is the acceptance rate. We calculate the model's average acceptance rate as the expected probability of accepting an offer for a particular application, $\int_{\tilde{x}}^{\overline{x}} \Gamma(x) \pi(x) \, dx$. In our model, a

[22] While the EOPP also has a firm module that contains information on the number of applications received by a firm, the SCE data lacks information on the firm side.

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 $\widetilde{x}$. In addition, workers experience an increased probability that at least one of their applications draws a higher match quality. This increased probability of drawing a higher match quality from another application leads the worker to more frequently reject a job offer of given quality x. As such, acceptance rates in our model decline by 45 percent, while they fall by 62 percent in the data. Although we do not target these changes, our model's predicted changes in offer probabilities and acceptance rates largely mimic the patterns observed in the data over time.

We emphasize that the decline in acceptance rates in our model does not solely stem from the increase in reservation wages. Across the two time periods, the reservation wages rises by 8 percent in the model, implying that the rise in selectivity only contributes to part of the decline in acceptance rates.[23] These predictions of the model align with the observed empirical patterns. In the data, the magnitude of the decline in acceptance rates is much larger than the magnitude of the rise in real hourly reservation wages. To understand how much acceptance rates would instead decline by if reservation match qualities remained constant, we conduct the following comparative static exercise. Holding fixed $\widetilde{x}$ at its level when $a = 3$ and keeping all other equilibrium objects at their $a = 6$ levels, acceptance rates still fall by 30 percent. Thus, acceptance rates decline in our model with higher applications not only because workers are more selective over the minimum quality job they are willing to accept, but also because workers are more likely to have drawn a high match quality offer in at least one of their other applications, reducing their need to accept the first offer they receive.

Taking stock Our model explains why a rise in applications need not lead to a trend increase in the outflow rate. Consistent with the data, the declines in the offer and acceptance probabilities mitigate the direct benefits of increased applications, causing little change in the outflow rate.

5.3 The role of costly information

The key insight delivered by the baseline model is that an increase in the number of applications does not necessarily translate into higher job-finding rates but does instead lead to the formation of better matches that are longer-lived. We now consider two thought experiments to uncover why the interaction of information acquisition with an increase in applications is crucial for this result. In the first experiment, we set $\kappa_I = 0$, and label this the "Full Information" (FI) model.[24] In the second experiment, we consider the other extreme and set $\kappa_I \to \infty$. We label this the "No Information" (NI) model. We re-calibrate the FI and NI models to match the same

[23] Because we assume that x is drawn from a beta distribution with support $[0, 1]$, our model-implied reservation wages are bounded between $[0, 1]$.

[24] While we use the term "Full information", 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.

Table 5: The role of firms' investment on information upon an increase in applications

	FI		NI		Log difference			
	$a = 3$	$a = 6$	$a = 3$	$a = 6$	Data	Model	FI	NI
Labor market tightness θ	0.69	0.76	0.70	0.77		-32	10	9
Reservation match quality $\widetilde{x}$	0.54	0.61	0.55	0.53		10	13	-5
Inflow rate	0.046	0.043	0.042	0.038	-58	-20	-6	-10
Outflow rate	0.44	0.50	0.45	0.34	-25	-5	12	-28
direct a effect	3	6	3	6		69	69	69
indirect a effect	0.15	0.08	0.15	0.06		-74	-57	-97

Note: This table summarizes the equilibrium variables and labor market flows 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 $\kappa_I \to \infty$. Data moments on labor market flows are obtained as averages from the CPS, where the 1976-1985 time period corresponds to the period with lower average number of applications $a = 3$ and the 2010-2019 time period corresponds to the period with higher average number of applications $a = 6$. The log difference is multiplied by 100.

targets as our baseline model.[25] In both of these models, the firm's investment in information acquisition does not vary with the number of applications. Hence, comparing the results from the FI and NI models against our baseline model allows us to isolate how variations in the firm's information decision in response to more applications would affect predictions of our model.

Equilibrium outcomes Table 5 details the results from our counterfactual exercises. Unlike our baseline model, both the FI and NI models observe an increase in labor market tightness, θ, with a 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 do not vary with the number of applications in the FI and NI economies, as firms either attain information for free or never acquire it. Since a higher number of applications lowers the probability of firms receiving zero applicants, this raises the expected benefit of creating a job. The rise in the expected benefit of a vacancy coupled with a constant cost of job creation causes vacancy creation and consequently, θ to rise with the increase in a in the FI and NI models.

Focusing on reservation match quality $\widetilde{x}$, the FI model predicts a rise in $\widetilde{x}$, while the NI model predicts a decline in $\widetilde{x}$ as applications increase. These differences stem from how workers' outside options change in the number of applications a 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 $\widetilde{x}$. Conversely, in the NI model, firms always randomly select candidates from their applicant pool. Thus, the increased probability of drawing a high match quality does not translate into more offers. Although labor market tightness improves in the NI model, the percentage increase in a outweighs

[25]Details of our calibration strategy and model fit can be found in Appendix C.1.

the percentage increase in θ. Consequently, the rise in a increases congestion amongst workers, leading to a worsening of workers' outside options and a fall in $\widetilde{x}$.

Understanding flows These equilibrium outcomes have implications for labor market flows. In contrast to our baseline model, both the FI and NI models predict non-trivial changes in the outflow rate and smaller declines in the inflow rate relative to the baseline model.

Focusing first on the FI model, the inflow rate falls by 6 percent while the outflow rate rises by 12 percent, opposite to the large decline in the inflow rate and lack of change in the outflow rate observed in the data. While the FI model also exhibits a greater formation of high quality matches as in the baseline model, the effects from increased worker selectivity far outweigh the effects from improved firm selection. Notably, the greater formation of high quality matches results in the incidence of match quality shocks falling by 4 percent, but conditional on a shock, the share of employed who draw a new match quality $x' < \widetilde{x}$ falls only by 6 percent, a magnitude much smaller than the 51 percent decline observed in our baseline model. The smaller decline is due to the worker's enlarged outside option. Since $\widetilde{x}$ is larger, employed individuals now observe a larger probability, $\Psi(\widetilde{x}|x)$, of drawing new match qualities below this higher threshold and exiting into unemployment. Notably, average match quality improves by about 5 percent when a doubles, but the rise in $\widetilde{x}$ is much larger. Consequently, the inflow rate declines by a mere 6 percent. In part, this is due to the fact that in the FI model, firms are always able to make offers to the best applicant in their pool. As such, the effects from improved firm selection upon a rise in applications are small in this environment when there is no change in the share of informed firms. In contrast, the worker selectivity effect is stronger relative to our baseline model, because congestion effects arising from increased applications are partially mitigated by the contemporaneous rise in vacancy creation in the FI model.

Focusing on outflows, it is useful to note that in the FI model, the probability of receiving an offer for a given match quality x from a firm with j applicants is given by $Pr(\text{offer} \mid x, j) = [\Pi(x)]^{j-1}$. Since $dPr(\text{offer} \mid x, j)/dx \geq 0$, this probability is increasing in x. Because an increase in applications implies that workers face a higher likelihood of drawing a high match quality in at least one of their applications, their probability of receiving an offer from at least one of their applications is higher. While the probability that a worker accepts a job of any match quality x, $\Gamma(x)$, is lower when a rises, it should be noted that $\Gamma(x)$ is increasing in x. Thus, the milder increase in congestion due to the rise in θ, and the higher likelihood of drawing a high x in at least one of their applications and receiving offers for that match quality drawn causes the outflow rate to increase in the FI model.

Switching now to the NI model, the outflow rate observes a larger decline of 28 percent than the inflow rate which declines by 10 percent. In this case, the decline in the inflow rate is largely driven by the worsening in workers' outside options and the fall in $\widetilde{x}$. Because workers become less selective and are willing to accept a lower minimum quality job when applications rise, their probability to separate into unemployment conditional on a match quality shock goes down. The frequency of match quality shocks in the NI model changes by less than one percent when a increases from 3 to 6. However, conditional on a shock, the lower $\widetilde{x}$ implies that the share of employed who draw new match qualities $x' < \widetilde{x}$ falls by 28 percent. Unlike our baseline model, declining worker selectivity here is the main driver behind the fall in the inflow rate as average match quality in the NI model barely improves when firms cannot identify high quality matches.

Finally, to understand why the outflow rate declines by a large amount in the NI model, it is useful to note that the worker's probability of receiving an offer for match quality x from a firm with j applicants is given by $Pr(\text{offer} \mid x, j) = 1/j$. Precisely because firms are uninformed about their applicants' qualities, the probability of an offer does not depend on x and only on the number of applicants at a firm, j. Since the increase in applications outweighs the increase in labor market tightness in the NI model, the distribution of applicants, $q(j)$, still shifts rightward, with the average number of applicants per vacancy, a/θ, rising by about 60 percent. As a result, workers face more competition at each vacancy and observe a lower probability of receiving an offer for a single application. Consequently, the unemployment outflow rate declines.

Overall, our results highlight that the interaction between a firm's information acquisition decision and the number of applications that unemployed workers submit is important for capturing the joint behavior in the inflow and outflow rate over time.

6 Discussion

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

6.1 Variable and endogenous number of applications

In the baseline model, we assume that the number of applications is exogenously determined. An alternative is to allow for a variable number of applications. Following Kaas (2010), a worker who exerts search effort ξ samples n vacancies from a Poisson distribution with parameter ξ. Search intensity ξ can be endogenized by introducing a search cost $c(\xi)$. In this set-up, 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 either exogenously raise ξ in a model with variable applications or to exogenously reduce the cost $c(\xi)$ in a model with endogenous application choice such that the mean number of applications rises from 3 to 6. Appendix C.2 provides a comprehensive discussion of these extensions and details our quantitative findings. Our results remain relatively unchanged when we extend the model to allow for variable applications. Table A7 shows that raising ξ from 3 to 6 still results in an 18 percent decline in the inflow rate and a 3 percent reduction in the outflow rate.

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. We first note that our assumption of a fixed cost of information in our baseline model is motivated by recent evidence by Davis and Samaniego de la Parra (2020) who find that 67 percent of vacancy postings originate from recruitment firms and staffing firms. Recruitment agencies in turn are paid placement fees which are typically some percentage of the worker's salary.[26] Given the prevalent use of recruiting and staffing agencies as well as their fee structures, we argue that the assumption of a fixed cost of information is a natural one. Nonetheless, in this section, we explore the consequences of assuming a marginal cost of information.

Incorporating a marginal cost structure would reduce but not eliminate 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 $\widehat{j}$ as the level such that for any $j > \widehat{j}$, 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 $j > \widehat{j}$. 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 $j^* \leq j \leq \widehat{j}$, the firm acquires information on all of its applicants, and for any $j > \widehat{j} \geq j^*$, the firm acquires information on a subset $\widehat{j}$ of its applicants. Appendix C.3 provides greater detail on such a setup.

Holding all else constant, an increase in applications still raises the average number of applicants per vacancy in this environment. So long as the mean applicants per vacancy is not far above $\widehat{j}$ in the initial steady state, the increase in applications still raises the share of informed firms in the economy and improves the distribution of realized match quality, contributing towards a lower inflow rate. As shown in Table A8, we find that the model is still capable of generating the differential trends observed for the inflow and outflow rate. The inflow rate falls by 8 percent in this environment while the outflow rate remains unchanged. In part, the more modest decline in the inflow rate in this model (8 percent) compared to our baseline model (20 percent) can be explained by the fact that, in this model, there is now an upper bound on the benefits of information. When $a = 6$, the average number of applicants exceeds $\widehat{j}$. Although more firms acquire information when $a = 6$ relative to $a = 3$, they only do so on a sub-set of their applicants. Hence, the improvement in the distribution of match qualities and the decline in the inflow rate are smaller in this model. Even then, the same mechanisms as in the baseline model remain: increased information acquisition by firms and the formation of better matches play a crucial role in reducing the inflow rate while the indirect effects through congestion and worker selectivity result in negligible changes to the outflow rate.

[26] See https://www.monster.co.uk/advertise-a-job/hr-resources/hr-strategies/recruitment-costs/what-are-the-general-costs-of-using-recruitment-agencies/ for example on the cost structures of recruitment agencies.

6.3 On-the-job search

Thus far, we have focused on the effects an increased number of applications sent by unemployed workers on unemployment flows. We restrict our attention to unemployed workers' applications because the EOPP data lacks information on the number of applications sent by employed job-seekers. Nonetheless, our model can be extended to include on-the-job search. In Appendix C.4, we provide details for the model with on-the-job search. Intuitively, adding on-the-job search provides firms an additional reason to acquire information, as workers hired into high quality matches have a lower probability of quitting when there is less of a ladder to climb. In other words, retention probabilities are increasing in match quality. Holding all else constant, an increase in applications raises the ability of employed workers to search the labor market for better opportunities. This in turn strengthens the firm's incentive to acquire information so as to find high quality matches that are longer-lived. As a result, the unemployment inflow rate would still decrease. Furthermore, an increase in the share of informed firms and a greater concentration of high quality matches reduces the share of employed individuals transitioning between jobs. Thus, holding all else constant, our model would suggest a decline in job-to-job flows as applications increase.

6.4 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 they can attain the entire surplus of their 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 because 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 that features multiple applications and costly information to show how an increase in applications need not precipitate any significant long-run change in the unemployment outflow rate but instead lead to the formation of longer-lived matches and a decline in the unemployment inflow rate. The extent to which the outflow rate changes in response to a rise in applications depends on how much the direct effect from an increased ability to contact more vacancies is mitigated by congestion and the endogenous declines in offer and acceptance probabilities. Meanwhile, the counteracting forces of improved firm selection and increased worker selectivity are key to understanding how much the inflow rate declines in response to a rise in worker applications.

Quantitatively, according to our model, the rise in the number of applications accounts for about one-third of the empirical decline in the inflow rate, while the outflow rate remains relatively unchanged. Our model also contains several testable implications. Overall, we find that changes in our model-predicted job offer and acceptance rates, reservation wages, and tenure distribution in response to a rise in applications largely mimic patterns in their data counterparts.

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 invariant to the rise in applications, either because information is free or infinitely costly, these alternative models fail to jointly generate the declining trend in the inflow rate and lack of a long-run trend in the outflow rate.

Our model can be extended in several dimensions. First, the number of applications that the unemployed 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 elaborate on details about the EOPP, SCE, and CPS, explain our calculations from these datasets, and provide additional results that complement the main text.

A.1 EOPP

The goal of the EOPP was to help participants 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 shown in Section A.3 below.

The survey incorporates both household-level and individual-level variables, which can be linked by household and individual identifiers. We use the individual-level dataset which contains the following modules: main record, training, job, unemployment insurance (UI), looking for work, disability, and activity spell. These modules provide data on demographics, earnings and hours 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.[27] For each of these individual-spell observations, we first calculate unemployment duration in months.[28] Using data on the number of job applications for each mode 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 sent during each spell by its duration to obtain the average monthly number of applications for that spell. Similarly, using information on the number of offers received through each mode of job search, we calculate the total number of offers received and the monthly number of offers received for each spell. The data also provides an indicator variable on whether the individual accepted any of the offers received. Using this variable, we also calculate the fraction of individuals who receive a certain number of job offers and accept an offer. Finally, the survey also contains information on the lowest hourly wage rate that the individual would accept during the unemployment spell.

[27]There 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.

[28]To 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.

We use this information to measure the reservation wage of the individual.[29]

A.2 SCE

The SCE Labor Market Survey was developed by the Federal Reserve Bank of New York.[30] The dataset provides information about respondents' 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). To maintain consistency with our EOPP analysis, we restrict the SCE sample to unemployed individuals aged 25-65 who are not self-employed and who submitted at least one application during each unemployment spell. This includes individuals who are unemployed at the time of the survey and individuals who, at the time of the survey, were employed for less than four months in their job and reported experiencing an unemployment spell prior employment. For both of these groups, we analyze their job search activities during each reported 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 unemployment spell duration information to convert the latter to the average number of job offers received per month of unemployment. 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 number of job applications and job offers received per month of unemployment. Since these individuals found employment after an unemployment spell, we infer that they accepted a job offer. Then, using information about the offers and acceptance decisions in our sample, we calculate the fraction of individuals who accept job offers. The SCE also asks the lowest wage the individual would accept, which we use to measure the reservation wage.[31]

[29] APLYJOBS and OFERJOBS respectively provide the number of job applications and job offers received through various job search methods. The indicator variable on offer acceptance is given by variable ACPTJOBS. The variable WAGEACPT provides reservation wage information.

[30] Source: Survey of Consumer Expectations, 2013-2019 Federal Reserve Bank of New York (FRBNY). The SCE data is 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.

[31] For 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

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.3 Comparison of EOPP, SCE, and CPS samples

In this section, we compare the EOPP and SCE samples to the CPS samples over time. This comparison lends credence to the validity of linking empirical findings on the long-run changes in unemployment flows observed in the CPS to changes in job search outcomes observed between the EOPP and SCE. Our results reveal that the EOPP and the SCE samples capture well the changes in educational attainment, marital status, female labor force participation, age composition, as well as earnings and hours over time.[32]

Table A1 compares demographics from samples across these three datasets. We highlight several results. First, the EOPP sample captures the education and age composition of the CPS 1980 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.[33] Importantly, the SCE and CPS 2015 have almost the same fraction of individuals with a college degree. This implies that the EOPP and the SCE samples capture the increase in educational attainment well. Third, the EOPP and SCE samples slightly overestimate the increase in older workers (age groups 45-54 and 55-64) in the working age population and underestimates the decline in the fraction of married individuals when compared to CPS.

Next, Table A2 compares labor market moments across the three datasets. Similar to the

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.

[32] When comparing the EOPP and SCE samples with CPS samples, we focus on individuals (employed or non-employed) aged 25-65 who are not self-employed.

[33] We also compared SCE and CPS samples for each year between 2013 and 2017. The results are very similar to the comparison made for 2015.

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

	EOPP 1980	CPS 1980	SCE 2015	CPS 2015
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

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.

CPS 1980 and the CPS 2015 samples, the EOPP and the SCE samples show a rise in the share of females participating in the labor force over time, although the magnitude of the increase is larger between the EOPP and the SCE samples than between the CPS samples. The remaining moments in relation to employment, weekly hours, and annual earnings are mostly comparable between the EOPP-SCE and the CPS samples, with the exception that the share of employed females is overstated in the EOPP sample relative to that observed in the CPS 1980 sample.

A.4 Job applications: Eliminating business cycle effects

In Section 2.1, 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 cyclical factors behind the differential outcomes observed between the 1979-1980 period and the 2013-2017 period. 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 is between 2013 and 2017 and 0 otherwise, the Unemp. rate and Real GDP are the cyclical

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	5.07	8.95	4.36	8.90	4.76	7.88	5.29
	(2.02)	(1.54)	(3.35)	(1.95)	(3.14)	(1.83)	(2.21)	(1.72)
Unemp. rate			-12.30	5.26			-26.71	23.30
			(14.93)	(10.17)			(39.91)	(29.21)
Real GDP					71.44	-12.70	-133.73	158.41
					(79.90)	(55.11)	(241.41)	(181.57)
Constant	6.82	7.65	5.28	8.27	5.65	7.85	5.65	7.90
	(0.59)	(1.19)	(1.91)	(1.96)	(1.33)	(1.67)	(1.33)	(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.

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.

A.5 Job applications: Demographic groups

In Section 2.1, we document moments regarding the change in the economy-wide average number of job applications sent during each month of unemployment between the EOPP (1979-1980) and the SCE (2013-2017). Here, we explore changes in the number of job applications across various demographic groups using the two datasets. Table A4 summarizes the results. It shows that the number of applications increased significantly across all demographics groups.

A.6 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).[34] Let U_t, U_t^S, and L_t be the number of unemployed individuals, the

[34]Importantly, 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

Table A4: Number of job applications over time across demographic groups

	EOPP 1979-1980		SCE 2013-2017		Log difference	
	Mean	Median	Mean	Median	Mean	Median
All	6.82	2.70	14.11	6.00	73	80
College	4.98	2.46	11.73	6.00	86	89
Non-college	7.36	2.82	15.11	7.00	72	91
Male	7.44	2.50	12.88	6.00	55	88
Female	6.13	2.86	15.11	6.00	90	74
Young	7.24	2.86	14.39	9.00	69	115
Old	4.27	1.67	13.94	6.00	118	128

Note: This table summarizes mean and median number of job applications for all individuals, individuals with a college degree, individuals without a college degree, males, females, young individuals (age 25-45), and old individuals (age 46 and above) using data from the EOPP 1979-1980 and SCE 2013-2017. The log difference is multiplied by 100.

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:

$$dU/dt = -f_t U_t + s_t \left(L_t - U_t\right). \tag{A1}$$

Moreover, we can write

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

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

Next, we solve the differential Equation (A1) forward and obtain

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

which defines the unemployment inflow rate s_t and probability $S_t = 1 - e^{-s_t}$, given data on unemployment, the labor force, and the unemployment outflow rate f_t. Following these steps,

for short-term unemployment by a constant of 1.16 for every time period after 1994, as in Elsby, Hobijn, and Şahin (2010). Shimer (2012) finds similar results with alternative ways of correcting the data.

we plot outflow probability F_t and inflow probability S_t in Figure 2 in Section 2.[35]

Shift share decomposition Here, we conduct a shift share decomposition analysis to understand the effects of demographic changes over the past four decades on inflow and outflow probabilities S_t and F_t.

Let subscript $k_g \in \{m, f\}$ denote gender where m and f indicate male and female workers; $k_a \in \{y, p, o\}$ denote age where y, p, and o stand for young workers (age 16-24), prime age workers (age 25-54), and old workers (age 55 and above); $k_e \in \{nc, c\}$ denote education where nc and c indicate workers without a college degree and with a college degree; and $k_i \in \{mf, nmf\}$ denote industry where mf and nmf mean workers in manufacturing and non-manufacturing industries, respectively. Further, let $\omega^l_{k_l,t}$ be the share of subgroup k_l in each group $l \in \{g, a, e, i\}$ at time t such that $\sum_k \omega^l_{k,t} = 1 \; \forall \, l, t$. Finally, let S_{t_1} and S_{t_2} denote the aggregate inflow probability at t_1 and t_2; $S_{k_e,k_g,k_a,k_i,t}$ and $\Delta S_{k_e,k_g,k_a,k_i}$ represent the inflow probability of workers in subgroup k_e, k_g, k_a, k_i at time t and the change in the inflow probability of workers in that subgroup over time, respectively; and t_1 represents the time period between 1976 and 1985 and t_2 represents the time period between 2010 and 2019. Then, we can write the change in the aggregate inflow probability over the two time periods as

$$\begin{aligned} S_{t_2} - S_{t_1} = & \sum_{k_e \in \{nc,c\}} \sum_{k_g \in \{m,f\}} \sum_{k_a \in \{y,p,o\}} \sum_{k_i \in \{mf,nmf\}} \omega^e_{k_e,t_1} \omega^g_{k_g,t_1} \omega^a_{k_a,t_1} \omega^i_{k_i,t_1} \Delta S_{k_e,k_g,k_a,k_i} \\ & + \sum_{k_e \in \{nc,c\}} \sum_{k_g \in \{m,f\}} \sum_{k_a \in \{y,p,o\}} \sum_{k_i \in \{mf,nmf\}} \Delta\omega^e_{k_e} \omega^g_{k_g,t_1} \omega^a_{k_a,t_1} \omega^i_{k_i,t_1} S_{k_e,k_g,k_a,k_i,t+1} \\ & + \sum_{k_e \in \{nc,c\}} \sum_{k_g \in \{m,f\}} \sum_{k_a \in \{y,p,o\}} \sum_{k_i \in \{mf,nmf\}} \omega^e_{k_e,t_1} \Delta\omega^g_{k_g} \omega^a_{k_a,t_2} \omega^i_{k_i,t_2} S_{k_e,k_g,k_a,k_i,t+1} \\ & + \sum_{k_e \in \{nc,c\}} \sum_{k_g \in \{m,f\}} \sum_{k_a \in \{y,p,o\}} \sum_{k_i \in \{mf,nmf\}} \omega^e_{k_e,t_1} \omega^g_{k_g,t_1} \Delta\omega^a_{k_a} \omega^i_{k_i,t_2} S_{k_e,k_g,k_a,k_i,t+1} \\ & + \sum_{k_e \in \{nc,c\}} \sum_{k_g \in \{m,f\}} \sum_{k_a \in \{y,p,o\}} \sum_{k_i \in \{mf,nmf\}} \omega^e_{k_e,t_1} \omega^g_{k_g,t_1} \omega^a_{k_a,t_1} \Delta\omega^i_{k_i} S_{k_e,k_g,k_a,k_i,t+1}, \end{aligned} \tag{A2}$$

where the first line represents the within-group component, and the second through the fifth lines represent the between-group components that account for changes in the education, gender, age, and industry composition of employment. The within-group measure holds the weights constant and measures how much of the total change in the aggregate inflow probability is attributed to changes in group-specific inflow probabilities. Conversely, the between-group measures hold the inflow probability within each group constant and measures how much of the total change in the aggregate inflow probability is due to compositional changes. Note that we can also write the same equation for the change in the aggregate outflow probability between t_1 and t_2 as well.

[35] We use monthly outflow probability F_t and inflow probability S_t instead of rates f_t and s_t, given that our model is in discrete time.

Table A5: Shift share decomposition exercise

	Inflows	Outflows	Outflows: 1976-85 vs 2019
Total change	-1.40	-7.38	2.28
Within-group change	-1.00	-6.63	3.37
Between-group: education composition change	-0.15	-0.04	-0.38
Between-group: gender composition change	0	0	-0.02
Between-group: age composition change	-0.24	-0.90	-0.94
Between-group: industry composition change	-0.01	0.19	0.25

Note: This table summarizes the results of the shift-share analysis for the change in the aggregate inflow and outflow probabilities between 1976-1985 and 2010-2019 (first two columns) as well as 1976-1985 vs 2019 for the outflow probability (last column). We report the total change over time as well as magnitudes of i) within-group flow probability changes (i.e., changes in group specific inflow and outflow probabilities); ii) between-group education flow probability changes (i.e., changes in flow probabilities due to change in the share of workers across education groups); iii) between-group gender flow probability changes (i.e., changes in flow probabilities due to change in the share of workers across gender groups); iv) between-group flow probability changes (i.e., changes in flow probabilities due to change in the share of workers across age groups); and v) between-group industry flow probability changes (i.e., changes in flow probabilities due to change in the share of workers across industry groups). Reported numbers are expressed in percentage points.

Table A5 summarizes the results of this shift-share analysis for the inflow and outflow probabilities. The average inflow probability across groups decreased from 3.6 percent in 1976-1985 period to 2.2 percent in 2010-2019 period.[36] Out of this 1.40 percentage points decline, 1 percentage point decline in inflow probability is due to within-group changes, implying that declines in group-specific inflow probabilities account for 71 percent of the total decline of the aggregate inflow probability. The remaining 29 percent is jointly explained by the rise in the fraction of workers with a college degree and the fraction of older workers, while changes in gender and industry composition did not have much impact on the aggregate inflow probability. Similarly, Table A5 also shows that the average outflow probability across groups decreased by around 7.4 percentage points from 38 percent 30.6 percent between the same two intervals. However, this decline is due to the slow recovery of the labor markets after the Great Recession, as we show in Figure 2. Looking at the group-specific outflows over time, we see that the slow recovery of the outflow probability after the Great Recession is observed across many groups. As such, Table A5 shows that the majority of the total change in outflows are explained by the within-group change. By 2019, outflow probabilities had returned back to their long-run average. This is evidenced by the last column of Table A5 where the total change in the outflow probability is only around 2.3 percentage points from 37.9 percent to 40.2 percent when we compare the average outflow probability in 1976-1985 period and in 2019. Demographic (between-group) changes actually result in close to a 1 percentage point decline in the outflow probability, while the within-group changes result in roughly a 3 percentage points increase. This result shows that even when we

[36]Notice that average inflow and outflow rates reported in this section differ from those we reported in Table 3. This is because we obtain the data inputs to Equation (A2), i.e. group specific weights and flows, from micro level data. In the main text, however, aggregate inflow and outflow rates are obtained by using aggregate level data on labor market stocks as discussed in the previous section.

control for compositional changes between the two time periods, the outflow probability does not exhibit any sizeable change over the long-run. Overall, these results emphasize that the trend decline in inflows and lack of trend in outflows are not driven by changes in worker demographics over time but rather reflect a more fundamental change in each group's labor market experience.

Calculating inflow and outflow rates from CPS panels The CPS underestimates the number 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 compare our findings with an alternative method of calculating monthly transition rates. This method relies on following individual employment transitions observed in the CPS panel data. The results are summarized in Figure A1. It shows that the inflow (EU) rate exhibits a secular trend, while the outflow (UE) rate does not exhibit any long-run trend, similar to our results in Figure 2. Moreover, the decline in the inflow rate over time is not driven by a secular trend in employment-to-out-of-the-labor-force (EN), UN, or NU rates, given that these flows do not exhibit any trend increase or decrease over time.

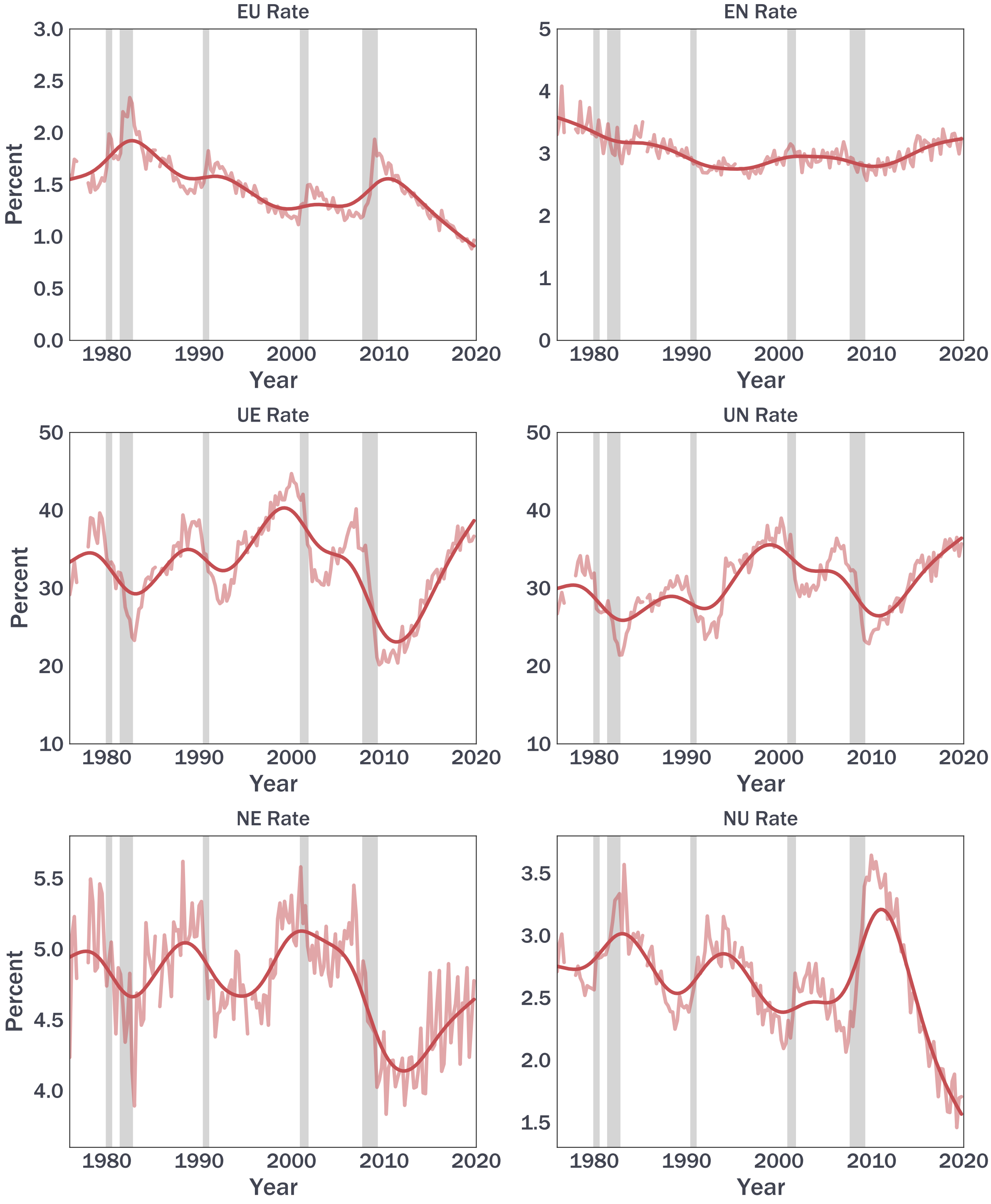
Distribution of reservation wage to mean wage ratio over time Figure 3 in Section 2.3 shows the distributions of reservation wages over time using the EOPP and SCE samples. In Figure 3, when comparing reservation wages between different time periods, we adjust reported reservation wages by a measure of inflation. Here, we also account for real wage growth. That is, we calculate the ratio of hourly reservation wages of the unemployed to the mean hourly wage of the employed for both the 1979-1980 and 2013-2017 periods. To do so, we use the CPS data to calculate the mean real hourly wage during these two time periods using samples of employed individuals aged 25-65 who are not self-employed. We then divide the real hourly reservation wages of unemployed obtained from the EOPP and SCE data by the mean real hourly wage.

Figure A2 plots the resulting distribution of the reservation wage to mean wage ratio over time. It shows that the distribution of the reservation wage to mean wage ratio has become more unequal over time. In particular, both the fraction of unemployed workers whose reservation wage is less than half of the mean and the fraction of unemployed workers whose reservation wage is more than the mean has increased over time. Overall, the average reservation wage to mean wage ratio has decreased around 5 percent between the two time periods.

B Model

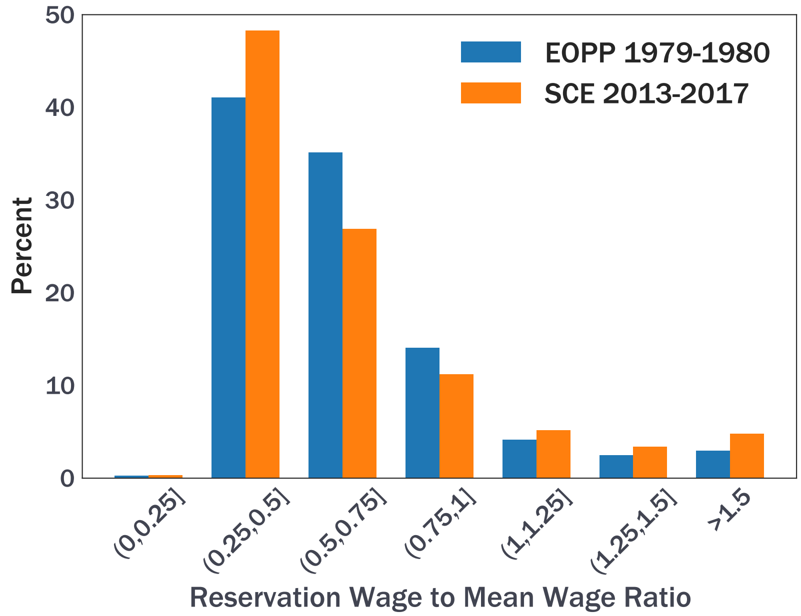
In this appendix, we provide proofs for the propositions in the main text.

Figure A1: 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), unemployment-to-out-of-labor-force rate (UN), out-of-labor-force-to-employment (NE), and out-of-labor-force-to-unemployment (NU) rates between 1976:Q1 - 2019:Q4. Quarterly time series are averages of monthly rates, which are calculated using CPS panels. Dark lines represent the trends, which are HP-filtered quarterly data with smoothing parameter 1600. Gray shaded areas indicate NBER recession periods.

Figure A2: Reservation wage to mean wage ratio



Note: This figure shows the distribution of reservation wage to mean wage ratio over time using data from the EOPP, SCE, and CPS. The EOPP and SCE samples incorporate unemployed individuals aged 25-65 with at least one job application during their unemployment spell. These two samples are used to calculate the distribution of hourly reservation wages for 1979-1980 period and 2013-2017 period, respectively. The CPS sample includes employed individuals aged 25-65 who are not self-employed. We use this sample to calculate the mean hourly wages of employed for the two time periods.

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 $V^W(x) - U = (1-\eta)S(x)$. Since surplus, $S(x)$, is increasing in match quality, x, 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 them 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:

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

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 $F_{j+z}(x)$ FOSD $F_j(x)$ for $z > 0$, it must be that

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

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 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.

C Extensions

In this appendix, we provide details of calibration outcomes for the "Full Information" (FI) and "No Information" (NI) models and discuss the details on versions of our baseline model with alternative assumptions or extensions and provide results.

C.1 Calibration details of FI and NI models

Recall that we set $\kappa_I = 0$ in the FI model and $\kappa_I \to \infty$ in the NI model in Section 5.3. Given that κ_I is already set, we leave out the recruitment cost to mean wage ratio, 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 A6 summarizes the calibration outcomes of the FI and NI models. Because we target the reservation wage to mean wage ratio in the data to pin down b, from Equation (9), the value of b is small when the continuation value from remaining unemployed is large relative to the continuation value of being employed at $\widetilde{x}$. In other words, to make it attractive for workers to choose employment and to attain the reservation to mean wage ratio in the data, b must be small.

Table A6: Calibration of FI and NI models

Parameter	Value		Target	Model		Data
	FI Model	NI Model		FI Model	NI Model	
κ_V	0.88	0.75	Outflow rate	0.44	0.45	0.41
δ	0.025	0.025	Inflow rate	0.046	0.042	0.041
λ	6.63	7.64	EU_{20}/EU_{80}	4.94	4.40	4.05
A	1.06	1.31	Fraction with no offers	0.34	0.33	0.38
B	1.77	0.88	Fraction accept given >1 offer	0.84	0.84	0.84
b	0	0	Reservation wage/mean wage	0.82	0.80	0.66

Note: This table provides a list of calibrated parameters in the "Full Information" (FI) and "No Information" (NI) models. Moments relating to unemployment flows are obtained from the CPS as averages between 1976 and 1985. The fractions of workers with no offers and the fraction who accept given more than one offer are obtained from the EOPP 1979-1980. Finally, reservation wage to mean wage ratio is obtained from using reservation wage data for the unemployed in the EOPP and mean wage data for the employed in the CPS.

C.2 Variable or endogenous number of applications

We provide further details about extending the model to incorporate variable or endogenous applications as discussed in Section 6.1.

As in Kaas (2010), consider a model where applicants search with intensity ξ and draw n applications from a Poisson distribution with parameter ξ. The probability that a worker applies to one particular vacancy is then given by $\frac{\xi}{v}$. Thus, the probability that a worker who exerts search intensity ξ applies to a vacancies is:

$$p(a,\xi) = \binom{v}{a}\left(\frac{\xi}{v}\right)^a \left(1-\frac{\xi}{v}\right)^{v-a} \approx \frac{1}{a!}\xi^n \exp(-\xi) \qquad \text{for } v \to \infty.$$

Similarly, a vacancy receives j applications drawn from a Poisson distribution with parameter

$\frac{\xi u}{v} = \frac{\xi}{\theta}$. When all workers search with intensity ξ, firm receives j applications with probability:

$$q(j) = \binom{u}{j}\left(\frac{\xi}{v}\right)^j\left(1-\frac{\xi}{v}\right)^{u-j} \approx \frac{1}{j!}\left(\frac{\xi}{\theta}\right)^j \exp\left(-\frac{\xi}{\theta}\right) \quad \text{for } u, v \to \infty.$$

Since unemployed workers are ex-ante identical, they exert the same search intensity ξ. For this reason, we suppress the dependence of $p(a,\xi)$ on ξ and write it as $p(a)$.

Firm's problem A key difference in this set-up is the expression for $\Gamma(x)$, i.e., the probability that a worker accepts a job offer of match quality x. Let $\Gamma(x,a)$ be the probability that a worker accepts a job offer of match quality x when the worker applied to a vacancies. This is given by:

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

and $\Gamma(x,a) = 0$ for $x \leq \tilde{x}$. Notice that the above equation is identical to Equation (2) in the main text but the expression is now indexed by the number of applications a. Upon meeting an applicant, the firm is unaware of how many applications the worker has sent out. Thus, the probability that a worker accepts an offer of match quality x is given by the following expectation:

$$\Gamma(x) = \sum_{a=0}^{\infty} p(a)\Gamma(x,a).$$

This new expression for $\Gamma(x)$ enters the firm's information acquisition problem which otherwise remains the same as the baseline model.

Worker's problem The probability that a worker is hired with match quality x given that they sent out a applications is now given by:

$$\phi(x,a) = \Gamma(x,a)\,Pr(\text{offer} \mid x) = \Gamma(x,a)\sum_{j=1}^{\infty} q(j)\,Pr(\text{offer} \mid x, j),$$

and the overall job-finding rate is given by:

$$\sum_{a=1}^{\infty} p(a)a\int_{\tilde{x}}^{\overline{x}} \phi(x,a)\pi(x)dx.$$

In this case, the job-finding rate does not allow for a linear decomposition of direct and indirect effects because the expectation over a appears inside the natural logarithm when we take log differences. Nonetheless, we will define the indirect effect as $\sum_{a=1}^{\infty} p(a)\int_{\tilde{x}}^{\overline{x}} \phi(x,a)\pi(x)dx$ and the direct effect as $\sum_{a=1}^{\infty} p(a)a$.

Next, the value of an unemployed worker who sends $a > 0$ applications is given by:

$$U(a) = b + \beta a \int_{\widetilde{x}}^{\overline{x}} \phi(x,a)\,\pi(x)\,V^W(x)\,dx + \beta\left[1 - a\int_{\widetilde{x}}^{\overline{x}} \phi(x)\,\pi(x)\,dx\right]U,$$

where the job-finding rate when sending a applications is given by $\int_{\widetilde{x}}^{\overline{x}} a\phi(x,a)\,\pi(x)\,dx$.

The value of a worker who sends 0 applications is given by:

$$U(0) = b + \beta U.$$

As such, the value of an unemployed worker before the number of applications a is realized is:

$$U = \sum_{a=1}^{\infty} p(a)\,U(a) + p(0)\,U(0)\,.$$

Besides these key changes, the problem of an employed worker and the wage bargaining problem remains the same as the baseline model.

Endogenous applications We note that endogenizing the number of applications is a straightforward extension of the model outlined above. One implementation would be to introduce a cost of exerting search intensity $c(\xi)$. The unemployed worker then selects the intensity ξ (application Poisson parameter) with which to search for jobs. Their problem is now given by:

$$\max_{\xi \geq 0}\; U = -c(\xi) + \sum_{a=1}^{\infty} p(a,\xi)\,U(a) + p(0,\xi)\,U(0)\,,$$

where argument ξ of $p(a,\xi)$ captures the fact that ξ is an endogenous choice which affects the probability of sending out a applications.

Numerical results We re-calibrate the model to examine the effects of the rise in applications in the variable applications model. Because the mean of a Poisson distribution is equal to the parameter ξ, our thought experiment involves raising ξ from 3 to 6. In other words, we assume that mean applications rise from 3 to 6. Table A7 shows the effect of raising the mean number of applications ξ from 3 to 6 on the unemployment inflow and outflow rate in this model. Similar to the baseline model, when the applications increase, the variable application model also predicts a large decline in inflows but a substantially smaller change in outflows.[37] The change in the outflow rate as applications rise is slightly smaller than that obtained in our baseline model as congestion effects are weaker when applications are a random variable. That is, the likelihood that more than 1 firm makes an offer to the same worker is lower when workers send a applications

[37] Our mechanism is also present when we further extend the variable applications model to allow for endogenous application/search intensity choice.

on average as opposed to all workers sending exactly a applications. This is similar to the findings in Kaas (2010).

Table A7: Impact on labor market flows: baseline vs. variable applications

	Impact on unemployment flows					
	Baseline		Variable a		Log difference	
	$a=3$	$a=6$	$a=3$	$a=6$	Baseline	Var. a
Inflow rate	0.043	0.035	0.039	0.033	-20	-18
Outflow rate	0.426	0.404	0.403	0.392	-5	-3
direct a effect	3	6	3	6	69	69
indirect a effect	0.142	0.193	0.150	0.070	-74	-76

Note: This table reports the model-predicted flow outcomes from our baseline model with uniform applications a against the outcomes from a model with variable applications. We measure the direct a effect as the change in mean applications sent a while the indirect a effect is now computed as the expected value of the probability that a worker is hired with match quality x when they send a applications $\sum_{a=1}^{\infty} p(a)\, a \int_{\widetilde{x}}^{\overline{x}} \phi(x,a)\, \pi(x)\, dx$. Note that the log difference in the direct and indirect effects here do not sum to the total change in the outflow rate because the terms are no longer separable. The log difference is multiplied by 100.

C.3 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. Formally, the firm's information problem takes the form of

$$\max\left\{V^{NI}, \overline{V}^{I}(j)\right\},$$

where

$$\overline{V}^{I}(j) = \max_{n\in\{1\ldots j\}} V^{I}(n) - \kappa_I n,$$

and

$$V^{I}(n) = \int_{\widetilde{x}}^{\overline{x}} V^{F}(x)\, \Gamma(x)\, d\left[\Pi(x)\right]^{n}.$$

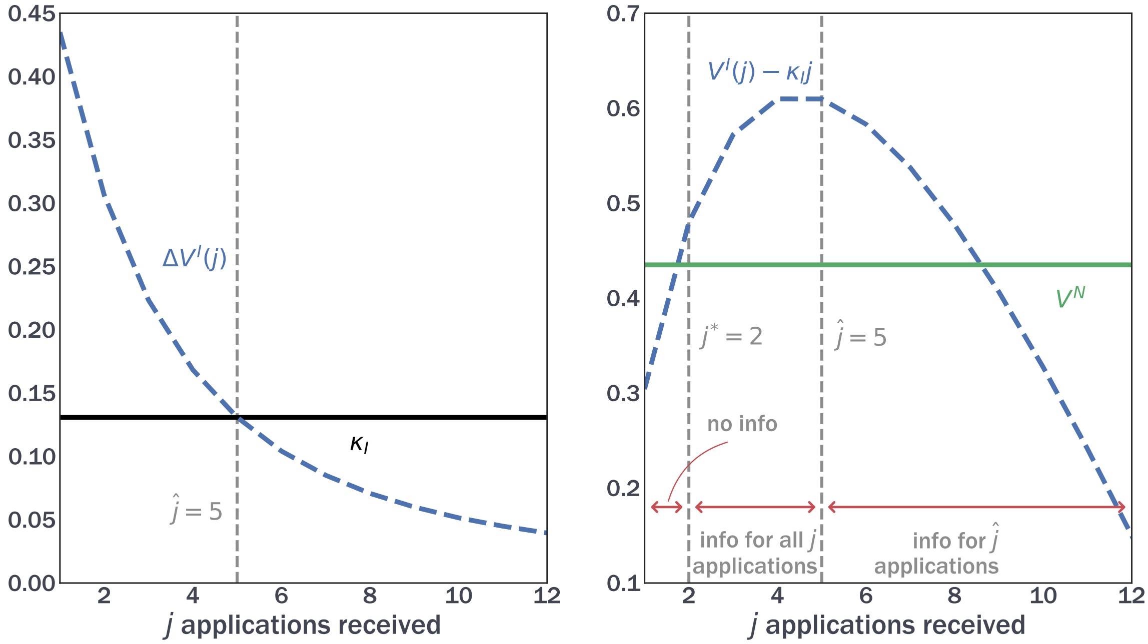
We assume that the firm decides on the optimal number of applicants, n, to acquire information on prior to learning the realizations of their match productivity. V^{NI} still takes the same form as in the baseline model:

$$V^{NI}(j) = V^{NI} = \int_{\widetilde{x}}^{\overline{x}} V^{F}(x)\Gamma(x)d\Pi(x).$$

Define $\widehat{j}$ as the highest number of applicants such that the additional gain from acquiring information is greater than or equals to the additional cost from acquiring information, i.e.:

$$V^{I}\left(\widehat{j}\right) - V^{I}\left(\widehat{j}-1\right) \geq \kappa_I,$$

Figure A3: 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 $j > \widehat{j}$, firms only acquire information on $\widehat{j}$ applicants.

and

$$V^I\left(\widehat{j}+1\right) - V^I\left(\widehat{j}\right) < \kappa_I.$$

The left panel of Figure A3 shows a numerical example where beyond $\widehat{j}$ 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 only acquires information on a random subset $\widehat{j} < j$ of its applicants. We assume that any applicant the firm does not acquire information on is automatically rejected. A similar assumption is also made in Wolthoff (2018).

The solution to the firm's problem in this environment then boils down to two thresholds $(j^*, \widehat{j})$. Note that the lower bound of when to acquire information still exists. 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., $\overline{V}^I(1) = V^I(1) - \kappa_I = V^{NI} - \kappa_I < V^{NI}$. More generally, the minimum number of applicants the firm requires before it acquires information, j^*, must satisfy $\overline{V}^I(j) \geq V^{NI}$. Thus, the firm's information acquisition strategy can be characterized as:

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

The right panel of Figure A3 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 $\widehat{j} < j$ applicants for any applicant pool size j such that $j^* \leq \widehat{j} < j$. The two thresholds $(j^*, \widehat{j})$, in turn imply the following probability of receiving an offer of quality x from a firm with j applicants:

$$
\begin{aligned}
Pr(\text{offer} \mid x, j) \;=\; & \overbrace{\mathbb{I}\left(j < j^*\right)\frac{1}{j}}^{\text{no information}} \\
& + \mathbb{I}\left(j^* \leq j \leq \widehat{j}\right)\left[\Pi\left(y\right)\right]^{j-1} \\
& + \mathbb{I}\left(j > \widehat{j}\right) \underbrace{\left[\Pi\left(y\right)\right]^{\widehat{j}-1}}_{\text{best out of } \widehat{j} \text{ applicants}} \frac{\widehat{j}}{j}.
\end{aligned}
$$

where in the final line of the above equation, $\widehat{j}/j$ refers to the probability that out of j applicants, the firm acquires information on this candidate when it selects only a subset $\widehat{j}$ to interview. Apart from this change in offer probabilities, the rest of the set-up for the worker's problem remains similar to our baseline model.

Table A8: Impact on labor market flows: baseline vs. marginal cost model

	Impact on unemployment flows					
	Baseline		Marginal cost		Log difference	
	$a = 3$	$a = 6$	$a = 3$	$a = 6$	Baseline	Marginal cost
Inflow rate	0.043	0.035	0.041	0.037	-20	-8
Outflow rate	0.426	0.404	0.488	0.486	-5	-1
direct a effect	3	6	3	6	69	69
indirect a effect	0.142	0.193	0.162	0.081	-74	-70

Note: This table reports the model-predicted flow outcomes from our baseline model with fixed costs of information against the outcomes from a model with marginal costs of information. The log difference is multiplied by 100.

Numerical results While Figure A3 illustrates the outcomes from a toy model, in order to quantitatively assess the effects of a rise in applications on unemployment flows, we re-calibrate the marginal cost model. Relative to our baseline model, Table A8 shows that in the marginal cost environment, the inflow rate still falls in response to a rise in applications but to a lesser degree. Since the benefits of information are limited when firms choose to only acquire information on a sub-set of applicants for applicant pool size $j > \widehat{j}$, the effects from improved firm selection are weaker. Consequently, the inflow rate declines by less relative to the baseline model. On the other hand, the outflow rate changes by a negligible amount. Thus, we conclude that the version of our baseline model with marginal cost of information acquisition also predicts a decline in the inflow rate while no change in the outflow rate as the applications increase.

C.4 On-the-job search

We make the following assumptions when extending the model to include on-the-job search.

1 Employed workers submit a_e applications every period. Unemployed workers submit a_u applications every period.

2 Markets are segmented by employment status. Thus, unemployed workers do not search in the same market as employed workers.

3 Wage bargaining only takes place after workers have chosen to accept a job and in doing so, have discarded all other offers prior to the bargaining stage. This implies that an employed worker who accepts a new offer, abandons his old job prior to moving to the bargaining stage. As such, the outside options of all job-seekers at the bargaining stage is equal to the value of unemployment.

4 We assume that the firm cannot observe the employed worker's match quality at their incumbent job.

With these assumptions, the model with on-the-job search largely resembles our baseline model. Below, we outline the changes in value functions as well as the change in the firm's information problem when it encounters an employed applicant.

Operating firm The value of an operating firm is given by:

$$V^F(x) = x - w(x) + \beta(1-\delta)\int_{\widetilde{x}}^{\overline{x}}\left[1 - a^e\int_z^{\overline{x}}\phi^e(y,z)\,\pi(y)\,dy\right]V^F(z)\,\psi(z \mid x)\,dz,$$

where $a^e\int_z^{\overline{x}}\phi^e(y,z)\,\pi(y)\,dy$ is the probability the employed worker finds a job elsewhere (on-the-job search). If the match is exogenously destroyed or the worker quits for another job, the firm shuts down. Because match quality shocks are drawn prior to search and matching, the probability that workers quit to new jobs depends on the new match quality z that employed workers draw in their current match. Note that although the employed and unemployed search in segmented markets, the value of an operating firm is still common in both markets.

Firm's information problem in the market for employed workers Denote $\Gamma^e(x,z)$ as the probability that an employed worker with match quality z at his current job accepts an offer of match quality x. Clearly if $x < z$, then $\Gamma^e(x,z) = 0$. For all $x \geq z$, the employed worker accepts the job if it is their best match quality drawn or if they drew higher match qualities in their other applications but those applications failed to yield offer. Thus, for a given $x \geq z$, we have:

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

For a firm who acquires no information, the firm takes expectation over the possible match quality z that the employed worker might currently have and expectation over the new match quality they may have drawn at the firm's vacancy:

$$V^{NI,e} = \int_{\widetilde{x}}^{\overline{x}} \int_{\widetilde{x}}^{x} \Gamma^{e}(x,z) V^{F}(x) g(z) dz\, \pi(x) dx.$$

As can be seen from the above equation, a key difference in this model is that the distribution of employed now affects the firm's information problem.

For the firm with j applicants who acquires information, the firm is unable to still observe the employed applicant's match quality at their incumbent firm. As such, the firm still takes expectation over the distribution of employed:

$$V^{I,e}(j) = \int_{\widetilde{x}}^{\overline{x}} \int_{\widetilde{x}}^{x} \Gamma^{e}(x,z) V^{F}(x) g(z) dz\, d[\Pi(x)]^{j}.$$

Given our assumptions on bargaining and information sets, the firm who acquires information optimally makes offers to its highest quality applicant as this maximizes both the surplus and the probability of acceptance.

Next, the information problem of firm in the market for employed workers is given by:

$$\Xi^{e}(j) = \max\left\{V^{I,e}(j) - \kappa_I, V^{NI,e}\right\}.$$

Accordingly, j_e^* is defined as smallest number of employed applicants for which the expected net benefit of information is greater than or equals to the expected value of no information, i.e.:

$$\begin{aligned} V^{I,e}(j) - \kappa_I \geq V^{NI,e} \qquad & \forall j \geq j_e^* \\ V^{I,e}(j) - \kappa_I < V^{NI,e} \qquad & \forall j < j_e^*. \end{aligned}$$

Finally, the free entry condition in the employed market takes the form of:

$$\kappa_v = \sum_{j=1}^{\infty} q^{e}(j)\, \Xi^{e}(j).$$

Employed worker's value The employed worker's value is given by:

$$
\begin{aligned}
V^W(x) &= w(x) + \beta(1-\delta)\int_{\widetilde{x}}^{\overline{x}}\left[1 - a^e\int_z^{\overline{x}}\phi^e(y,z)\pi(y)\,dy\right]V^W(z)\psi(z\mid x)\,dz \\
&\quad + \beta(1-\delta)\int_{\widetilde{x}}^{\overline{x}}\left[a^e\int_z^{\overline{x}}V^W(y)\phi^e(y,z)\pi(y)\,dy\right]\psi(z\mid x)\,dz \\
&\quad + \beta\left[\delta + (1-\delta)\Psi(\widetilde{x}\mid x)\right]U,
\end{aligned}
$$

where the employed worker's problem has been modified accordingly to take into account the possibility of on-the-job search. On the other hand, the unemployed worker's problem remains the same as the baseline model.

Surplus Given that workers must accept an offer and discard all other offers prior to bargaining, under Nash-bargaining every period, surplus can be written as:

$$
\begin{aligned}
S(x) &= x + \beta(1-\delta)\int_{\widetilde{x}}^{\overline{x}}\left[1 - a^e\int_z^{\overline{x}}\phi^e(y,z)\pi(y)\,dy\right]S(z)\psi(z\mid x)\,dz \\
&\quad + \beta(1-\delta)\eta a^e\int_{\widetilde{x}}^{\overline{x}}\left[\int_z^{\overline{x}}S(y)\phi^e(y,z)\pi(y)\,dy\right]\psi(z\mid x)\,dz \\
&\quad - (1-\beta)U.
\end{aligned}
$$

Notice the additional term stems from the worker's gain since they can do on-the-job search. If we set $a^e = 0$, i.e. no on-the-job search, we are back to our baseline model.

Laws of motion Unlike our baseline model, the distribution of employed workers must be solved jointly with the key equilibrium variables $(\theta_u, \theta_e, \widetilde{x}, j_e^*, j_u^*)$.

In steady state, the measure of unemployed is:

$$
u = \frac{\delta + (1-\delta)\int_{\widetilde{x}}^{\overline{x}}\Psi(\widetilde{x}_t\mid x)\,g(x)\,dx}{\int_{\widetilde{x}}^{\overline{x}}a^u\phi(x)\pi(x)\,dx + \left[\delta + (1-\delta)\int_{\widetilde{x}}^{\overline{x}}\Psi(\widetilde{x}_t\mid x)\,g(x)\,dx\right]},
$$

and the distribution of employed with match quality less than or equals to x is:

$$
G(x) = (1-\delta)\int_{\widetilde{x}}^{\overline{x}}\int_{\widetilde{x}}^{x}\left(1 - a^e\int_x^{\overline{x}}\phi^e(h,z)\pi(h)\,dh\right)\psi(z\mid y)\,dz\;g(y)\,dy + a^u\int_{\widetilde{x}}^{x}\phi^u(y)\pi(y)\,dy\frac{u}{1-u}.
$$

These expressions summarize the key differences between the baseline model and the model with on-the-job search.