Job Applications and Labor Market Flows*

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Abstract

The number of job applications has increased over time. Despite this rise, job-finding rates remain relatively unchanged while separation rates have declined sharply. We argue that increased applications improve the probability of finding a good match rather than the probability of finding a job. Using a search model with multiple applications and costly information acquisition, we show that when workers send more applications, firms invest more in finding good matches, reducing separations. Concurrently, higher congestion and increased selectivity over which offer to accept mitigate the rise in job-finding rates. Quantitatively, our model replicates the empirical 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 worker applications over time. Despite the increase in the number of applications, the unemployment outflow (job-finding) rate in the U.S. has not observed any long-run change. Conversely, unemployment inflow (job separation) rates have 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 the number of applications has not led to any sustained changes in unemployment outflow rates. In this paper, 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 separation rates.

To address this question, we make two contributions. First, we empirically document the trends in unemployment flows and worker applications. Using data from the Current Population Survey (CPS), we show that the decline in the unemployment inflow rate largely occurs within group, that is, compositional changes explain only a small portion of the overall decline in the unemployment inflow rate. Our results concur with recent literature examining the decline in job separations and the changes in the tenure distribution.[1] We obtain a similar finding for outflows: the lack of change in the unemployment outflow rate cannot be solely explained by compositional changes. We then provide novel findings on how worker applications have changed over time using information from the Employment Opportunity Pilot Project (EOPP) and the Survey of Consumer Expectations (SCE). In particular, the median number of applications submitted by unemployed workers per month has doubled since the 1980s. Second, we build a tractable equilibrium labor search model to quantitatively analyze how a doubling in the number of applications can drive a decline in unemployment inflow rates without precipitating simultaneous trend increases or declines in unemployment outflow rates. Our model departs from the standard labor search model in two ways. First, to explore the consequences of rising applications, we allow workers to send multiple applications and vacancies to be contacted by multiple applicants. Second, we introduce information frictions in the form of costly information acquisition by firms. The assumption of costly information captures the notion that a rising number of applications increases the firm's burden of identifying the best applicant for the job. Notably, the endogenous change in firms' hiring behavior is a key channel through which increased applications can replicate the observed changes in labor market flows over time.

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

[1] See Molloy, Smith, and Wozniak (2020), Pries and Rogerson (2019) and Hyatt and Spletzer (2016) for example.

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

Having developed our model, we apply our framework to the data. We calibrate our model to match aggregate labor market moments and application outcomes for the period 1976-1985.[2] 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. While the behavior of inflow and outflow rates are our main variables of interest, we also document how our model's predictions on application outcomes such as the offer probability, the acceptance rate, the reservation wage and the tenure distribution largely mimic patterns observed in the data.

Under our calibrated model, unemployment inflow rates decline by about 20 percent when applications increase, about one-third of the decline observed in data.[3] Why does the model suggest that an increase in applications would contribute to a decline in inflow rates? 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. However, the ability to contact more vacancies also elevates workers' outside options. This raises workers' selectivity, leading to higher reservation match quality and more job destruction. Quantitatively, the effects from an improved distribution of realized match quality dominate the rise in worker selectivity. As such, the model predicts that inflow rates decline with the rise in applications.

Notably, our model suggests that the decline in unemployment inflow rates is largely driven by the sharp fall in the share of individuals employed in low quality and high turnover jobs, consistent with recent evidence that document a stark decrease in the share of short duration jobs. When more firms acquire information in response to a higher number of applications, fewer low quality matches are formed, as such the share of short duration jobs in our model declines. At the same time, our model can also replicate the empirical finding that median tenure has remained unchanged despite the decline in short duration jobs. In our model, the increase in

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

[3]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.

worker selectivity and rise in reservation match quality, implies that for a job of a given match quality, the probability of endogenously separating into unemployment is higher. This is because workers must re-draw new match qualities above the higher reservation quality threshold for a job to be sustained. Thus, while the distribution has shifted towards higher quality jobs, median tenure remains unchanged due to the increase in reservation match quality.

Turning to outflows, our model predicts that a rise in applications causes the unemployment outflow rate to decline by a marginal 5 percent. These results are in line with the fact that outflow rates exhibit no long-run change over time, a finding we highlight in greater detail in Section 2. Why does the model generate a muted response of outflow rates despite the rise in applications? Similar to inflows, an increase in applications has an ambiguous effect on outflows. While outflow rates can rise due to the increased contact between job-seekers and vacancies, whether job-finding rates actually increase ultimately depends on the probability that these contacts are converted into offers and acceptances. The probability a single application yields an offer falls when there is increased competition amongst workers, while the probability that an offer is accepted falls when workers contact more vacancies and can choose from more options. The decline in offer and acceptance probabilities is sizeable, and counteracts the worker's benefit from contacting more vacancies. These offsetting forces cause increased applications to have a negligible impact on outflows. Importantly, our model-implied changes in job offer and acceptance probabilities largely follow the patterns observed in the EOPP and SCE. As in the data, our model predicts that the rise in worker applications has been accompanied by an overall decline in job offer and acceptance rates. Notably, the decline in acceptance rates is not solely driven by the increase in reservation match quality and hence, reservation wages. Holding fixed reservation match quality, acceptance rates still decline substantially, suggesting that increased applications cause workers to reject jobs more often when they can choose from more offers.

Finally, we demonstrate why endogenizing the firm's information acquisition problem is a necessary feature to understand how a rise in applications affects trends in labor market flows. We consider two thought experiments: a case where information about a firm's applicants is free (full information), and a case where information is infinitely costly (no information). We find that both models predict counterfactual unemployment flows, especially in terms of outflows.

Intuitively, the effective cost of job creation is unchanged 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 receiving zero applicants is lower, vacancy creation increases. The rise in vacancies partially mitigates some of the congestion caused by an increased number of applications. 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. Relative to our baseline model, unemployment outflow rates rise by a non-trivial amount in the full information environment, as relatively lower congestion levels and workers' higher probabilities of at least one application drawing a high match quality raise the likelihood of an offer. Conversely, unemployment outflows decline substantially in the no information environment, as 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 in the no information model and a large decline in unemployment outflow rates. While both counterfactuals predict declines in the inflow rate, the magnitudes are small relative to our baseline model's predictions. 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 labor market 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) and Galenianos and Kircher (2009) focus on the efficiency properties of such models in a directed search environment. Extending the model, Gautier, Moraga-Gonzalez, and Wolthoff (2016) and Albrecht, Cai, Gautier, and Vroman (2020) examine the efficiency properties when the number of applications is endogenous. In a similar vein, 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 in his model can only send one application. Because our question concerns how rising applications can affect labor market flows, we allow for multiple applications on both sides of the market. Closely related to our work is the seminal paper by Wolthoff (2018), who uses a directed search model with multiple applications to study the business-cycle properties of firms' recruiting decisions. He finds that the number of applicants interviewed by firms is procyclical when applicants vary by match quality. Our paper instead focuses on long-run trends in the labor market. Specifically, it addresses how an increase in applications strengthens firms' incentives to acquire information, which in turn affects labor market flows. To our knowledge, this is the first paper to link a rise in applications to long-run trends in labor market flows.

Our work also contributes to the literature on the 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) also report evidence of a decline in separation rates and a shifting of the tenure distribution. In particular, the authors find a sharp decline in the share of short duration jobs, and relatively no change in median tenure. Our paper shows how the rise in applications can jointly generate these empirical patterns.

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 increases in the share of informed firms in our model are 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 over the long-run 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 lead to workers finding better matches and observing less separations, without necessarily observing 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 and tenure - 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 inflow and outflow rates, and application outcomes across education groups. Section 3 discusses our model, and Section 4 provides the calibration strategy. Section 5 presents our results, Section 6 provides a discussion on the robustness of our main results, and Section 7 concludes.

2 Empirical Findings

In this section, we discuss our empirical findings that motivate the model and quantitative exercises. In Section 2.1, we first document that the number of job applications during a month of unemployment spell has increased significantly since 1980s. Next, in Section 2.2, we show that the unemployment outflow rate has not exhibited any trend over the past four decades despite the large increase in the number of job applications. On the other hand, the unemployment inflow rate has declined dramatically over the same time period. Finally, in Section 2.3, we provide new findings on how the application outcomes have changed over time. Specifically, we find that while the unemployed now submit more applications and report higher reservation wages, they tend to receive fewer offers and are less likely to accept an offer.

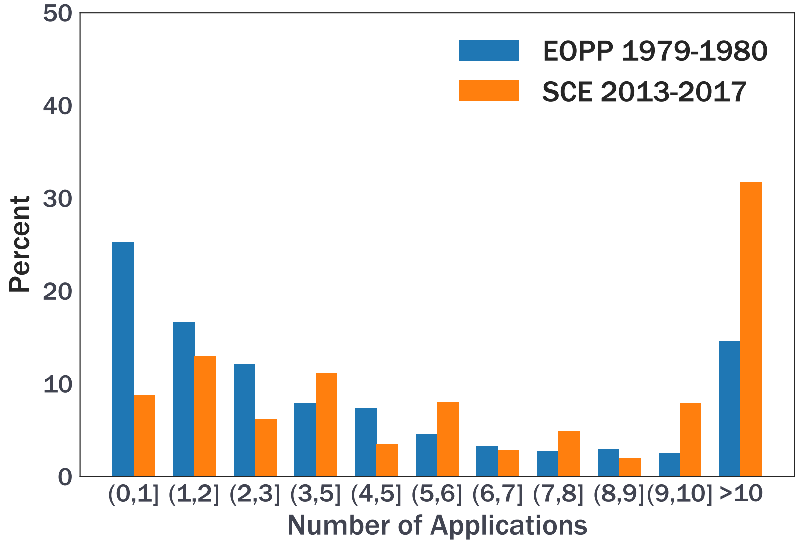
2.1 Job applications

Using information from two datasets, the EOPP and SCE Labor Market Survey, we provide novel evidence on how the application behavior of workers has evolved over time. A unique feature of both datasets is that they offer insights into job search behavior and, unlike other household surveys, provide detailed information on the job application process such as the number of job applications sent, the number of offers received, and the offer acceptance decisions of workers. In addition, these datasets offer 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 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. In order to evaluate the comparability of these datasets with more widely used surveys, Table A1 and Table A2 in Appendix A compare the EOPP and SCE samples to the CPS over the same time period. Overall, the EOPP 1979-1980 and SCE 2013-2017 samples capture well the demographic changes observed in the CPS between both time periods.

In both of these datasets, we study a sample of unemployed individuals aged 25-65 with at least one job application during their unemployment spell. 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 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 common across various demographic groups. Overall, our findings imply that the number of job applications has increased over the past four decades.

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.

2.2 Labor market flow rates

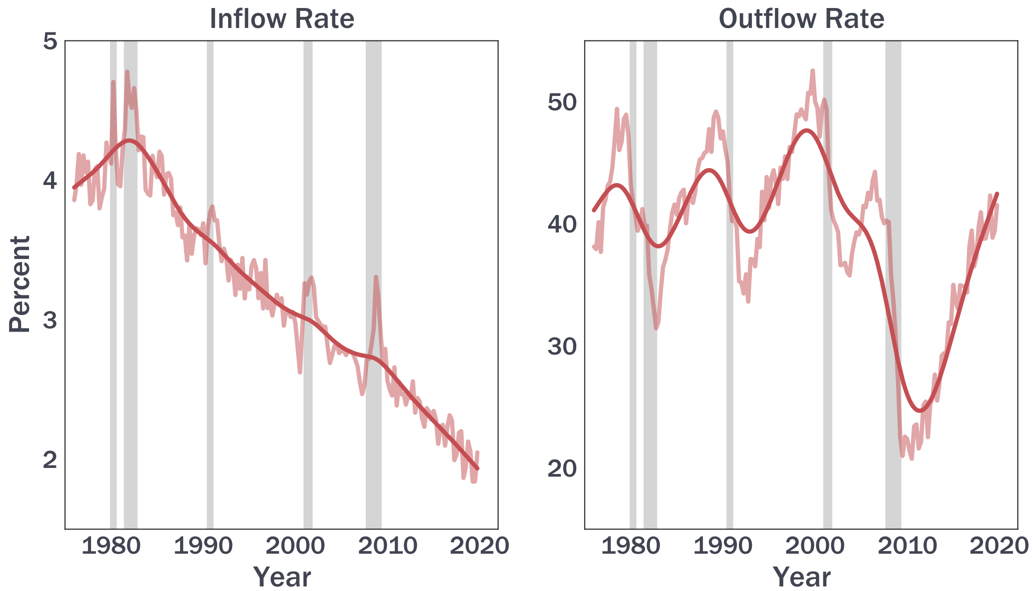
Despite this increase in the number of applications since 1980s, the unemployment outflow rate has not exhibited any trend, while the unemployment inflow rate has declined dramatically. Using monthly data from the CPS on the number of employed, unemployed, and short-term unemployed, defined as respondents who are unemployed for at most five weeks, we calculate the unemployment outflow rate and the unemployment inflow rate over time using standard procedures found in the literature. Appendix A provides details on our data and methodology.[4] Figure 2 plots quarterly averages of monthly outflow and inflow rates for the period 1976:Q1 - 2019:Q4. Reinforcing the findings of earlier studies, Figure 2 shows how the unemployment outflow and inflow rate has behaved very differently over the long-run.[5] Since the 1980s, the outflow rate has exhibited little to no secular change, while the inflow rate has fallen around 50 percent, from 4 percent to 2 percent.

Given that the U.S. labor force underwent some significant demographic changes over this period of time, a natural question arises as to whether the decline in the unemployment inflow rate can be attributed to changes in worker demographics or whether the decline reflects a more fundamental change in each group's labor market experience. Similarly, do these demographic changes somehow affect the lack of trend in the aggregate outflow rate? To answer these ques-

[4]The CPS measure of short-term unemployed workers is underestimated given that some workers who enter unemployment exit unemployment within the same month. We follow Shimer (2012) to account for this bias. In Figure A1 of Appendix A, we also present results when we calculate monthly transition rates following individuals in CPS panels.

[5]See Crump, Eusepi, Giannoni, and Şahin (2019), for example.

Figure 2: Unemployment outflow and inflow rates



Note: This figure plots the unemployment outflow rate (left panel) and inflow rate (right panel) between 1976:Q1 - 2019:Q4. Quarterly time series are averages of monthly outflow and inflow 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.

tions, we implement a shift-share decomposition exercise on aggregate outflow and inflow rates in Appendix A.[6] We find that the within-group decline explains the predominant share (71 percent) of the decline in the inflow rate. In terms of the aggregate outflow rate, the lack of trend is observed across all demographic groups.

In summary, we find that the unemployment outflow rate has not exhibited any long-run trend, while the inflow rate has declined substantially decline over time. Importantly, these trends are not merely due to changes in worker demographics but rather reflect a more fundamental change in each group's labor market experience.

2.3 Offer arrival and acceptance rates and reservation wages

As our goal is to understand why a rise in applications has not led to a trend increase in unemployment outflow rates, we further use the EOPP and SCE data to shed light on how application outcomes such as offer probabilities, acceptance rates and reservation have changed since the 1980s. Intuitively, an increase in applications may lead to higher competition among workers, lowering the probability of receiving an offer. In the same vein, increased applications can also impact workers' offer acceptance decisions and reservation wages. Since these factors in turn affect job-finding rates, we document how these variables have changed over time and show later in Section 5.1, how these changes act as testable implications for our model.

We calculate the distribution of job offers received during a month of unemployment, the

[6]Table A6 summarize the results of this exercise.

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 some offer; and distributions of real hourly reservation wages over time. Reservation wages are in 1982-1984 dollars. These moments are calculated from 1979-1980 using the EOPP sample and from 2013-2017 using a pooled SCE sample incorporating unemployed individuals aged 25-65 with at least one job application during their unemployment spell.

fraction of unemployed with non-zero offers who accept a job, and the distribution of real hourly reservation wages. We calculate these data moments for 1979-1980 using the EOPP sample and for 2013-2017 using a pooled SCE sample. Figure 3 summarizes the results.

We highlight several important results. Between the two time periods, unemployed workers observe a decline in job offers during a month of unemployment. The fraction of individuals with no offers increased from 38 percent to 45 percent. Further, among the unemployed who received more than one job offer during a month of unemployment, the fraction of individuals who accept an offer decreased from 84 percent to 35 percent. Finally, the distribution of real hourly reservation wages shifts rightward across these two time periods. The mean real hourly reservation wage (in 1982-1984 dollars) increased from \$5.83 to \$6.94.[7] While acceptance rates have fallen by a large margin, the coincident rise in reservation wages has not been to the same magnitude, suggesting that the increase in reservation wages may only partially explain the sharp decline in acceptance rates.

Overall, we conclude that while the unemployed now submit more applications than they used to, they tend to also receive fewer offers, reject these offers more often, and demand higher wages. In Table A5, we show that these trends are also observed across various demographic groups.We argue that any model that seeks to explain the impact of the rise in job applications on labor flows should also jointly account for changes in application outcomes. In what follows, we develop a framework that allows us to examine how a rise in applications can affect labor market flows and application outcomes.

[7]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.

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 $\Psi(y \,|\, x)$, where $d\Psi(y \,|\, x)/dx > 0$, implying that new draws of match quality y are positively correlated with previous values of x. We further assume that $\rho(x)$ is decreasing in x, implying that higher-productivity matches observe a lower frequency of match quality shocks. Employed workers endogenously exit into unemployment whenever their new match quality draw is such that the match is no longer sustainable. Employed workers also exogenously exit into unemployment with probability δ.

Job search Search is random. Only unemployed workers search for jobs. An unemployed worker can costlessly send multiple applications, with number of applications a worker can send each period denoted by a. A worker sends each application to a separate vacancy. For each vacancy contacted, she observes her match quality x for that particular application. Vacancies can be contacted by multiple applicants, where the number of applicants at a vacancy is a random variable. Unlike workers, firms do not observe their applicants' match qualities. A firm, however, can choose to pay a fixed cost, κ_I, to learn its applicants' qualities. While paying κ_I reveals to the firm information about its applicants' match qualities, it does not inform the firm about the number of offers applicants have nor does it provide information about their match qualities at other jobs.[8] As such, information is asymmetric as a worker knows her match qualities across all applications and her number of offers received, while a firm that acquires information only knows its applicants' match qualities at its own vacancy. We restrict our attention to symmetric equilibria in pure strategies; that is, all firms with j number of applicants employ the same information acquisition and hiring strategy. Finally, each vacancy costs κ_V to post.

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

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

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

where $\theta = v/u$ is the ratio of vacancies to unemployed job-seekers. Importantly, the rate at which the firm receives applications is not the same as its job-filling probability. 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. We assume that newly separated workers must wait one period before searching in the labor market. Following this, unemployed workers submit applications and observe their match quality at each vacancy contacted. Firms receive applications and choose whether to acquire information. Firms then make offers to their chosen applicants, and workers decide whether to accept offers. Once an offer has been accepted, wage bargaining commences and firms that did not acquire information learn about their worker's match quality. Wages are re-bargained every period. We assume that once a worker accepts an offer, she discards all other offers, implying that at the bargaining stage, the worker's unemployment value forms her outside option. Finally, production occurs. Having described the environment, we proceed to defining the worker's and firm's end-of-period value functions, i.e., after search and matching has occurred. We begin with the firm's problem.

3.2 The firm's problem

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

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

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 $\Psi(y \mid x)$, with $\psi(y \mid x)$ being 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. Then, so long as the expected value of a match is increasing in quality x, the firm always makes an offer to the most productive applicant.

Lemma 1 (Firm's hiring choice)**.** *The firm always makes an offer to the applicant with the highest match quality.*

Proof. See Appendix B. □

Intuitively, by making an offer to the highest-quality applicant, the firm maximizes its expected value since the value of an operating firm, $V^F(x)$ – which itself is a function of surplus – is increasing in match quality x. 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.[9]

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

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

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

Proof. See Appendix B. □

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

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

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

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

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

3.4 Employed workers

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

$$\begin{aligned} V^W(x) \;&=\; w(x) + \beta(1-\delta)(1-\rho(x))V^W(x) \\ &\quad + \beta\left[\delta + (1-\delta)\rho(x)\Psi(\widetilde{x} \mid x)\right]U + \beta(1-\delta)\rho(x)\int_{\widetilde{x}}^{\overline{x}} V^W(y)\,\psi(y \mid x)\,dy, \end{aligned} \tag{4}$$

where $w(x)$ is the worker's current wage. With probability δ, the match is exogenously destroyed and the worker becomes unemployed. Jobs that are not exogenously destroyed are subject to a match quality shock with probability $\rho(x)$. If the new match quality drawn is above the reservation match productivity, i.e., $y \geq \widetilde{x}$, 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. When the employment value, $V^W(x)$, is increasing in match quality, the worker always prefers to accept her highest match quality drawn so long as that value is above $\widetilde{x}$. Consider a worker who draws match quality $x \geq \widetilde{x}$ from one of her a applications and receives an offer for this draw. The worker will accept this offer of quality x if 1) it is her highest match quality, or 2) it is not her highest match quality but other applications with higher match quality failed to yield offers. Thus, the worker's probability of accepting an offer with match quality $x \geq \widetilde{x}$ for a particular application is given by:

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

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

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

where

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

and $\widehat{q}(\ell) = q(\ell) / \sum_{\ell=1}^{\infty} q(\ell)$.[10] 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 (5) depicts the case where the worker accepts an offer of match quality x because it is her highest match quality drawn. This occurs with probability $[\Pi(x)]^{a-1}$. The second term corresponds to the cases where the worker has drawn match quality $y > x$ in her i other applications for $i \in \{1, 2, \ldots, a-1\}$, and match qualities less than x for her remaining $(a - 1 - i)$ applications. This occurs with probability $(a-i)[1-\Pi(x)]^i[\Pi(x)]^{a-1-i}$. Since her i applications that drew match quality greater than x failed to yield an offer, she accepts her next best outcome which is x. Equation (6) represents the probability that a worker with match quality $y > x$ receives an offer for that application, while Equation (7) represents the offer probability associated with a worker who draws match quality y at a firm with ℓ applicants. The first term on the right-hand-side of Equation (7) depicts the case where the worker meets a firm that chooses to acquire information because it received $\ell \geq j^*$ applicants.[11] Since this firm observes its applicants' match qualities, the worker receives an offer only when she is the best applicant. This occurs with probability $[\Pi(y)]^{\ell-1}$. The second term depicts the case where the worker meets a firm with $\ell < j^*$ applicants. Since the firm does not acquire information and randomly selects an applicant, the worker receives an offer with probability $1/\ell$. Summing across ℓ and conditioning on $y > x$ yields Equation (6).

[10] 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 sub-set of firms who have applicants.

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

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

$$\phi(x) = \Gamma(x) Pr(\text{offer} \mid x) = \Gamma(x) \sum_{j=1}^{\infty} \widehat{q}(j) Pr\left(\text{offer} \mid x, j\right). \tag{8}$$

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

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

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

3.6 Surplus and wage determination

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

$$w(x) = \arg\max_{w} \left[V^F(x)\right]^{1-\eta} \left[V^W(x) - U\right]^{\eta}, \tag{10}$$

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

$$S\left(x\right) \quad = \quad \frac{x + \beta\left(1-\delta\right)\rho(x)\int_{\widetilde{x}}^{\overline{x}} S\left(y\right)\psi\left(y \mid x\right)dy - \left(1-\beta\right)U}{1 - \beta\left(1-\delta\right)\left(1-\rho(x)\right)}, \tag{11}$$

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 (11) shows that $S(x)$ is increasing in x, implying that $V^F(x)$ and $V^W(x)$ are also increasing in x. Thus, workers always accept their highest quality offer and firms always extend offers to their best applicant.

3.7 Labor market flows

Unemployed The steady state unemployment rate is implicitly given by:

$$u\int_{\widetilde{x}}^{\overline{x}} a\phi(x)\pi(x)dx = (1-u)\left[\delta + (1-\delta)\int_{\widetilde{x}}^{\overline{x}} \rho(x)\Psi\left[\widetilde{x}\mid x\right]g\left(x\right)dx\right], \tag{12}$$

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

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

$$\begin{aligned}\left[\delta + (1-\delta)\rho\left(x\right)\right]g\left(x\right)(1-u) \quad &= \quad (1-\delta)\int_{\widetilde{x}}^{\overline{x}} \rho\left(y\right)\psi\left(x\mid y\right)g\left(y\right)dy(1-u) \\ &\quad +a\phi\left(x\right)\pi\left(x\right)u.\end{aligned} \tag{13}$$

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

3.8 Equilibrium

All equilibrium objects defined thus far depend on $\{\widetilde{x}, \theta, j^*\}$. 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* (3) *and the following conditions:*

$$\widetilde{x} = b + \beta\eta\int_{\widetilde{x}}^{\overline{x}} a\phi\left(y\right)S\left(y\right)\pi\left(y\right)dy - \beta\left(1-\delta\right)\rho(\widetilde{x})\int_{\widetilde{x}}^{\overline{x}} S\left(y\right)\psi\left(y\mid\widetilde{x}\right)dy, \tag{14}$$

and

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

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

Equation (14) 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 (15) determines j^* which is the smallest number of applicants firms must have for them to acquire information. Finally, the free entry condition, Equation (3), provides information on θ.[12]

3.9 Forces at play

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

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

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

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

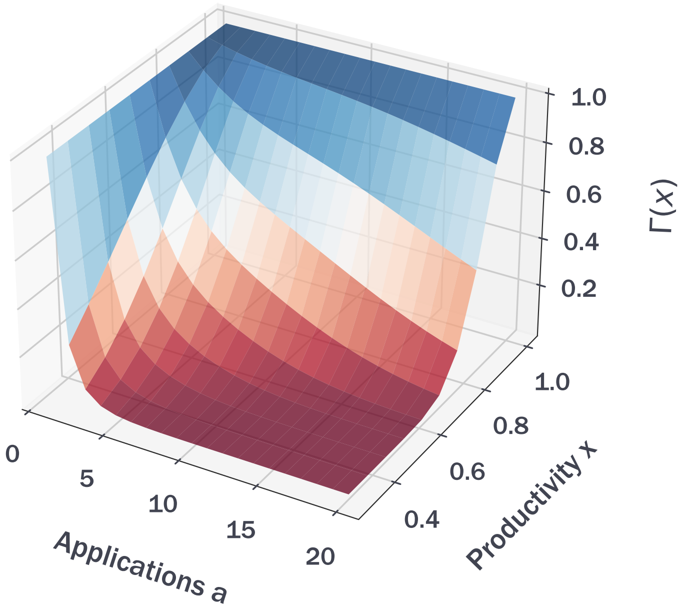
While the direct effect of a contributes positively towards the outflow rate, an increased number of applications also indirectly affects the probability that a single application yields an offer. From Equation (8), the offer probability, $Pr(\text{offer} \mid x)$, depends on the distribution of applicants across vacancies $q(j)$, which in turn responds to changes in a. Under the Poisson distribution, the mean number of applicants per vacancy is a/θ. For expositional purposes, assume a is a continuous variable. Differentiating $q(0)$ 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 (7), the probability that a worker receives an offer for this application is weakly declining

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

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



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

in j.[13] Thus, as the distribution of applications received by firms, $q\,(j)$, shifts rightward with higher a, each applicant faces more competition at the same vacancy, reducing the probability that they receive an offer for their match quality x.

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

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

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

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

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 $j \geq j^*$ applications, and thus the share of informed firms. Following from Lemma 1, when more firms acquire information, they identify and hire the most productive applicant

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

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 1976-1980. We choose this interval of time as it covers the period under which the EOPP survey was conducted.[14] Because we are interested in long-term trends, we take the average of the trend component when calculating inflow and outflow rates. 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 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 thus 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 per month and the probability of accepting a job given more than 1 offer.

Within each period, a worker is subject to a match quality shock with probability $\rho(x) = \min\{x_{ref} - x, 1\}$ 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 with their match quality x. This formulation allows

[14]Unless otherwise stated, all moments are taken from the CPS.

us to reflect the fact that low wage jobs observe higher unemployment risk.[15] Conditional on receiving a match quality shock, we assume that individuals draw their new match qualities from the joint 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.

Labor market We target the average aggregate unemployment inflow rate over the period 1976-1980 to pin down the exogenous separation probability δ. Since λ affects the persistence between match quality draws, we target the ratio of unemployment inflow rates of the bottom 20th percentile (EU_{20}) in real hourly wage earnings in 1976-1980 to the inflow rates of the top 20th percentile (EU_{80}). In the data, this ratio is about 4.19, suggesting that individuals at the lower end of the wage distribution observe more frequent transitions into unemployment than individuals at the top end of the wage distribution.

We choose the vacancy posting cost, κ_V, to match the monthly unemployment outflow rate of 0.422, which is the average of the trend component in job-finding rates for the period 1976-1980. Since the fixed cost of information, κ_I, affects recruiting costs, we follow Gavazza et al. (2018) and set κ_I to match a ratio of recruiting costs to average wages of 0.928. In our model, we calculate the expected recruiting costs which 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 out when choosing whether or not to create a vacancy. Finally, the level of home production, b, is set to match the ratio of reservation wage to mean wage of 0.672. Table 1 shows that our calibrated model fits the data moments fairly well.[16]

5 Quantitative Results

5.1 Equilibrium response to an increase in applications

Having calibrated the model, we now analyze how an increase in the number of applications, a, affects unemployment flows and job search outcomes. In the data, the median number of

[15]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.

[16]The firm's decision on whether to acquire information depends on its own idiosyncratic state (the number of applicants received) and also the actions of others (through its impact on the worker's acceptance rate). Thus, while the firm's decision to acquire information may be weakly increasing in the number of other firms who acquire information, we find that under our current parametrization, a unique equilibrium exists.

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 levels and flows are obtained from the CPS as averages between 1976 and 1980. The fractions of workers with no offers and the fraction who accept given more than one offer are obtained from the EOPP 1979-1980.

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 begin by documenting the changes in the equilibrium objects $\{\widetilde{x}, \theta, j^*\}$. Table 2 highlights our results. First, an increase in the number of worker applications shifts the distribution of applicants per vacancy, $q(j)$, rightward as exhibited in Figure 5. This rightward shift in $q(j)$ increases the firm's incentive to acquire information as a larger number of applicants per vacancy raises the likelihood that at least one of the firm's applicants is a high quality match. At the same time, when workers send more applications and sample more vacancies, they are less likely to accept lower quality jobs at any particular application if their other applications yield offers with higher match qualities. As a result, the combination of worker rejection probabilities declining in match quality, together with an on-average higher number of applicants per vacancy works towards reinforcing the firm's incentive to acquire information about its applicants. In our model, the share of firms that acquire information rises from 44.1 percent when $a = 3$ to 95.3 percent when $a = 6$.

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 $y > x$.[17] 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 in our model when applica-

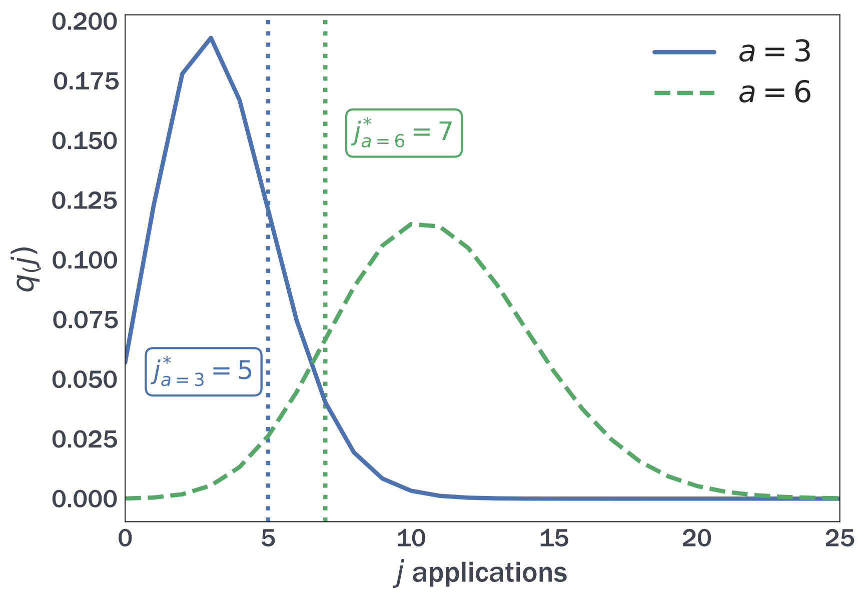
[17] To see this, consider the acceptance rate, $\Gamma(x)$. The second term in $\Gamma(x)$ refers to the event that the worker accepts a job of match quality x because her applications with higher match qualities $y > x$ failed to yield an offer. The probability of this event occurring is smaller when firms acquire more information.

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

Figure 5: Firms receive more applications as a increases



Note: The figure 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.

tions double. The rise in $\widetilde{x}$ is modest as there exists counteracting forces that mitigate the extent to which a rise in applications can improve 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 being to find a good match raises the worker's outside option and increases the worker's selectivity over the minimum quality job she is willing to accept. On the other hand, a greater number of worker 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 her 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 unemployment inflow and outflow rates, we take 10-year averages of the trend components as we are interested in long-run differences. We emphasize, however, that the U.S. economy underwent a slow recovery after the Great Recession. As a result, the reported outflow rates in the data are below the average observed in Figure 2. By 2019, however, unemployment outflow rates had recovered to their long-run average of 0.41. We detail the results of our exercise in Table 3.

5.2.1 Inflow rates

Table 3 highlights that a rise in applications, a, alone can cause unemployment inflow rates to decline by 20 percent, accounting for one-third of the decline observed in data. This is despite the improvement in workers' outside options stemming from an increased ability to contact more vacancies. To explain how the effect of improved firm selection can lead to a decline in separations, we focus our discussion on how the distribution of employed across match quality changes with a rise in applications, and how the change in this realized distribution affects the frequency of shocks and the probability that a match becomes unsustainable given a shock.

Figure 6 highlights how the distribution of employed over match quality changes with the rise in a. Because more firms acquire information when a increases, a larger share of firms are able to identify and hire high quality applicants, giving rise to a greater formation of high quality matches and a decline in the share of low-to-middling quality matches. In our model, the frequency of match quality shocks, $\rho(x)$, is decreasing in x. The greater formation 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, - and key to our results - 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.[18] 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 $\widetilde{x}$ on separation rates. Consequently, unemployment inflow rates in our model decline as the effects from improved firm selection dominate the effects from increased worker selectivity.

The effects from improved firm selection from a rise in a also have implications on the tenure distribution, especially for the share of short duration jobs. As the realized distribution of match quality shifts rightward and towards high quality matches, the share of low quality jobs with high turnover declines. As such, our model predicts that the share of short duration jobs declines significantly while the share of jobs with long duration falls by less. Table 4 shows that the share

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

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
Outflow rate (2019)		0.408		0.409		0
direct a effect	3		6		69	
indirect a effect	0.142		0.067		-74	

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

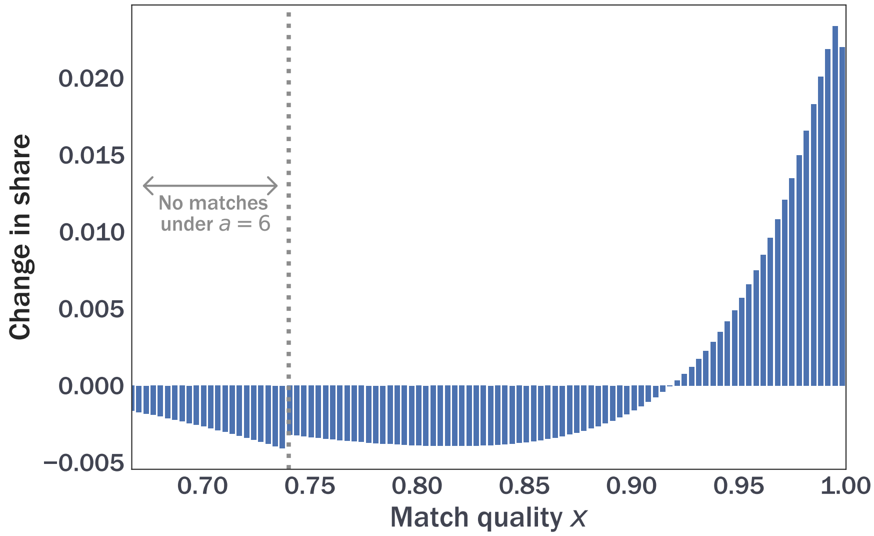
of employed in jobs lasting less than a quarter falls by 70 percent when a increases. Conversely, the share of employed in jobs lasting more than a year and less than three years falls by a smaller 36 percent. These results highlight that the driving force behind the drop in average separation rates and the rightward shift in the tenure distribution in our model stems from a greater concentration of employed individuals in high x jobs. High quality jobs that existed when $a = 3$ and which continue to exist when $a = 6$ in fact observe a marginally higher separation rate due to the rise in $\widetilde{x}$. To see this, observe that for a given x, the probability of endogenous separation for that given x is $\rho(x)\Psi(\widetilde{x} \mid x)$. Since $\widetilde{x}$ is higher under $a = 6$, this raises $\Psi(\widetilde{x} \mid x)$,[19] implying that a match of given x quality is now more prone to separation.

Table 4 demonstrates that our results concur with findings in the data showing that short tenure employment relationships have observed the sharpest decline.[20] Importantly, recent work by Molloy, Smith, and Wozniak (2020) suggest that the median tenure has remained relatively unchanged over time, despite the severe decline in jobs with short tenure length. This empirical finding is inconsistent with the predictions of a 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 and an increase in all tenure lengths, and as such a rise in median tenure. In contrast, our model would not only suggest a sharp decline in jobs of very short tenure length as fewer firms form low quality matches with high separation rates, but also that jobs of high match quality now observe larger separation rates and lower tenure lengths stemming from the increase in reservation match quality. As such, the tenure of the median worker in our model rises by 0.07 percent moving from $a = 3$ to $a = 6$.

[19] 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.

[20] See Molloy, Smith, and Wozniak (2020), Hyatt and Spletzer (2016), Pries and Rogerson (2019) for further evidence on the decline in short tenure jobs.

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 $[G(x_2)_{a=3} - G(x_1)_{a=3}] - [G(x_2)_{a=6} - G(x_1)_{a=6}]$.

Taking stock In sum, the model is capable of generating accounting for one third of the empirical decline in inflow rates. The decline in our model-predicted inflow rates stems from the sharp drop in the formation of low quality and high turnover jobs. Nonetheless, median tenures remain relatively unchanged in our model as in the data. These results reflect the fact there exists two opposing forces on separation rates: the effects from improved firm selection and the effects from increased worker selectivity. The former dominates the latter and gives rise to the aggregate decline in unemployment inflow rates.

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 outflow rates in the data are 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, outflow rates had returned back to their long-run average of 0.41. As such, we view the modest changes in outflow rates predicted by our model to be largely successful in generating the absence of long-run changes in empirical outflow rates.

Why does our model predict relatively small changes in the unemployment outflow rate? Recall from Section 3.9 that the manner by which outflow rates vary with applications depends on whether the direct effect of a higher number of applications outweighs its indirect effects on offer and acceptance probabilities. Specifically, we decompose the percent change in the outflow

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

Panel A: Outflow rate components

	$a = 3$		$a = 6$		Log difference	
	Model	Data	Model	Data	Model	Data
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

Panel B: 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

Note: This table summarizes the average application outcomes when the number of worker applications a increases from 3 to 6. Data moments are obtained as averages from the EOPP for the period 1979-1980 and from the SCE for the period 2013-2017, where the former period corresponds to the period with the lower average number of worker applications $a = 3$ and the latter period corresponds to the period with the higher average number of worker applications $a = 6$. Reservation wages in the data are average hourly reservation wages in 1982-1984 dollars. The log difference is multiplied by 100. Data on the share of jobs that last < 1 quarter is taken from Pries and Rogerson (2019). Data on the share employed in jobs lasting $1 \leq t < 3$ years and median tenure are taken from Molloy, Smith, and Wozniak (2020)

rate between two time periods t_1 and t_2 as:

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

Table 3 shows that the indirect effects stemming from endogenous changes in household 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 outflow rates to be slightly lower.

Further unpacking the change in outflow rates The model's ability to reproduce observed trends in unemployment outflows originates from its predicted declines in both job offer and acceptance rates. Table 4 compares the changes in job 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 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. 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 unemployment outflows is the acceptance rate. Table 4 shows how changes in our model-implied acceptance rates compare to the data. We calculate the model's average acceptance rate as the expected probability of accepting an offer for a particular application, $\int_{\widetilde{x}}^{\overline{x}} \Gamma(x)\,\pi(x)\,dx$. In our model, a higher number of applications results in workers becoming more selective over the minimum job they are willing to accept – as depicted by the increase in $\widetilde{x}$. Besides this, workers also experience a higher probability that at least one of their applications draws a higher match quality. As foreshadowed in Section 3.9, the increased probability of drawing a higher match quality from another application leads 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. Despite the fact that we do not target moments in the second time period, our model's predicted outcomes on offer probabilities and acceptance rates largely mimic the patterns observed in the data.

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, our model-implied reservation wages rise by 8 percent, implying that the rise in selectivity only contributes to part of the decline in acceptance rates.[21] If we were to instead conduct the following comparative static exercise, where we hold fixed reservation match quality at its level when $a = 3$ and keep all other equilibrium objects at their $a = 6$ levels, we find that acceptance rates would have still fallen 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 Overall, our model explains why a rise in applications need not lead to a trend increase or decline in unemployment outflow rates. Consistent with the data, the declines in the offer and acceptance probabilities mitigate the direct benefits of increased applications, causing little change in outflow rates.

5.3 The role of costly information

We now consider two thought experiments to uncover how information acquisition interacts with an increase in applications to affect labor market flows. In the first experiment, we set $\kappa_I = 0$, and label this the "Full Information" (FI) model.[22] In the second experiment, we consider

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

[22] 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
Outflow rate (2019)					0	-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, average labor market flows, and worker application outcomes when the number of applications a increases from 3 to 6. Model refers to the baseline scenario in which there is a fixed cost κ_I of acquiring information on the applicants' match quality for firms. FI is the "Full information" model in which $\kappa_I = 0$, and NI is the "No information" model in which $\kappa_I \to \infty$. Data moments on labor market flows are obtained as averages from the CPS, and data moments on application outcomes are obtained as averages from the EOPP for the period 1979-1980 and from the SCE for the period 2013-2017, where the former time period corresponds to the period with lower average number of applications $a = 3$ and the latter time period corresponds to the period with higher average number of applications $a = 6$. The log difference is multiplied by 100.

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 targets as our baseline model.[23] Throughout, we compare the results of the FI and NI model against our baseline model where only applications a increased. In both of these models, the firm's investment in information acquisition does not vary with the number of applications. Hence, these experiments allow us to demonstrate how ignoring changes in the firm's information decision in response to more applications would affect predictions of our model.

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 change when the number of applications increase 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 economies.

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 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

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

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 extend offers to randomly selected candidates from their applicant pool. Thus, the increased probability of drawing a high match quality does not translate into more offers since firms cannot identify good matches. Although labor market tightness improves in the NI model, the percentage increase in a outweighs the percentage increase in θ. Consequently, the rise in a serves to only increase congestion amongst workers, leading to a worsening in 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 outflow rates and smaller declines in the inflow rate relative to the baseline model.

Focusing first on the FI model, the unemployment inflow rate falls by a small 6 percent while the outflow rate rises by 12 percent, opposite to the large decline in inflow rates and lack of change in outflow rates 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, while the greater formation of high quality matches results in the incidence of match quality shocks falling by 4 percent, 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 in the latter is precisely the outcome of an enlarged outside option for workers. Since $\widetilde{x}$ is much 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, leading to a smaller decline in the inflow rate upon a rise in applications. Notably, average match quality improves by about 5 percent when a doubles, but reservation match quality rises by more than twice that amount. Consequently, inflow rates in the FI model decline by a mere 6 percent. In part, this is due to the fact that in the FI model, firms were always able to identify the best worker and make offers to the best applicant in their pool. As such, the effects from improved firm selection are more modest 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 first 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 have a higher likelihood of at least one of their applications drawing a high match quality, this also implies that they have a higher likelihood of receiving an offer. As a result, the unemployment outflow rate increases in the FI model, because workers are more likely to draw high x in at least one of their applications when a increases and FI firms can always identify and make offers to applicants who are high quality matches.

Switching now to the NI model, the inflow rate declines by 10 percent while the outflow rate declines by 28 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 are less selective and willing to accept a lower minimum quality value, they are less likely to separate into unemployment conditional on a match quality shock. The frequency of match quality shocks in the NI model changes by less than a 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 unemployment inflow rates as average match quality in the NI model barely improves when firms cannot identify high quality matches.

Finally, to understand why outflow rates decline 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 receive a lower probability of receiving an offer. Consequently, unemployment outflow rates decline.

Overall, our results highlight that the interaction between a firm's information acquisition decision and the number of applications is important for capturing the joint behavior in inflows and outflows. Unlike the two models where the share of informed firms remains constant in the number of applications, our results suggest that allowing for an endogenously changing share of informed firms is a necessary ingredient for replicating the trends in unemployment flows.

6 Discussion

6.1 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 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.[24] Given the prevalence

[24]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.

in the 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 limit how much the benefits of information can increase with the number of applicants at a vacancy. Consider an economy where firms pay a cost κ_I for *each* applicant it screens. Denote $\widehat{j}$ 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.2 provides greater detail on such a setup.

Holding all else constant, an increase in applications would still raise the average number of applicants per vacancy in this environment. So long as the mean applicants per vacancy is not far above $\widehat{j}$ in the initial steady state, the increase in applications would still raise the share of informed firms in the economy and improve the distribution of realized match quality, contributing towards a lower unemployment inflow rate. As shown in Table A8, we find that inflow rates fall by 8 percent in this environment while outflow rates continue to remain unchanged. In part, the lower outflow rates can be explained by the fact that there is now an upper bound on the benefits of information. When $a = 6$, the average number of applicants exceeds $\widehat{j}$. As such firms acquire information only on a sub-set of their applicants and inflow rates decline by less.

6.2 Variable and endogenous number of applications

In the baseline model, we assume that the number of applications is exogenously determined. An alternative framework would 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.3 provides a more comprehensive discussion of this extension. Numerically, our results remain relatively unchanged when we extend the model to allow for variable applications. Table A9 shows that raising the Poisson parameter from 3 to 6 still results in an 18 percent decline in unemployment inflows but only triggers a 3 percent reduction in unemployment outflows.

6.3 Wage protocols

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

7 Conclusion

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

Quantitatively, our model predicts a small change in the unemployment outflow rate whilst accounting for about one third of the empirical decline in the inflow rate. Our model also contains several testable implications for the change in application outcomes. Overall, we find that changes in our model-predicted number of job offers, acceptance rates, reservation wages and tenure distribution in response to a rise in applications largely mimic patterns in their data counterparts. Notably, these application outcomes are themselves factors which have a first-order effect on inflow and outflow rates. As such, our model sheds light on how the different components add up to keep outflow rates unchanged and provides insight on the forces that drive the decline in inflow rates.

Finally, we show that the endogenous response in the firm's information acquisition decision to an increase in applications is critical for replicating the observed empirical patterns. When the firm's investment in information is unvarying, either because information is free or infinitely costly, these alternative models fail to generate the observed trends in labor market flows.

Our model can be extended in several dimensions. First, the number of applications that unemployed individuals submit can vary over the business cycle. This, together with the fact that applications have increased over time could have implications for firms' hiring behavior and the emergence of slow labor market recoveries following economic downturns. Second, incorporating ex-ante worker and firm heterogeneity into our model would be useful to understand why some firms receive relatively more applications and how this affects labor market power and earnings inequality over time. Finally, our model can be extended to include on-the-job search. Notably, job-to-job transitions have also declined over the same time period. In addition, incorporating on-the-job search in our model would likely further heighten the firm's incentive to acquire information as higher quality workers are less likely to search for an alternative job. Our model suggests that as more firms choose to acquire information in response to the rise in applications, more high quality matches would be formed. Job-to-job separations would then decline as workers are already employed in good matches. We leave these considerations for future research.

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Appendix

A Data

In this data appendix, we discuss more details on 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 to find a job in the private sector during an intensive job search assistance program. Individuals had to be unemployed and meet income eligibility requirements to be able to participate in this program. The survey was created to analyze the effects of the program on the labor market outcomes of the participants. As a result, by design, the survey oversampled low-income families, but this did not greatly weaken moments pertaining to the aggregate economy, as 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. The individual-level dataset, which is the dataset we use, contains main record, training, job, unemployment insurance (UI), looking for work, disability, and activity spell modules. These modules provide data on demographics, earnings and hours information for each job held, unemployment spells and durations, job search activities and methods during each unemployment spell, UI receipt, and reservation wages.

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

[25] 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.

[26] 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.

spell. We use this information to measure the reservation wage of the individual. We separately report all of these moments across education groups.[27]

A.2 SCE

The SCE Labor Market Survey was developed by the Federal Reserve Bank of New York.[28] The data provide the respondent's demographics, job information if employed (i.e., earnings, hours, industry, employer size, etc), job search activities, and reservation wages.

We use the annual survey between 2013-2017. Because of the small sample size relative to the EOPP data, we pool the SCE observations across these years, as in Faberman, Mueller, Şahin, and Topa (2020). For the SCE, as for the EOPP, we study a sample of unemployed individuals aged 25-65 who are not self-employed and who submitted at least one job application during each unemployment spell. This includes individuals who are unemployed at the time of the survey and employed individuals who had an unemployment spell previously and started their new job less than four months prior to the time of the survey. For both of these groups, we analyze their job search activities during each unemployment spell. For currently unemployed individuals, the survey provides the total number of job applications during the past four weeks, the total number of job offers received during the past four weeks; and, if no job offers were received in the past four weeks, the total number of job offers received in the last six months, where we use the unemployment spell duration information to convert the latter to the average monthly number of job offers received. Moreover, the survey also provides information on whether the individual accepted or will accept a job offer. For currently employed individuals with a previous unemployment spell, the survey also provides the total number of job applications and the total number of job offers received during the unemployment spell. Again, we use information on the duration of the unemployment spell to convert these numbers to the average monthly number of job applications and job offers received. For these individuals, given that they are currently employed after an unemployment spell, we infer that they accepted a job offer. Then, using information about the offers and offer acceptance decisions for all individuals in the sample, we calculate the fraction of individuals accepting job offers the same as for the EOPP. Moreover, the SCE also asks the lowest wage the individual would accept, which we use to measure the reservation wage. We separately report all of these moments across education groups.[29]

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

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

[29] For currently unemployed individuals, variables JS14, JS19, JS19b, JS23, and L7 give the total number of

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 the SCE samples to the CPS samples over time. This is important, as the comparison reveals that the EOPP and the SCE samples mostly capture the changes in educational attainment, marital status, labor force participation of females, the age decomposition of the labor force, as well as earnings and hours over time.[30]

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

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

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

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

	EOPP 1980	CPS 1980	SCE 2015	CPS 2015
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.

Next, Table A2 compares labor market moments from samples across these three datasets. Importantly, when compared to the CPS 1980 and the CPS 2015 samples, the EOPP 1980 and the SCE 2015 samples generate the rise in the labor force share of females over time, although the magnitude of the increase is larger between the EOPP and the SCE samples than between the CPS samples. The remaining labor markets moments in relation to employment, weekly hours, and annual earnings are mostly comparable between the EOPP and the SCE and the CPS samples, with the exception that the share of employed females is overstated in the EOPP sample relative to that in 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 some aggregate labor market differences between the 1979-1980 period and the 2013-2017 period, which may have some effect on this conclusion. For example, unemployed individuals may send more applications during an expansion than during a recession. In order to ensure that this change is not driven by cyclical changes in the labor market, we now control for aggregate moments to eliminate these business cycle effects. In particular, we use the EOPP and the SCE samples to estimate the following regression equation:

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

where i indexes individuals with at least one job application during an unemployment spell, t indexes years, y is the number of monthly job applications, X is a vector of demographic

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.

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 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 during a month of unemployment spell between the EOPP (1979-1980) and the SCE (2013-2017). Here, we now 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 Application outcomes: Demographic groups

In Section 2.3, we show that the offer arrival and offer acceptance rates decreased and that the real hourly reservation wages increased over time. We now measure changes in the offer arrival and acceptance rates as well as real hourly reservation wages over time across various demographic groups using the EOPP and SCE samples. Table A5 summarizes results.

We highlight several results. First, fractions of individuals with positive offers during a month of unemployment spell are quite close to each other in the EOPP. Second, all groups experienced a decline in the fraction with positive offers over time except non-college and old individuals. Third, job acceptance rates across subpopulations are also very close to each other in the EOPP

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	0.73	0.80
College	4.98	2.46	11.73	6.00	0.86	0.89
Non-college	7.36	2.82	15.11	7.00	0.72	0.91
Male	7.44	2.50	12.88	6.00	0.55	0.88
Female	6.13	2.86	15.11	6.00	0.90	0.74
Young	7.24	2.86	14.39	9.00	0.69	1.15
Old	4.27	1.67	13.94	6.00	1.18	1.28

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), old individuals (age 46 and above) using data from the EOPP 1979-1980 and SCE 2013-2017.

and that all groups experienced a similar decline in their job acceptance rates over time. Finally, real hourly reservation wages increased across groups with the exception that the reservation wage growth of non-college workers is negligible over time.

A.7 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).[31] Let U_t, U_t^S, and L_t be the number of unemployed individuals, the number of short-term unemployed individuals, and the number of individuals in the labor force at time t, respectively. Also, let s_t and f_t denote the unemployment inflow (job separation) rate and unemployment outflow (job-finding) rate at time t, respectively. Then, we can define the change in the number of unemployed individuals between time t and $t+1$ as follows:

$$dU/dt = -f_t U_t + s_t \left(L_t - U_t\right). \tag{17}$$

Moreover, we can write

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

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

Table A5: Application outcomes over time across demographic groups

	Fraction > 0 offer		
	EOPP	SCE	Log difference
All	0.62	0.55	-0.12
College	0.74	0.43	-0.53
Non-college	0.58	0.60	0.03
Male	0.62	0.53	-0.15
Female	0.61	0.56	-0.08
Young	0.63	0.55	-0.13
Old	0.55	0.55	-0.002

	Acceptance rate		
	EOPP	SCE	Log difference
All	0.80	0.43	-0.61
College	0.81	0.51	-0.45
Non-college	0.79	0.41	-0.67
Male	0.80	0.40	-0.68
Female	0.79	0.45	-0.56
Young	0.81	0.44	-0.60
Old	0.72	0.43	-0.53

	Reservation wage		
	EOPP	SCE	Log difference
All	5.83	6.94	0.17
College	7.27	9.75	0.29
Non-college	5.59	5.72	0.02
Male	7.22	7.70	0.06
Female	4.71	6.28	0.29
Young	5.77	6.75	0.16
Old	6.14	7.04	0.14

Note: This table summarizes the fraction of unemployed individuals with positive job offer, offer acceptance rate, and reservation wage for all individuals, individuals with a college degree, individuals without a college degree, males, females, young individuals (age 25-45), old individuals (age 46 and above) using data from the EOPP 1979-1980 and SCE 2013-2017.

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

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

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

Next, we solve the differential Equation (17) 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 and labor force as well as the unemployment outflow rate f_t. Following these steps, we plot outflow probability F_t and inflow probability S_t in Figure 2 in Section 2.[32]

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, respectively; $k_a \in \{y, p, o\}$ denote age where y, p, o stands in for young workers (age 16-24), prime age workers (age 25-54), and old workers (age 55 and above), respectively; $k_x \in \{nc, c\}$ denote education where nc and c indicate workers without a college degree and with a college degree, respectively; and $k_i \in \{mf, nmf\}$ denote industry where mf and nmf mean workers in manufacturing and non-manufacturing industries, respectively. Further, let $\omega_{k_l,t}^l$ to be the share of subgroup k_l at time t in each group $l \in \{g, a, x, i\}$ such that $\sum_k \omega_{k,t}^l = 1 \ \forall l, t$. Finally, let S_{t_1} and S_{t_2} denote the aggregate inflow probability at t_1 and t_2, respectively; $S_{k_x,k_g,k_a,k_i,t}$ and $\Delta S_{k_x,k_g,k_a,k_i}$ represent the inflow probability of workers in subgroup k_x, 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 the in aggregate inflow probability over the two

[32] We use 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 A6: Shift share decomposition exercise

Fraction of change accounted by	Inflows	Outflows
Within-group change	70.7	89.8
Between-group: education composition change	11.1	0.5
Between-group: gender composition change	-0.1	0.1
Between-group: age composition change	17.1	12.2
Between-group: industry composition change	1.2	-2.6

Note: This table summarizes the results of the shift-share analysis for the change in the aggregate inflow and outflow probabilities between 1976-85 and 2010-2019 periods. We report the fraction of the total change explained by i) within-group change (i.e., change in group specific inflow and outflow probabilities); ii) between-group education composition change (i.e., change in the share of workers across education groups); iii) between-group gender composition change (i.e., change in the share of workers across gender groups); iv) between-group age composition change (i.e., change in the share of workers across age groups); and v) between-group industry composition change (i.e., change in the share of workers across industry groups). Fractions reported are in percents.

time periods as

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

where the first line represents within-group measure, the second line represents between-group measure accounting for the change in the education composition, the third line represents between-group measure accounting for the change in the gender composition, the fourth line represents between-group measure accounting for the change in the age composition, and the fifth line represents between-group measure accounting for the change in the industry composition of employment. Here, the within-group measure holds the weights constant and measures how much of the total change in the aggregate inflow probability can be attributed to the changes in the 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. Similarly, we can also write the same equation for the change aggregate outflow probability between t_1 and t_2 as well.

Table A6 summarizes the results of this shift-share analysis for the inflow and outflow probabilities. We find that around 70 percent of the total decline in aggregate inflows is due to within-group changes, implying that declines in group specific inflow probabilities account for more than two-thirds of the total decline in aggregate inflow probability. The remaining 30 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 compositions only had a negligible impact on the aggregate inflow probability. Similarly, Table A6 also shows that around 90 percent of the trend behavior in aggregate outflows is accounted by within-group trends. In particular, unemployment outflow probabilities of workers in various education, gender, age, and industry groups also have not exhibited any long-run trend as in the aggregate outflow probability. 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.

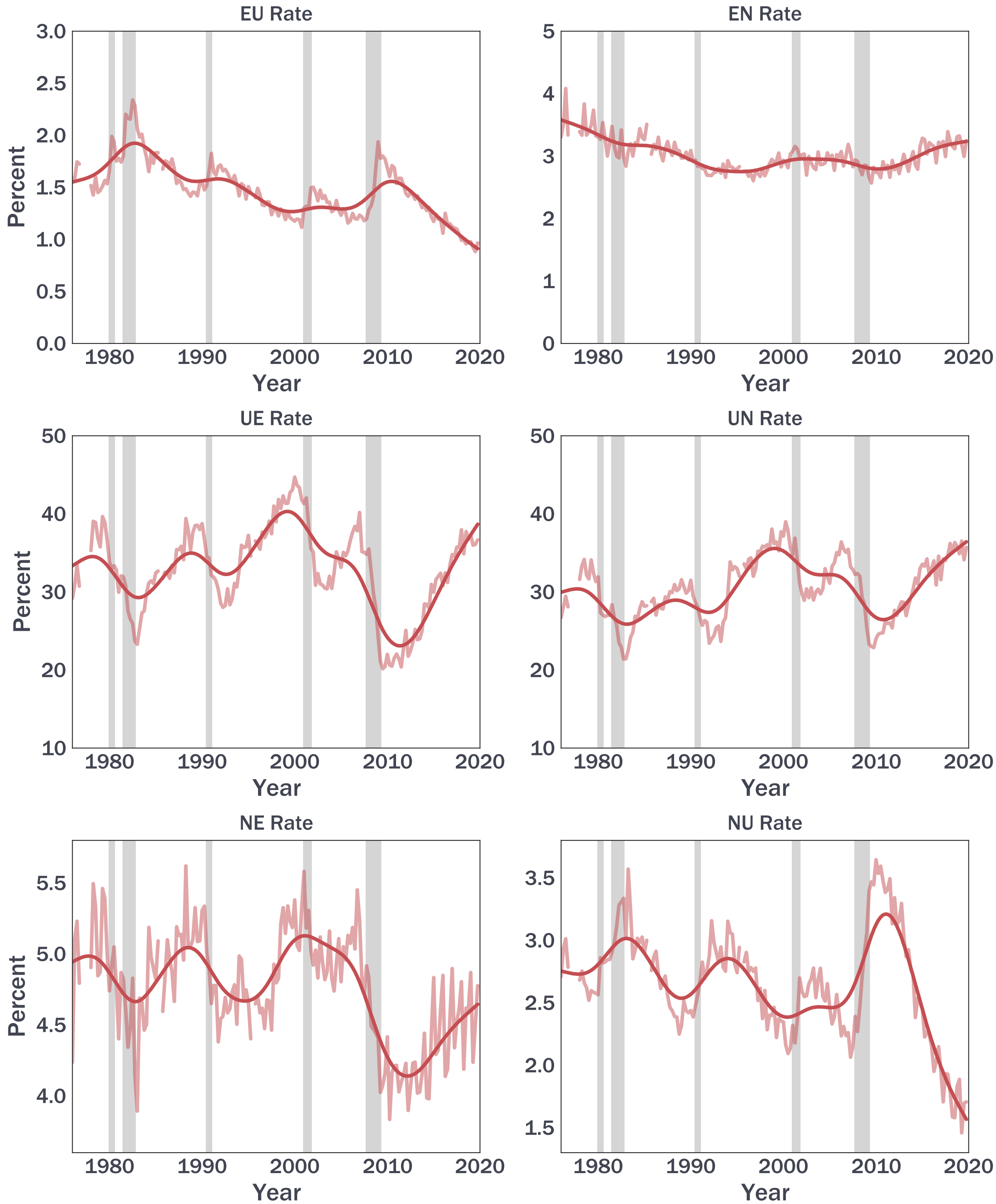
Calculating inflow and outflow rates from CPS panels The CPS measure of short-term unemployed workers is underestimated given that some workers who enter unemployment exit unemployment within the same month. However, the methodology outlined above accounts for this bias, which is referred to as time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

We now calculate monthly transition rates following individuals in CPS panels. The results are summarized in Figure A1. It shows that the inflow (EU) rate exhibit 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 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 now also account for the real wage growth. That is, we calculate the ratio of hourly reservation wages of unemployed to mean hourly wage of employed in 1979-1980 and 2013-2017 periods. To do so, we use the CPS data to calculate the mean hourly real wage for 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 with the mean hourly real wage.

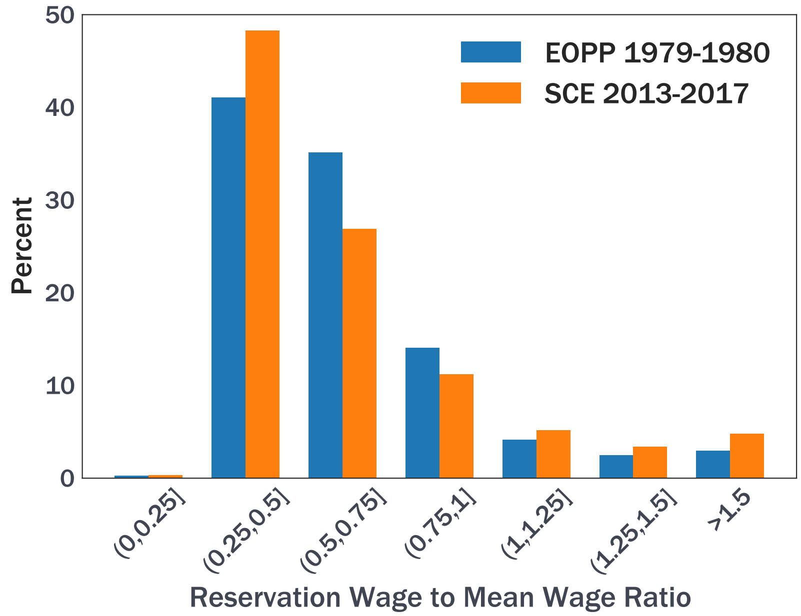
Figure A2 plots the resulting distribution of reservation wage to mean wage ratio over time. It shows that the distribution of reservation wage to mean wage ratio has become more unequal over time. In particular, both the fraction of unemployed workers whose reservation wage is less than half of the 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 changed less than 5 percent over time.

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.

B Model

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

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

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

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

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

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

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

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 constant fixed cost of acquiring information κ_I is finite and that $V^I(j)$ is increasing in j, it is then straightforward to show that the net value of acquiring information must cut the value of not acquiring information once from below at j^*.

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

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

C Extensions

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 A7 summarizes the calibration outcomes of the FI and NI models.

Table A7: 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 levels and 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.

C.2 Marginal cost of information

We now elaborate on our discussion for the model with a marginal cost of information acquisition in Section 6.1. 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

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

and

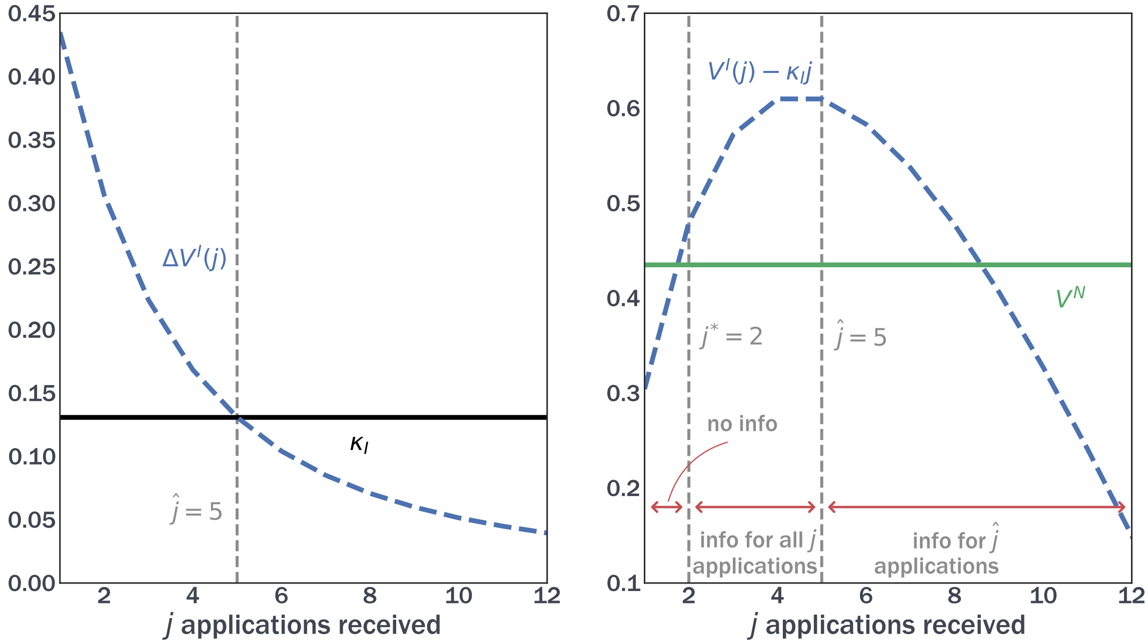
$$V^{I}(n) = \int_{\widetilde{x}}^{\overline{x}} V^{F}(x)\,\Gamma(x)\,d\left[\Pi(x)\right]^{n}$$

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

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.

information is greater than or equals to the additional cost from acquiring information: i.e.

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

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 optimally only acquires information on a subset $\widehat{j} < j$ of its applicants.

Thus, the solution to the firm's problem in this environment 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

$\overline{V}^I(j) > V^{NI}$. 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 $j^* \leq \widehat{j} < j$.

While Figure A3 illustrates the outcomes from a toy model, we re-calibrate the model under a marginal cost to examine how outcomes would change. Table A8 shows our results. Overall, we find that inflow rates still fall with a rise in applications but to a lesser degree since the benefits of information are limited once firms choose to only acquire information on a sub-set of applicants.

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

	Impact on unemployment flows					
	Baseline		Marginal cost		Log difference	
	$a = 3$	$a = 6$	$a = 3$	$a = 6$	Model	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	-0
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.

C.3 Variable or endogenous number of applications

We provide further details about extending the model to incorporate variable and endogenous applications as discussed in Section 6.2.

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 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 $\Gamma(x)$ which is 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 they 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 $x \leq \tilde{x}$. This is identical to Equation 5 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 identical to 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:

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

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

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

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

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 given by:

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

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 xi (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.

Table A9 shows the effect of raising the mean number of applications xi from 3 to 6 when we allow for variable applications. Similar to the baseline model, we observe a large decline in unemployment inflows but a substantially smaller change in unemployment outflows.[33]

Table A9: Impact on labor market flows: baseline vs. variable applications

	Impact on unemployment flows					
	Baseline		Variable a		Log difference	
	$a = 3$	$a = 6$	$a = 3$	$a = 6$	Model	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 $\sum_{a=1}^{\infty} p(a) a \int_{\underline{x}}^{\overline{x}} \phi(x, a) \pi(x) dx$. The log difference is multiplied by 100.

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