BANK OF CANADA
BANQUE DU CANADA

Staff Working Paper/Document de travail du personnel — 2021-49

Last updated: October 12, 2021

Job Applications and Labour Market Flows

by Serdar Birinci,[1] Kurt See,[2] Shu Lin Wee[2]

[1]Federal Reserve Bank of St. Louis
St. Louis, Missouri, United States of America 63102

[2]Canadian Economic Analysis Department
Bank of Canada, Ottawa, Ontario, Canada K1A 0G9

serdar.birinci@stls.frb.org, KGSee@bank-banque-canada.ca,
ShuLinWee@bank-banque-canada.ca

ISSN 1701-9397

Acknowledgements

We would like to thank Sushant Acharya, Ross Doppelt, Niklas Engbom, Jonathan Heathcote, Kyle Herkenhoff, Greg Kaplan, Fatih Karahan, Philipp Kircher, Moritz Kuhn, Jeremy Lise, Guido Menzio, Giuseppe Moscarini, Christian Moser, Ludo Visschers, Ronald Wolthoff, and participants at the Annual Meeting of the Canadian Economics Association, Bank of Canada, Barcelona GSE Summer Forum, Copenhagen Search and Matching, Federal Reserve Bank of Cleveland Search and Matching Workshop, Federal Reserve Bank of Minneapolis, Federal Reserve Bank of St. Louis, NBER Summer Institute 2021 (Macro Perspectives), Ohio State University, the Universities of Bonn and Mannheim Workshop on Labor Markets, the University of Melbourne, and Western University for their useful comments and suggestions. We thank Aaron Amburgey for his excellent research assistance and Glenna Jenkins for her excellent editorial assistance. This research was supported in part through computational resources provided by the BigTex High Performance Computing Group at the Federal Reserve Bank of Dallas.

Abstract

Job applications have risen over time, yet job-finding rates have remained unchanged. Meanwhile, job separations have declined. We argue that an increase in the number of applications raises 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, we show that when applications increase, firms invest in identifying good matches, thereby reducing separations. Concurrently, increased congestion and selectivity over which offer to accept temper increases in job-finding rates. Our framework contains testable implications for changes in offers, acceptances, reservation wages, applicants per vacancy, and tenure, factors that enable us to generate the trends in unemployment flows.

Topics: Labour markets, Productivity

JEL codes: E24, J63, J64

1 Introduction

Improvements in search technology have led to an increase in the number of job applications over time. Despite a large increase in the number of applications, the unemployment outflow (job-finding) rate in the U.S. has not observed any long-run change. Conversely, the unemployment inflow (job-separation) rate has undergone a steady decline since the 1980s. Given that unemployment flows are inextricably tied to job-search behavior, a natural question arises as to why an increase in the number of applications has not led to any sustained increase in the outflow rate. We argue that the main benefit of increased applications has not been to increase the probability of finding a job but rather the probability of finding a good match, as evidenced by the decline in the separation rate.

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

In our model, workers submit multiple applications to separate job vacancies and costlessly observe the match quality drawn for each application. Match quality evolves over time but is persistent as future draws are correlated with current values and high-productivity matches are less susceptible to match-quality shocks. Employment relationships endogenously dissolve if match quality falls below a reservation threshold. Firms can receive more than one application. Unlike workers, firms can only observe the match quality of their applicants at the time of meeting if they pay a fixed cost of acquiring information. Firms' incentives to acquire information increase with the number of applications, as a higher number of applicants per vacancy increases the probability that a firm has at least one high-productivity candidate. Firms, however, can only exploit this benefit if they acquire information and are able to rank applicants. Because wages are increasing in match quality, acquiring information also confers an additional benefit to firms. In particular, firms minimize their rejection probabilities whenever they extend offers to their highest-quality applicants.

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

In our calibrated model, the inflow rate declines by 20 percent when applications increase, or about one-third of the decline observed in the data.[1] Why does the model predict that an increase in applications leads to a decline in the inflow rate? In the model, an increase in the number of 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, increases the share of informed firms. A higher number of informed firms leads to a greater formation of high-productivity matches that–because of the persistence in match quality–are less susceptible to job destruction, thereby reducing inflows. On the other hand, the ability to contact more vacancies elevates workers' outside options. This raises workers' selectivity, leading to higher reservation match quality and more job destruction. Quantitatively, the effects from an improved distribution of realized match quality dominate the rise in worker selectivity. As such, the inflow rate declines with the rise in applications.

In the model, the decline in the inflow rate is largely driven by a sharp fall in the share of individuals employed in low-quality, high-turnover jobs, consistent with the observed patterns in the data. When more firms acquire information in response to an increase in applications, fewer low-quality matches are formed. Consequently, the share of short duration jobs declines. At

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

the same time, our model replicates the empirical finding that the median tenure has remained unchanged despite the decline in the number of short duration jobs. Because each high-quality match now observes a marginally higher separation probability due to increased worker selectivity, the median tenure remains unchanged despite the lower concentration of short duration jobs.

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

Finally, we demonstrate why endogenizing the firm's information acquisition problem is necessary toward understanding how an increase in applications affects trends in unemployment flows. To do so, we consider two thought experiments: a case where information about a firm's applicants is free (full information) and a case where information is infinitely costly (no information). We find that both models predict changes in unemployment flows that are inconsistent with the data. Intuitively, the effective cost of job creation is invariant to the number of applications in either of these models as information is either free or firms never choose to pay for

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

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

Related literature Our paper is not the first to consider a labor search model with multiple applications. Earlier papers in the literature by Albrecht et al. (2006), Kircher (2009), Galenianos and Kircher (2009), Gautier et al. (2016) and Albrecht et al. (2020) focus on the efficiency properties of such models. Gautier et al. (2018) use Danish data and show how an increase in the number of applications can lead to negative congestion effects. Separately, Gautier and Wolthoff (2009) consider a model where workers send, at most, two applications, and focus on ex-ante heterogeneity on the firm side. In contrast, we incorporate heterogeneity among workers, creating a role for information acquisition in firms' hiring decisions. Bradley (2020) features a similar setup where firms pay a cost to reveal information about their applicants. Although Bradley (2020) allows firms to receive multiple applications, workers can only send one application. Because our question concerns how rising numbers of applications can affect labor market flows, we allow for multiple applications on *both* sides of the market. Closely related to our work is the seminal paper by Wolthoff (2018), who uses a directed search model with multiple applications to study the business-cycle properties of firms' recruiting decisions. Our paper instead focuses on long-run trends in the labor market. To our knowledge, this is the first paper to link a rise in applications to long-run trends in unemployment flows.

Our work also contributes to the literature that studies secular changes in labor market flows. Crump et al. (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 et al. (2020) report evidence of a decline in separation rates and changes in the tenure distribution. Despite a sharp decline in the share of short-duration jobs, Molloy et al. (2020) report that median tenure remains unchanged. Our paper shows how increased applications can replicate these findings.

On the theoretical side, Engbom (2019) extends the labor search model to incorporate rich firm dynamics and entrepreneurial choice and shows how an aging workforce contributes to the decline in worker dynamics over time. We focus on how changes in application behavior affect labor market flows through their effects on household search behavior and firms' 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 that have occurred since the early 1980s. In our paper, an improvement in information via a higher share of informed firms also affects labor market flows. However, the increase in the share of informed firms in our model is an *endogenous* response to rising applications. Separately, Martellini and Menzio (2020) study an economy with search frictions along a balanced growth path and show how *both* inflow and outflow rates can remain unchanged since the 1950s even if search technology improves. While our starting point is that improvements in job-search technology have led to increases in job applications, our paper's focus is on explaining how this increase since the 1980s enabled workers to find better matches and observe fewer job separations, without triggering a simultaneous increase in their job-finding probabilities. By focusing on the effects of increased job applications, our model also has testable implications for the changes in application outcomes, such as offer probabilities, acceptance rates, reservation wages, tenure, and the number of applicants per vacancy–factors that 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 vacant positions. Gavazza et al. (2018) show that the decline in recruiting intensity during recessions is due to equilibrium effects where increased slack in the labor market allows firms to exert less effort to fill positions. 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, increasing the potential for large losses from hiring unsuitable workers. While we do not focus on the business cycle, our paper provides a micro-foundation to firms' recruiting intensities as the higher number of applicants per vacancies affects the share of firms investing in information and, thus, the rate at which firms fill positions.

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

2 Empirical Findings

In this section, we discuss our empirical findings that motivate the model and quantitative exercises. In Section 2.1, we provide evidence on how the number of applications has changed over time. Next, in Section 2.2, we outline the trends in unemployment flows. Finally, in Section 2.3, we document how application outcomes have changed over time.

2.1 Job applications

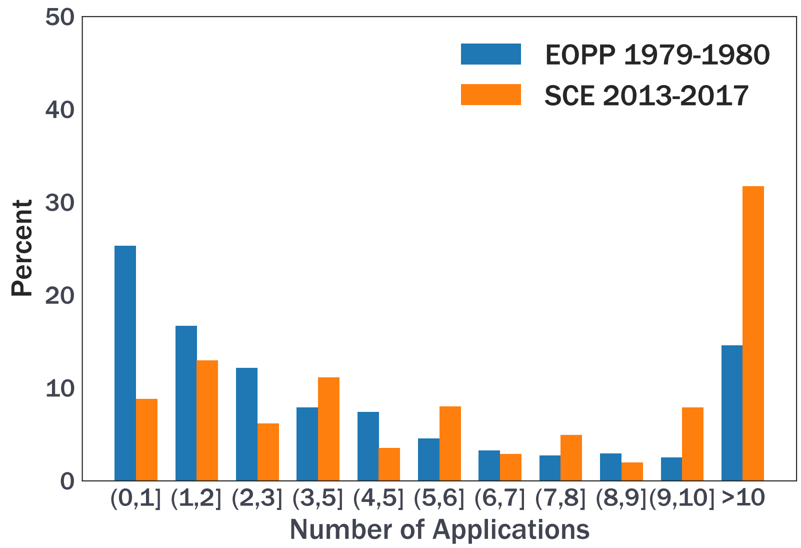
Using information from the EOPP and the SCE Labor Market Survey, we provide novel evidence on how the application behavior of unemployed workers has evolved over time. A unique feature of these datasets is that they offer insights into job search behavior and, unlike other household surveys, provide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

The EOPP was designed to analyze the impacts of an intensive job search and a work-and-training program. This household survey took place between February and December 1980, and covers unemployment spells and job search activities of unemployed workers, from 1979 to 1980. Around 80 percent of the survey interviews occurred between May and September, 1980, 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 2013-2017. Both datasets provide individual-level information on demographics, employment, wages, and regular working hours. Appendix A provides a list of the variables we use and explains how we calculate moments using these variables. To evaluate the comparability of these datasets with more widely used surveys, Tables A1 and A2 in Appendix A compare the EOPP and SCE samples to the CPS over the same time period. Overall, samples from the EOPP for 1979 to 1980 and the SCE for 2013 to 2017 capture well the demographic changes observed in the CPS between the two time periods.

In both datasets, we consider a sample of unemployed individuals aged 25 to 65 who sent at least one job application during their unemployment spell.[3] Figure 1 highlights how the distribution of applications submitted per month by the unemployed has shifted rightward over time. Between the two surveys, the median number of applications per month increased from 2.7 to 6, implying that the median number of applications more than doubled between the periods 1979-1980 and 2013-2017. To ascertain whether the increase in the number 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 has been a common pattern across various

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

Figure 1: Change in number of job applications over time



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

demographic groups. Overall, our findings imply that the number of applications has increased over the past four decades.

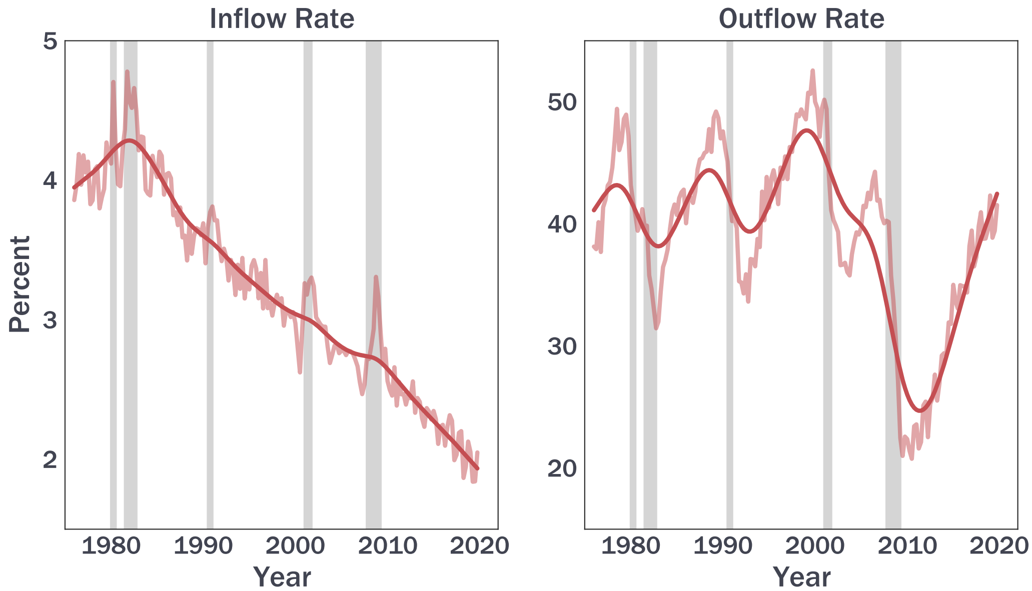
2.2 Labor market flow rates

Turning now to unemployment flows, we use monthly data from the CPS on the total employed, unemployed, and short-term unemployed; i.e., respondents who are unemployed for at most five weeks, and calculate the outflow and inflow rates over time, using standard procedures found in the literature. Appendix A provides details on our data and methodology.[4] Echoing previous studies, Figure 2 shows that the outflow rate has exhibited almost no secular change since the 1980s, while the inflow rate has fallen by 58 percent, from 4.1 to 2.3 percent.

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

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

Figure 2: Unemployment outflow and inflow rates



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

of a trend remains true even after controlling for compositional changes. Overall, we find that changes in demographics explain very little of the trends observed in unemployment flows.

2.3 Offer arrival and acceptance rates and reservation wages

Flows out of unemployment are inextricably tied to job search behavior. As our goal is to understand why a rise in applications has not led to a trend increase in unemployment outflow rates, we use the EOPP and SCE data to shed further light on how application outcomes, such as offer probabilities, acceptance rates, and reservation wages, have changed since the 1980s. Intuitively, an increase in applications allows workers to contact more vacancies. Higher competition among workers, however, can lower the probability of receiving an offer. Increased applications can also affect workers' acceptance decisions and reservation wages. Since these factors affect job-finding rates, we document how these variables have changed over time. In Section 5.1, we show how these findings serve as testable implications for our model.

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

We highlight several results. Between the two time periods, unemployed workers observed a decline in the number of offers received during a month of unemployment. The fraction of individuals with no offers increased from 38 percent to 45 percent. Among those who received

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

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

more than one offer during a month of unemployment, the fraction of individuals who accepted an offer decreased from 84 percent to 35 percent. Finally, the distribution of real hourly reservation wages shifted rightward across these two time periods. The mean real hourly reservation wage (in 1982-1984 US dollars) increased from \$5.83 to \$6.94.[5] While acceptance rates fell by a large margin, the coincident rise in reservation wages has not been to the same magnitude, suggesting that the increase in the latter only partially explains the sharp decline in the former.[6]

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

3 Model

3.1 Environment

Time is discrete. The economy comprises a unit mass of infinitely lived workers who are ex-ante identical. Workers are risk neutral and discount the future with factor β. Workers can either be employed or unemployed. Unemployed workers consume home production b. Employed workers consume their wages and are attached to firms that can employ at most one worker.

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

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

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

Job search Search is random. Only unemployed workers search for jobs. An unemployed worker can costlessly send multiple applications, with the exogenous number of applications a worker sends each period denoted by a.[7] A worker sends each application to a separate vacancy. For each vacancy contacted, they observe their match quality x for that particular application. Vacancies can be contacted by multiple applicants, where the number of applicants at a vacancy is a random variable. Unlike workers, firms do not observe their applicants' match qualities. A firm, however, can choose to pay a fixed cost, κ_I, to learn its applicants' qualities.[8] While paying κ_I reveals to the firm information about its applicants' match qualities, it does not inform the firm about the number of offers applicants have received nor does it provide information about their match qualities at other jobs.[9] As such, information is asymmetric as a worker knows their match qualities across all applications and the number of offers received but a firm that acquires information only knows its applicants' match qualities at its own vacancy. We restrict our attention to symmetric equilibria in pure strategies; that is, all firms with j number of applicants employ the same hiring strategy. Finally, each vacancy costs κ_V to post.[10]

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

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

where $\theta = v/u$ is the ratio of vacancies to unemployed job-seekers. Importantly, the rate at which the firm receives applications is not the same as its job-filling probability. The job-filling probability depends not only on its rate of contacting applicants but also on the acceptance

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

decision of workers, which in turn is affected by the firm's information acquisition problem.

Timing At the beginning of each period, firms post vacancies. Next, existing matches observe both separation and match-quality shocks. Newly separated workers must wait one period before searching the labor market. Following this, unemployed workers submit applications and observe their match quality at each vacancy contacted. Firms receive applications and choose whether to acquire information. Firms then make offers to their chosen applicants and workers decide whether to accept offers. Firms can only make an offer to one candidate and there is no recall. Once an offer has been accepted, firms that did not acquire information learn about their worker's match quality and wage bargaining commences. Wages are re-bargained every period. We assume that once a worker accepts an offer, they discard all other offers, implying that at the bargaining stage the worker's unemployment value forms their outside option. Finally, production occurs. Having described the environment, we proceed to defining the worker and the firm's end-of-period value functions. We begin with the firm's problem.

3.2 The firm's problem

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

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

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

3.3 The firm's information acquisition problem

No information acquisition Consider a firm that has j applicants. If the firm chooses not to acquire any information, it is unable to rank any of its applicants and randomly selects a candidate from its pool of j applicants. The expected value of not acquiring information, $V^{NI}(j)$, is then given by

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

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

With information acquisition Consider a firm with j applicants that chooses to pay cost κ_I to learn the match qualities of all its applicants. As we show in Section 3.6, wages are determined via surplus splitting and the surplus is increasing in quality x. Since the firm's gain from matching is a share of the surplus, the firm always makes an offer to the most productive applicant.

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

Proof. See Appendix B. □

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

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

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

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

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

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

Proof. See Appendix B. □

As the number of applicants, j, at a firm increases, the likelihood that at least one of the applicants is a high-quality match also increases. Thus, the expected benefit of information acquisition, $V^I(j)$, is strictly increasing in j, as only firms that 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 a high match quality is increasing in j, the firm with no information cannot take advantage of this because it can only make offers randomly.

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

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

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

3.4 Employed workers

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

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

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

3.5 Unemployed workers

To understand the unemployed worker's problem, we first characterize the acceptance decision of a job-seeker. Since the employment value, $V^W(x)$, is increasing in match quality, the worker always prefers to accept their highest match quality drawn so long as that value is above $\widetilde{x}$. Consider a worker who draws match quality $x \geq \widetilde{x}$ from one of their a applications and receives an offer for this draw. The worker will accept this offer of quality x if 1) it is their highest match quality, or 2) it is not their highest match quality but other applications with higher match qualities failed to yield offers. Thus, the worker's probability of accepting an offer with match quality $x \geq \widetilde{x}$ for a particular application is given by

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

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

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

where

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

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

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

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

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

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

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

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

3.6 Surplus and wage determination

Wages are determined by Nash bargaining only after the worker has accepted an offer.[12] In accepting an offer, the worker discards all other offers prior to bargaining. Similarly, we assume that there is no recall: firms that have made offers to particular candidates have rejected all their other applicants.[13] Further, firms that did not acquire information learn about their worker's match quality at this stage. This implies that at the bargaining stage, the outside options of the firm and the worker are equal to their values from remaining unmatched. Further, wages are re-bargained each period. The wage for a job of quality x is

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

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

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

with

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

The surplus of a match is given by the current output plus the expected value from a match-quality shock less what the worker gains from remaining unemployed. Equation (7) shows that $S(x)$ is increasing in x, implying that $V^F(x)$ and $V^W(x)$ are also increasing in x. Thus, workers always accept their highest-quality offer and firms always extend offers to their best applicants.

3.7 Labor market flows

Unemployed The steady state unemployment rate is implicitly given by

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

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

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

where $g(x)$ is the density of employed workers with match quality x and $G(x)$ is the cdf. The left-hand side of Equation (8) represents the outflows from unemployment. The right-hand side represents inflows into unemployment from exogenous and endogenous separations.

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

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

The left-hand side denotes outflows from exogenous separations and from workers who observe a match-quality shock. The first term on the right-hand side of the equation describes the inflows from the pool of employed workers who experienced match-quality shocks and drew new match quality x, while the second term represents the inflows from unemployment.

3.8 Equilibrium

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

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

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

and

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

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

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

3.9 Forces at play

Before turning to our main results, it is useful to understand how the different components of the unemployment inflow and outflow rates respond to changes in the number of applications, a.

[14] In Appendix B, we show that neither all firms acquiring information regardless of their applicant size nor no firms acquiring information can be an equilibrium of this model for a finite $\kappa_I > 0$.

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

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 $\phi(x) = \Gamma(x) \times Pr(\text{offer } \mid x)$, we can write the outflow rate as

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

The unemployment outflow rate is a function of three components: 1) the number of applications a worker sends, a; 2) the probability they receive an offer; and 3) the probability they accept an offer. The first component in Equation (11) represents the direct effect an increased number of worker applications, a, has on the outflow rate. Holding all else constant, the ability to send out more applications and contact more vacancies raises the likelihood that at least one application returns a high match quality and yields an offer, thereby increasing the outflow rate.

While the direct effect of a contributes positively to the outflow rate, an increased number of applications also indirectly affects the probability that a single application yields an offer. From Equation (5), the offer probability, $Pr(\text{offer} \mid x)$, depends on the distribution of applicants across vacancies, $q(j)$, which in turn responds to changes in a. For expositional purposes, assume a is a continuous variable. Differentiating $q(0)$ with respect to a, we get

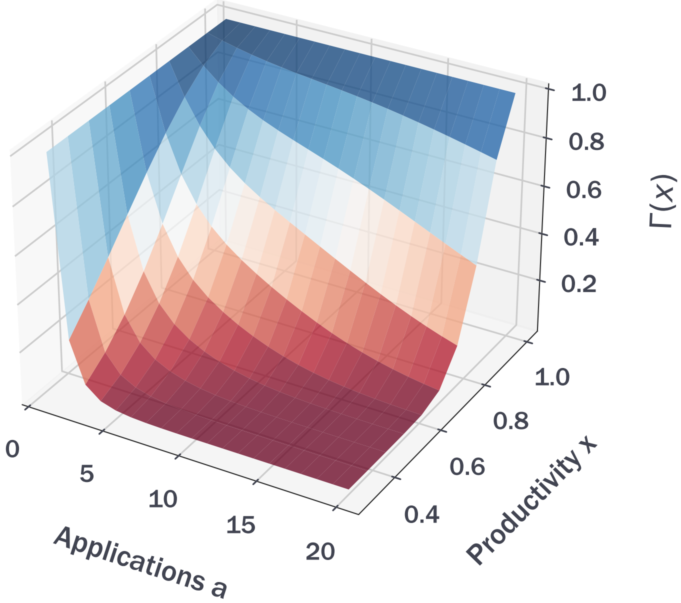
$$q_a(0) = -\frac{1}{\theta} \exp\left(-\frac{a}{\theta}\right).$$

The above derivative shows that the probability that a firm is visited by zero applicants, $q(0)$, is strictly declining in the number of applications, a, implying that the distribution, $q(j)$, shifts rightward away from zero applications with an increase in a. The probability that a single application yields an offer falls when firms have more applicants, on average. To see this, consider a worker who applies to a firm that has received j applications and who draws match quality $x > \widetilde{x}$. From Equation (4), the probability that this worker receives an offer for this application is weakly declining in j.[16] Thus, as the distribution of applications received by firms, $q(j)$, shifts rightward with higher a, each applicant faces more competition at the same vacancy, reducing the probability that they receive an offer for their match quality, x.

The final component in the outflow rate in Equation (11) is the acceptance probability $\Gamma(x)$. Notably, $\Gamma(x)$ is also a function of the applications, a. Numerically, we show that holding all else constant, $\Gamma(x)$ is weakly decreasing in a, as depicted in Figure 4. Intuitively, as workers submit more applications, they are able to sample more vacancies, raising the probability that one of their *other* applications draws a match quality that is greater than x. This in turn reduces the

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

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



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

probability of accepting an offer with match quality x.

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

Inflows into unemployment The unemployment inflow rate can be written as

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

The first term refers to exogenous separations, while the second term refers to endogenous separations. Holding $\theta, \widetilde{x}$, and j^* constant, an increase in applications, a, raises the share of firms receiving $j \geq j^*$ applicants and, thus, the share of informed firms. From Lemma 1, when more firms acquire information they identify and hire the most-productive applicants within their applicant pools, causing the distribution of the realized match quality, $G(x)$, to improve. An economy with a larger concentration of matches at high match quality values, x, observes 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, firms' 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 one month. We calibrate the initial steady state to the period 1976-1985. We choose this interval of time as it covers the period of the EOPP survey that provides information for the period 1979-1980. Because we are interested in long-term trends, we treat the 10-year period around 1979-1980 as a steady state. We set the discount factor, $\beta = 0.993$, and the worker's bargaining power, $\eta = 0.5$, as is standard in the literature. The median number of applications per month in the EOPP is 2.7. In our model, the number of applications, a, takes integer values. As such, we set $a = 3$. We now proceed to discuss our strategy for the model parameters that will be calibrated internally.

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

Within each period, a worker is subject to a match-quality shock with probability $\rho(x) = \min\{\exp(x_{ref} - x), 1\}$, where x_{ref} is set equal to the mean of the unconditional distribution of match qualities; i.e. $x_{ref} = A/(A + B)$. This implies that workers who draw and accept job offers with match qualities below the mean of the distribution observe a match-quality shock

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

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. The moments relating to unemployment flows are obtained from the CPS and are presented as averages for the period 1976-1985. The fraction of workers with no offers and the fraction that accept given more than one offer are obtained from the EOPP for 1979-1980. Finally, the reservation wage to the mean wage ratio is obtained from reservation wage data for the unemployed in the EOPP and mean wage data for the employed in the CPS.

with probability 1. In contrast, the frequency of match-quality shocks for workers who draw match qualities above the mean is strictly declining in x. This formulation allows us to reflect the fact that low-wage jobs observe higher unemployment risk.[18] Conditional on receiving a match-quality shock, we assume that individuals draw their new match qualities from the joint distribution $\Psi(x, x')$ which is constructed using a Gumbel copula:

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

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 endogenous separations. Thus, we use λ to match the ratio of the unemployment inflow rates of the bottom 20th percentile (EU_{20}) in real hourly wage earnings to the inflow rates of the top 20th percentile (EU_{80}) in the data. Using data from the CPS for the period 1976-1985, we find this ratio to be 4.05, suggesting that individuals at the bottom quintile of the wage distribution are around four times more likely to separate from their jobs than individuals at the top quintile.

Labor market While the unemployment inflow rate is a function of both endogenous and exogenous separations, we target the average unemployment inflow rate over the period 1976-1985 to pin down the exogenous separation probability δ. We choose the vacancy posting cost,

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

Table 2: Impact on key equilibrium variables from an 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.

κ_V, to match an average outflow rate of 0.41.[19] Since the fixed cost of information, κ_I, affects recruiting costs, we follow Gavazza et al. (2018) and set κ_I to match the ratio of recruiting costs to average wages of 0.928. In our model, the expected recruiting cost takes the form of $\kappa_V + \sum_{j \geq j^*}^{\infty} q(j)\kappa_I$. This is the recruiting cost a firm can expect to pay when choosing whether to create a vacancy. Finally, the level of home production, b, is set to match the ratio of the unemployed workers' reservation wages to the mean wages. In the data, we calculate the average hourly reservation wage of the unemployed in the EOPP and the average hourly wage of the employed in the CPS and find a ratio of 0.66. Table 1 shows that our calibrated model fits the data moments fairly well.

5 Quantitative Results

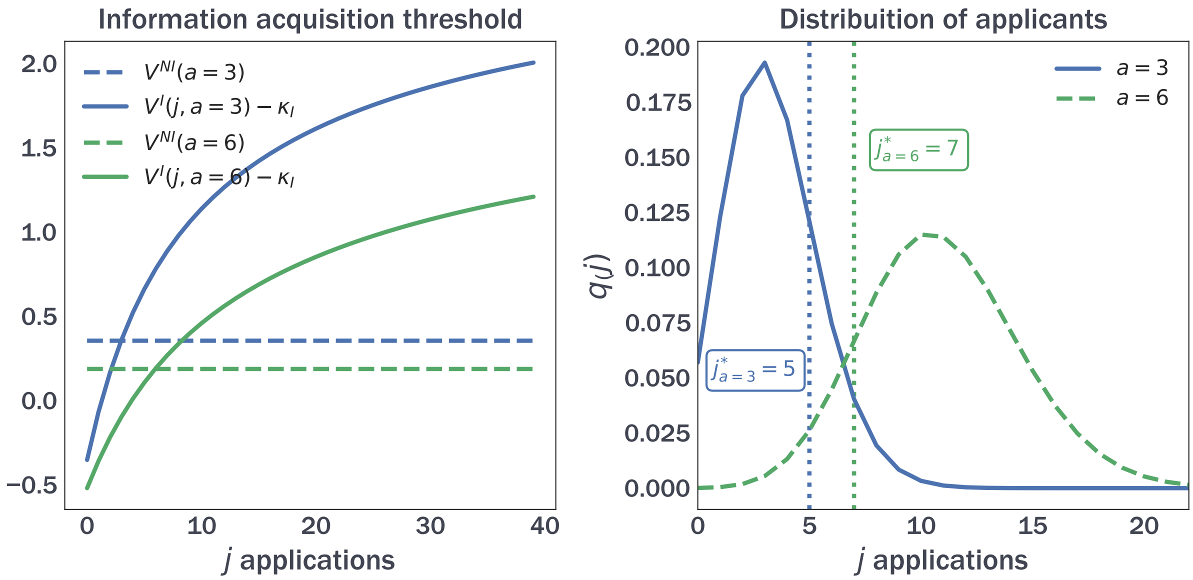
5.1 Equilibrium response to an increase in applications

Using our calibrated model, we now analyze how an increase in the number of applications, a, affects unemployment flows and application outcomes. In the data, the median number of applications roughly doubled from 3 to 6 between the periods 1979-1980 and 2013-2017. Thus, for our main quantitative exercise, we ask how doubling the number of applications from 3 to 6 affects the labor market moments in our calibrated model, holding all other parameters fixed.

To build intuition for our results, we first document the changes in the equilibrium objects $\{\widetilde{x}, \theta, j^*\}$. Table 2 highlights our results. First, an increase in the number of applications, a, raises the share of firms acquiring information, despite an increase in the information threshold, j^*. The latter occurs because the expected value of acquiring information, $V^I(j)$, decreases more when acceptance probabilities decline with an increase in a. The left-hand panel of Figure 5 shows how $V^I(j)$ and V^{NI} vary with a. Intuitively, for a given number of applicants, j, information is less valuable if workers are more likely to reject an offer. Nonetheless, the right-hand panel of Figure 5 shows that an increase in a causes the distribution of applicants per vacancy, $q(j)$, to shift to the right, resulting in a larger share of firms with $j > j^*$ applicants. Consequently, more

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

Figure 5: Firms increase their information acquisition threshold but receive more applications as a increases



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

firms acquire information when a is higher, with the share of informed firms increasing from 44.1 percent to 95.3 percent.

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

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

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

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

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

5.2 The response of inflow and outflow rates

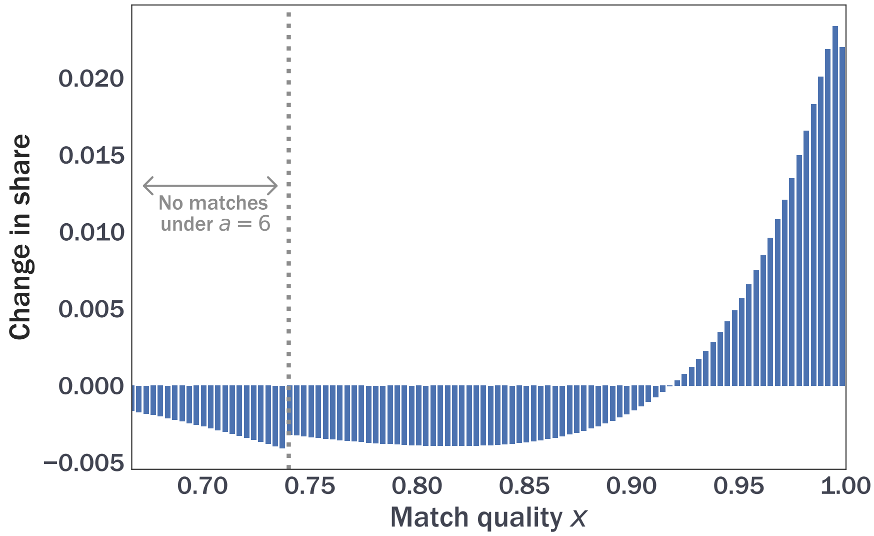
We now examine how inflow and outflow rates are affected by an increase in the number of applications, a. Importantly, we compare our model predictions for unemployment flows and job search outcomes against the available data for the periods 1976-1985 and 2010-2019. These two time intervals cover the EOPP (1979-1980) and the SCE (2013-2017). For the inflow and outflow rates, we take 10-year averages of the trend components as we are interested in the long-run differences. We emphasize, however, that the U.S. economy underwent a slow recovery after the Great Recession. As a result, the reported outflow rates between 2010 and 2019, in the data, are below the long-run average observed in Figure 2. By 2019, however, the outflow rates had recovered to their long-run average of around 0.41. We detail the results of our exercise in Table 3.

5.2.1 Inflow rates

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

Figure 6 highlights how the distribution of the employed over match quality changes with the rise in applications, a. As more firms acquire information when a increases, a larger share of firms are able to identify and hire high-productivity applicants, giving rise to a greater formation of high-quality matches and a decline in the share of low-to-middling quality jobs. In our model, the frequency of match-quality shocks, $\rho(x)$, is decreasing in x. The larger share of high-quality

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

matches thus leads to a 4.5 percent fall in the frequency of these shocks, implying greater job stability as jobs remain longer at their current productivity levels. In addition, workers are also less likely to separate from their jobs, in the event of a match-quality shock, when the distribution of the employed is concentrated among high-quality matches. Conditional on a shock, the share of the employed who draw a new match quality, $x' < \widetilde{x}$, and separate into unemployment falls by 51 percent when a doubles.[20] The combined effects of a lower frequency of match quality shocks and a large decline in the likelihood of drawing new qualities below the reservation match level outweigh the effect of a higher reservation match quality, $\widetilde{x}$, on separation rates. Consequently, the inflow rate in our model declines substantially as the effects from improved firm selection dominate the effects from increased worker selectivity.

Our model also produces testable implications for the changes in the tenure distribution, especially for the share of short-duration jobs. As the realized distribution of match quality shifts rightward and towards high-quality matches, the share of low-quality jobs with high turnover declines. Thus, the share of short-duration jobs declines significantly in our model while the share of jobs with long duration falls by less. Table 4 shows that the share of workers employed in jobs lasting less than a quarter falls by 70 percent when a increases, while the share of the employed in jobs lasting more than a year and less than three years falls by a smaller 36 percent.

Our results concur with empirical findings on how the tenure distribution has changed over time. Empirically, short tenure employment relationships have observed the sharpest decline. Molloy et al. (2020) use data from the CPS and show that the median tenure has remained rela-

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

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

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

5.2.2 Outflow rates

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

Why does our model predict relatively small changes in the outflow rate despite a doubling in the number of applications? Recall from Section 3.9 that the extent to which the outflow rate varies with the number of applications depends on whether the direct effect of submitting more applications outweighs its indirect effects on offer and acceptance probabilities. Specifically, we

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

Table 4: Testable implications on the impact of an increase in applications on application outcomes

Panel A: Tenure distribution

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

Panel B: Outflow rate components

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

Note: This table summarizes the changes in the employment tenure distribution and outflow rate components (the average fraction > 0 offer, the average acceptance rate, and the average reservation wage) when the number of worker applications, a, increases from 3 to 6. The data moment on the share of jobs that last $t < 1$ quarter is taken from Pries and Rogerson (2019) who use data from the QWI. The data moments on the share employed in jobs lasting $1 \leq t < 3$ years and median tenure are taken from Molloy et al. (2020), who use CPS data. The data moments on the mean number of applicants per vacancy are taken from Faberman and Menzio (2018) for 1980 and Marinescu and Wolthoff (2020) for 2011. The data moments on outflow rate components are obtained as averages from the EOPP for the period 1979-1980 and from the SCE for the period 2013-2017, where the former period corresponds to the period with the lower average number of worker applications, $a = 3$, and the latter period corresponds to the period with the higher average number of worker applications, $a = 6$. Reservation wages in the data are average hourly reservation wages in 1982-1984 dollars. The log difference is multiplied by 100.

decompose the percent change in the outflow rate between two time periods, t_1 and t_2, as

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

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

Crucially, the model's ability to reproduce the lack of a long-run trend in the outflow rate in the data originates from its predicted declines in offer and acceptance rates. Table 4 compares the changes in offer and acceptance probabilities in the model relative to those observed in the data. In our model, the fraction of applicants with offers declines by 41 percent. The fraction with offers also declines in the data, albeit by less. The larger decline in our model stems from the fact that both the decline in vacancy creation and the higher number of applications contributes to increased congestion among workers. Notably, labor market tightness, θ, is only one component that affects the amount of competition among job-seekers when workers can submit multiple applications. A more relevant measure in this setting is the average number of applicants per vacancy, a/θ. In our model, a/θ increases by 103 percent. Using data from the EOPP, Faberman and Menzio (2018) report an average of 24 applicants per vacancy in 1980 while Marinescu and Wolthoff (2020) find an average of 59 applicants per vacancy in 2011, using data from CareerBuilder. Overall, our model's increase in the average number of applicants per vacancy is close to the 90 percent rise observed in the data.[22]

The decline in the fraction of workers receiving offers is one of the outcomes serving to counteract the positive direct effect of a higher a on the outflow rates. The other key variable that affects the outflow rate is the acceptance rate. We calculate the model's average acceptance rate as the expected probability of accepting an offer for a particular application, $\int_{\widetilde{x}}^{\overline{x}} \Gamma(x)\, \pi(x)\, dx$. In our model, a higher number of applications results in workers becoming more selective over the minimum quality job they are willing to accept–as depicted by the increase in $\widetilde{x}$. In addition, workers experience an increased probability that at least one of their applications draws a higher match quality. This increased probability of drawing a higher match quality from another application leads the worker to more frequently reject a job offer of given quality x. As such, the acceptance rates in our model decline by 45 percent, while they fall by 62 percent in the data. Although we do not target these changes, our model's predicted changes in offer probabilities and acceptance rates largely mimic the patterns observed in the data over time.

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

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

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

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

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

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

reducing their need to accept the first offer they receive.

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

5.3 The role of costly information

The key insight the baseline model delivers is that an increase in the number of applications does not necessarily translate into higher job-finding rates but instead leads to better matches that are longer-lived. We now consider two thought experiments to uncover why the interaction of information acquisition with an increase in applications is crucial for this result. In the first experiment, we set $\kappa_I = 0$ and label this the "Full Information" (FI) model.[24] In the second experiment, we consider the other extreme and set $\kappa_I \to \infty$. We label this the "No Information" (NI) model. We re-calibrate the FI and NI models to match the same targets as our baseline model.[25] In both of these models, the firm's investment in information acquisition does not vary with the number of applications. Hence, comparing the results from the FI and NI models against our baseline model allows us to isolate how variations in firms' information decisions in response to more applications would affect the predictions of our model.

[24] While we use the term "Full information," it should be noted that firms only observe the match qualities of applicants at their vacancies. They cannot observe the applicants' match qualities at other jobs or the applicants' number and quality of competing offers.

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

Equilibrium outcomes Table 5 provides details of 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 an increase in applications. While the firms in our baseline model face higher expected job creation costs whenever more firms anticipate that they will acquire information, job creation costs do not vary with the number of applications in the FI and NI economies because 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 increase in the expected benefit of a vacancy coupled with the constant cost of job creation causes vacancy creation and, consequently, θ to rise with the increase in a in the FI and NI models.

Focusing on reservation match quality $\widetilde{x}$, a rise in applications causes $\widetilde{x}$ to increase in the FI model, and $\widetilde{x}$ to decrease in the NI model. These differences stem from how workers' outside options change with the number of applications, a, across the two models. In the FI model, firms always identify the highest-quality applicant. When workers submit more applications, there is an increased probability that at least one application draws a high match quality and yields an offer. This strengthens the worker's outside option, encouraging a rise in $\widetilde{x}$. Conversely, in the NI model, firms always randomly select candidates from their applicant pool. Thus, for the worker, the increased probability of drawing a high match quality does not translate into more offers. Although labor market tightness improves in the NI model, the percentage increase in a outweighs the percentage increase in θ. Consequently, the rise in a increases congestion among workers, leading to a worsening in the workers' outside options and a fall in $\widetilde{x}$.

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

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

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

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

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

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

6 Discussion

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

6.1 Variable and endogenous number of applications

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

6.2 Assuming a marginal cost of information acquisition

While our model nests both the FI and NI models, a natural question arises as to whether our model mechanisms would differ if we were to instead assume a marginal cost of information. We first note that our assumption of a fixed cost of information in our baseline model is motivated by recent evidence by Davis and Samaniego de la Parra (2020), who find that 67 percent of vacancy postings originate from recruitment firms and staffing firms. Recruitment agencies, in turn, are paid placement fees–i.e., fees that are paid only when the agency fills a vacancy–and these are typically some percentage of the worker's salary.[26] Given the prevalent use of recruiting and staffing agencies as well as their fee structures, we argue that the assumption of a fixed cost of information is a natural one. Nonetheless, in this section, we explore the consequences of assuming a marginal cost of information.

Incorporating a marginal cost structure would reduce but not eliminate the extent to which 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

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

benefit; i.e., $\kappa_I > V^I(j+1) - V^I(j)$ for any $j > \widehat{j}$. There still exists a lower bound $j^* > 1$ where for any $j < j^*$, the value of not acquiring information exceeds the net benefit of acquiring information; i.e, $V^{NI} > V^I(j) - \kappa_I j$ for $j < j^*$. Thus, for any $j^* \leq j \leq \widehat{j}$, the firm acquires information on all of its applicants, and for any $j > \widehat{j} \geq j^*$, the firm acquires information on a subset $\widehat{j}$ of its applicants. Appendix C.3 provides greater detail on such a setup.

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

6.3 On-the-job search

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

6.4 Wage protocols

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

7 Conclusion

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

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

Finally, we show that the endogenous response in the firm's information acquisition decision to an increase in applications is critical for replicating the observed empirical patterns. When the firm's investment in information is invariant to the rise in applications, either because information is free or infinitely costly, these alternative models fail to jointly generate the declining trend in the inflow rate and lack a long-run trend in the outflow rate.

Our model can be extended in several dimensions. First, the number of applications that the unemployed submit can vary over the business cycle. This, together with the fact that applications have increased over time could have implications for firms' hiring behaviors 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 for understanding why some firms receive relatively more applications and how this affects labor market power and earnings inequality over time. We leave these considerations for future research.

References

Acharya, S. and S. L. Wee (2020): "Rational inattention in hiring decisions," *American Economic Journal: Macroeconomics*, 12, 1–40.

Albrecht, J., X. Cai, P. Gautier, and S. Vroman (2020): "Multiple applications, competing mechanisms, and market power," *Journal of Economic Theory*, 190.

Albrecht, J., P. A. Gautier, and S. Vroman (2006): "Equilibrium directed search with multiple applications," *Review of Economic Studies*, 73, 869–891.

Bradley, J. (2020): "Worker-firm screening and the business cycle," Tech. rep., University of Nottingham.

Crump, R. K., S. Eusepi, M. Giannoni, and A. Şahin (2019): "A unified approach to measuring u," Tech. rep., National Bureau of Economic Research.

Davis, S. and B. Samaniego de la Parra (2020): "Application Flows," Tech. rep.

Elsby, M. W., B. Hobijn, and A. Şahin (2010): "The labor market in the Great Recession," Tech. rep., National Bureau of Economic Research.

Elsby, M. W., R. Michaels, and G. Solon (2009): "The ins and outs of cyclical unemployment," *American Economic Journal: Macroeconomics*, 1, 84–110.

Engbom, N. (2019): "Firm and worker dynamics in an aging labor market," Tech. rep., Working paper 756, Federal Reserve Bank of Minneapolis.

Faberman, R. J. and G. Menzio (2018): "Evidence on the relationship between recruiting and the starting wage," *Labour Economics*, 50, 67–79.

Faberman, R. J., A. I. Mueller, A. Şahin, and G. Topa (2020): "Job search behavior among the employed and non-employed," Tech. rep., National Bureau of Economic Research.

Galenianos, M. and P. Kircher (2009): "Directed search with multiple job applications," *Journal of Economic Theory*, 144, 445–471.

Gautier, P., P. Muller, B. van der Klaauw, M. Rosholm, and M. Svarer (2018): "Estimating Equilibrium Effects of Job Search Assistance," *Journal of Labor Economics*, 36, 1073–1125.

Gautier, P. A. and J. L. Moraga-Gonzalez (2018): "Search intensity, wage dispersion and the minimum wage," *Labour Economics*, 50, 80–86.

Gautier, P. A., J. L. Moraga-Gonzalez, and R. P. Wolthoff (2016): "Search costs and efficiency: Do unemployed workers search enough?" *European Economic Review*, 84, 123–139.

Gautier, P. A. and R. P. Wolthoff (2009): "Simultaneous search with heterogeneous firms and ex post competition," *Labour Economics*, 16, 311–319.

Gavazza, A., S. Mongey, and G. L. Violante (2018): "Aggregate recruiting intensity," *American Economic Review*, 108, 2088–2127.

Hyatt, H. R. and J. R. Spletzer (2016): "The shifting job tenure distribution," *Labour Economics*, 41, 363–377.

Kaas, L. (2010): "Variable search intensity with coordination unemployment," *The B.E. Journal of Macroeconomics*, 10, 1–33.

Karahan, F., S. Ozkan, and J. Song (2019): "Anatomy of Lifetime Earnings Inequality: Heterogeneity in Job Ladder Risk vs. Human Capital," Staff Reports 908, Federal Reserve Bank of New York.

Kircher, P. (2009): "Efficiency of simultaneous search," *Journal of Political Economy*, 117, 861–913.

Marinescu, I. and R. Wolthoff (2020): "Opening the Black Box of the Matching Function: The Power of Words," *Journal of Labor Economics*, 38, 535–568.

Martellini, P. and G. Menzio (2020): "Declining search frictions, unemployment, and growth," *Journal of Political Economy*, 128, 4387–4437.

Mercan, A. Y. (2017): "Fewer but better: The decline in job mobility and the information channel," Tech. rep., Working paper, University of Melbourne.

Molloy, R., C. Smith, and A. K. Wozniak (2020): "Changing Stability in U.S. Employment Relationships: A Tale of Two Tails," NBER Working Papers 26694, National Bureau of Economic Research, Inc.

Polivka, A. E. and S. M. Miller (1998): "The CPS after the redesign: Refocusing the economic lens," in *Labor statistics measurement issues*, University of Chicago Press, 249–289.

Postel-Vinay, F. and J.-M. Robin (2002): "Equilibrium wage dispersion with worker and employer heterogeneity," *Econometrica*, 70, 2295–2350.

Pries, M. J. and R. Rogerson (2019): "Declining worker turnover: The role of short duration employment spells," Tech. rep., National Bureau of Economic Research.

Shimer, R. (2005): "The cyclical behavior of equilibrium unemployment and vacancies," *American Economic Review*, 95, 25–49.

——— (2012): "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 15, 127–148.

Shimer, R. and K. Abraham (2002): "Changes in unemployment duration and labor force attachment. Russel Sage Foundation," *The Roaring Nineties*.

Wolthoff, R. (2018): "Applications and interviews: Firms' recruiting decisions in a frictional labour market," *Review of Economic Studies*, 85, 1314–1351.

Appendix

A Data

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

A.1 EOPP

The goal of the EOPP was to help participants find a job in the private sector during an intensive job search assistance program. Individuals had to be unemployed and meet income eligibility requirements to be able to participate in this program. The survey was created to analyze the effects of the program on the labor market outcomes of the participants. As a result, by design, the survey over-sampled low-income families, but this did not greatly weaken the moments pertaining to the aggregate economy, as shown in Section A.3 below.

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

In our study, we analyze a sample of unemployed individuals aged 25-65 who are not self-employed and who submitted at least one job application during each unemployment spell that occurred in 1979 and 1980. This gives us $5,410$ unique individual-spell observations.[27] For each of these individual-spell observations, we first calculate the unemployment duration in months.[28] Using data on the number of job applications for each mode of job search (e.g., private employment agencies, newspapers, labor unions, friends and relatives, etc.), we obtain the total number of job applications for each spell. Then, we divide the total number of job applications sent during each unemployment spell by its duration to obtain the average monthly number of applications for that spell. Similarly, using information on the number of offers received through each mode of job search, we calculate the total and monthly number of offers received for each spell. The data also provides an indicator variable on whether the individual accepted any of the offers received. Using this variable, we also calculate the fraction of individuals who received a certain number of job offers and accepted an offer. Finally, the survey also contains information on the lowest hourly wage rate the individual would accept during their unemployment spell.

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

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

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

A.2 SCE

The SCE Labor Market Survey was developed by the Federal Reserve Bank of New York.[30] The dataset provides information about respondents' demographics, job information if employed (i.e., earnings, hours, industry, employer size, etc.), job search activities, and reservation wages.

We use the annual survey between 2013 and 2017. Because of the small sample size relative to the EOPP data, we pool the SCE observations across these years, as in Faberman et al. (2020). To maintain consistency with our EOPP analysis, we restrict the SCE sample to unemployed individuals aged 25-65 who are not self-employed and who submitted at least one application during each unemployment spell. This includes individuals who were unemployed at the time of the survey and individuals who, at the time of the survey, were employed for less than four months in their jobs and reported experiencing an unemployment spells prior employment. For both of these groups, we analyze their job search activities during each reported unemployment spell. For currently unemployed individuals, the survey provides the total number of job applications during the past four weeks, the total number of job offers received during the past four weeks; and, if no job offers were received in the past four weeks, the total number of job offers received in the last six months, where we use unemployment spell duration information to convert the latter to the average number of job offers received per month of unemployment. The survey also provides information on whether the individual accepted or will accept a job offer. For currently employed individuals with a previous unemployment spell, the survey also provides the total number of job applications and job offers received during their unemployment spells. Again, we use information on the duration of the unemployment spell to convert these numbers to the average number of job applications and job offers received per month of unemployment. Since these individuals found employment after an unemployment spell, we infer that they accepted a job offer. Then, using information about the offers and acceptance decisions in our sample, we calculate the fraction of individuals who accepted job offers. The SCE also asked individuals to note the lowest wage they would accept, which we use to measure the reservation wage.[31]

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

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

[31] For currently unemployed individuals, variables JS14, JS19, JS19b, JS23, and L7 give the total number of job applications sent 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 previously experienced an unemployment spell, 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

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 the EOPP, SCE, and CPS samples. In all datasets, the samples consist 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 the EOPP, SCE, and CPS samples

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

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

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

the unemployment spell, respectively. The variable RW2h_rc provides the reservation wage information.

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

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

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

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

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

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

A.4 Job applications: eliminating business cycle effects

In Section 2.1, we use data from the EOPP and SCE samples and show that the unemployed are now sending more applications than they did in the 1980s. One concern may be that there are cyclical factors behind the differential outcomes observed between the 1979-1980 and 2013-2017 periods. 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 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 the years, y is the number of monthly job applications, X is a vector of the individual's demographic characteristics, d_{t2} is an indicator variable that takes the value of 1 if the year is between 2013 and 2017 and 0 otherwise, and the Unemp. rate and Real GDP are the cyclical components of HP-filtered series of the unemployment rate and real GDP. Table A3 summarizes

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 differentials in the number of job applications between the periods 1979-1980 and 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.

the results. We find that from the 1979-80 period to the 2013-2017 period the average monthly number of job applications significantly increased (between 4.36 and 8.95, depending on the specification) even after we control for changes in aggregate economic conditions.

A.5 Job applications: Demographic groups

In Section 2.1, we document moments regarding the change in the economy-wide average number of job applications sent during each month of unemployment between the EOPP (1979-1980) and the SCE (2013-2017). Here, we explore the 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.

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

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

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

A.6 CPS

Calculating inflow and outflow rates In this section, using the CPS, we first provide details on the measurement of unemployment inflow and outflow rates over time. In doing so, we follow Shimer (2005), Elsby et al. (2009), Elsby et al. (2010), Shimer (2012), and Crump et al. (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 (which we define as the short-term unemployed).[34] Let U_t, U_t^S, and L_t be the number of unemployed individuals, the number of short-term unemployed individuals, and the number of individuals in the labor force at time t, respectively. Also, let s_t and f_t denote the unemployment inflow (job separation) rate and unemployment outflow (job-finding) rate at time t, respectively. Then, we can define the change in the number of unemployed individuals between time t and $t+1$ as follows:

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

Moreover, we can write

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

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

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

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

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

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

which defines the unemployment inflow rate s_t and probability $S_t = 1 - e^{-s_t}$, given data on unemployment, the labor force and the unemployment outflow rate f_t. Following these steps, we plot outflow probability F_t and inflow probability S_t in Figure 2 in Section 2.[35]

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

[35] We use monthly outflow probability F_t and inflow probability S_t instead of rates f_t and s_t, given that our

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

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

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

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

Table A5 summarizes the results of this shift share analysis for the inflow and outflow probabilities. The average inflow probability across groups decreased from 3.6 percent during the

model is in discrete time.

Table A5: Shift share decomposition exercise

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

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

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

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

these results emphasize that the trend decline in inflows and the lack of trend in outflows are not driven by changes in worker demographics over time but rather reflect a more fundamental change in each group's labor market experience.

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

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

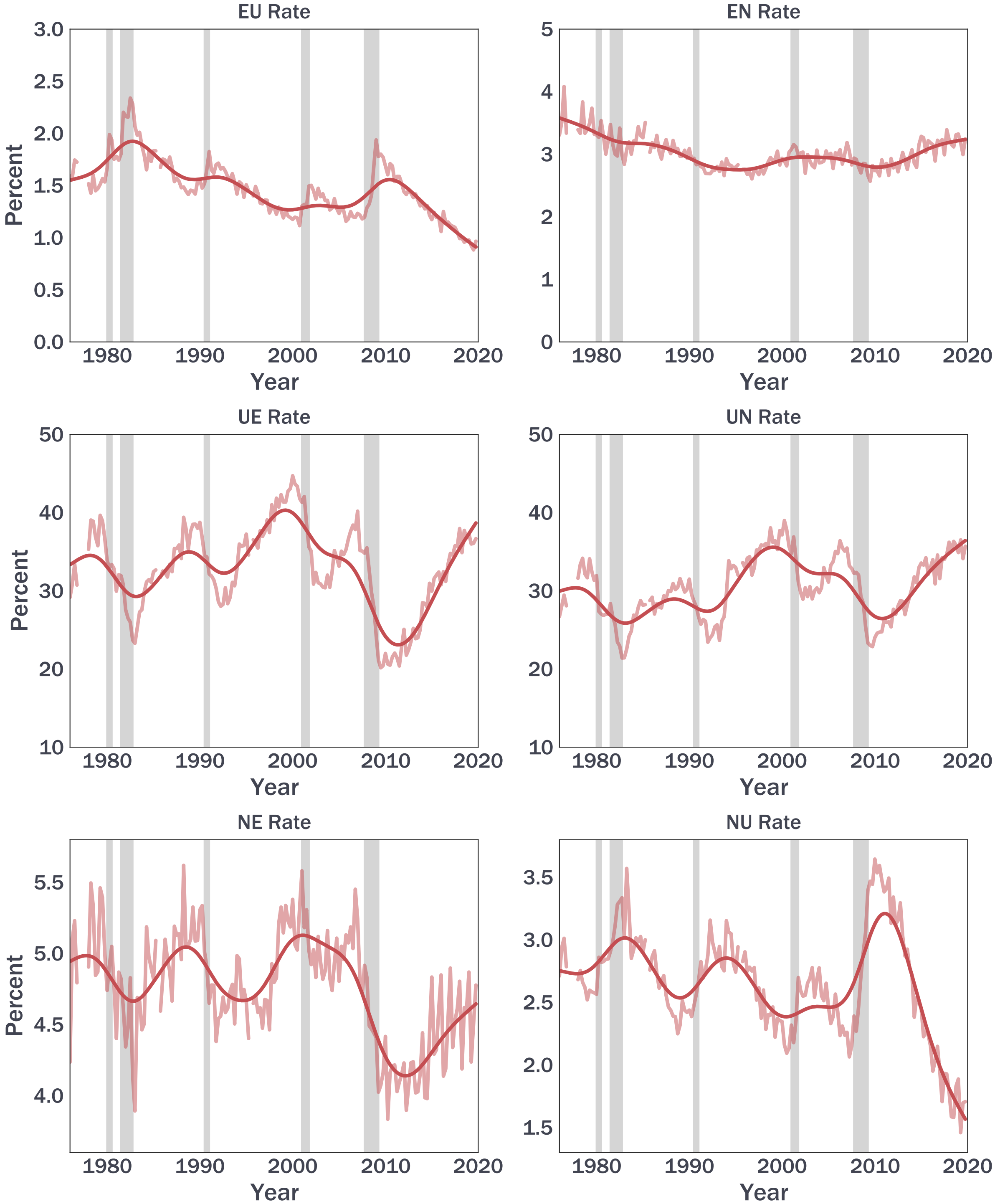
Distribution of the reservation wage to the mean wage ratio over time Figure 3 in Section 2.3 shows the distributions of reservation wages over time, using the EOPP and SCE samples. In Figure 3, when comparing reservation wages between different time periods, we adjust the reported reservation wages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

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

B Model

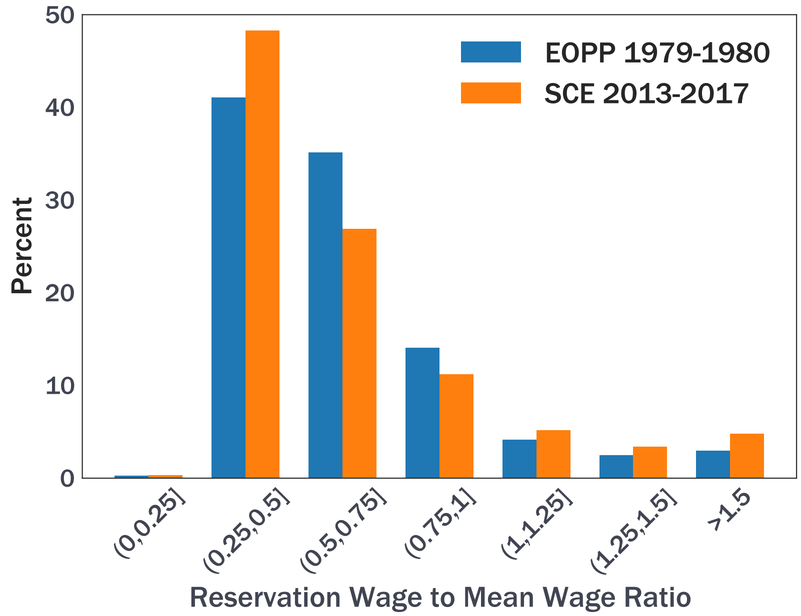
In this appendix, we provide proofs for the propositions in the main text.

Figure A1: Transition rates using CPS panels



Note: This figure shows the unemployment inflow rate (EU) and outflow rate (UE) as well as employment-to-out-of-labor-force rate (EN), unemployment-to-out-of-labor-force rate (UN), out-of-labor-force-to-employment (NE), and out-of-labor-force-to-unemployment (NU) rates between 1976:Q1 and 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 the reservation wage to the 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 the periods 1979-1980 and 2013-2017, respectively. The CPS sample includes employed individuals aged 25-65 who are not self-employed. We use this sample to calculate the mean hourly wages of employed for the two time periods.

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

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

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

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

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

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

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

Ruling out other pure-strategy equilibria It is trivial to show that all firms acquiring information regardless of their number of applicants, j, cannot be an equilibrium. To see this, suppose that 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 the surplus of applicants is increasing in x, the worker always accepts the highest match-quality offer. Thus, a firm that is able to make an offer to its highest-quality applicant lowers its probability of being rejected. Since the likelihood of a firm having a high-quality applicant is increasing in j, the expected benefit of information is strictly increasing in j. This, together with finite information cost, κ_I, implies that a single firm with high enough j applicants has a profitable deviation and would choose to acquire information. Thus, an equilibrium where no firm acquires information is not possible for a finite κ_I.

C Extensions

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

C.1 Calibration details of FI and NI models

Recall that in Section 5.3 we set $\kappa_I = 0$ in the FI model and $\kappa_I \to \infty$ in the NI model. Given that κ_I is already set, we leave out the ratio of recruitment costs to the mean wage, which was used as a calibration target for κ_I in our calibration of the baseline model. For the rest of the parameters, we target the same moments as in the baseline model given in Table 1. Table A6 summarizes the calibration outcomes of the FI and NI models. Because we target the ratio of the reservation wage to the mean wage in the data to pin down b from Equation (9), the value of b is small when the continuation value from remaining unemployed is large relative to the continuation value of being employed at $\widetilde{x}$. In other words, to make it attractive for workers to choose employment and to attain the ratio of the reservation wage to the mean wage observed in the data, b must be small.

Table A6: Calibration of FI and NI models

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

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

C.2 Variable or endogenous number of applications

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

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

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

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

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

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

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

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

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

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

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

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

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

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

and the overall job-finding rate is given by

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

more than one firm makes an offer to the same worker is lower when workers send a applications, on average, as opposed to all workers sending exactly a applications. This is similar to the findings in Kaas (2010).

Table A7: Impact on labor market flows: baseline versus variable applications

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

Note: This table reports the model-predicted flow outcomes from our baseline model with uniform applications a against the outcomes from a model with variable applications. We measure the direct a effect as the change in the mean number of 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 $\sum_{a=1}^{\infty} p(a)\, a \int_{\tilde{x}}^{\overline{x}} \phi(x,a)\,\pi(x)\,dx$. Note that the log difference in the direct and indirect effects here does not sum to the total change in the outflow rate because the terms are no longer separable. The log difference is multiplied by 100.

C.3 Marginal cost of information

We now elaborate on our discussion for the model with a marginal cost of information acquisition, which we presented in Section 6.2. Suppose that, instead, κ_I is the marginal cost the firm pays for each applicant it acquires information on. Formally, the firm's information problem takes the form of

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

where

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

and

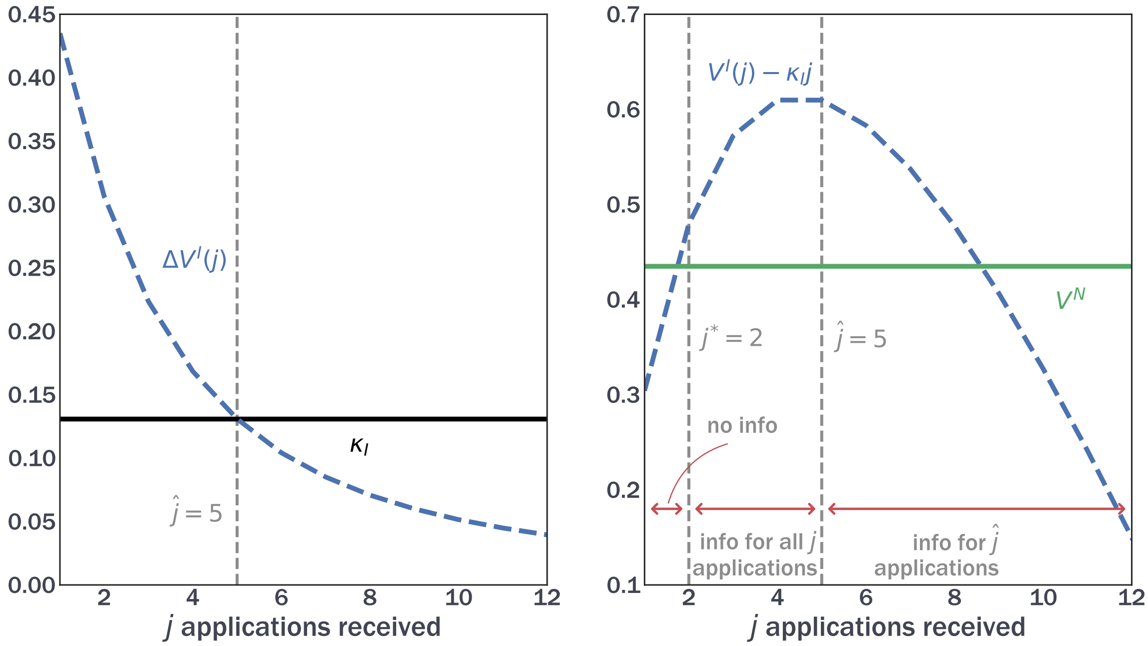
$$V^{I}(n) = \int_{\tilde{x}}^{\overline{x}} V^{F}(x)\,\Gamma(x)\,d\left[\Pi(x)\right]^{n}.$$

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

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

Define $\widehat{j}$ as the highest number of applicants such that the additional gain from acquiring

Figure A3: Upper bound on how the benefits of information rises with j with the marginal cost of information



Note: In this numerical example, we treat κ_I as the marginal cost of information. The left-hand 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-hand 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 equal 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-hand 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 its marginal benefit, the firm only acquires information on a random subset $\widehat{j} < j$ of applicants. We assume that any applicant the firm does not acquire information on is automatically rejected. A similar assumption is also made in Wolthoff (2018).

The solution to the firm's problem in this environment then boils down to two thresholds, $(j^*, \widehat{j})$. Note that the lower bound of when to acquire information still exists. For any $\kappa_I > 0$, the firm would not acquire any information for $j = 1$ applicants since the firm is always better off acquiring no information; i.e., $\overline{V}^I(1) = V^I(1) - \kappa_I = V^{NI} - \kappa_I < V^{NI}$. More generally, the minimum number of applicants the firm requires before it acquires information, j^*, must satisfy $\overline{V}^I(j) \geq V^{NI}$. Thus, the firm's information acquisition strategy can be characterized as

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

The right-hand 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 versus not acquiring information, the firm's value is maximized when it only acquires information on a subset, $\widehat{j} < j$, of applicants for any applicant pool size, j, such that $j^* \leq \widehat{j} < j$. The two thresholds, $(j^*, \widehat{j})$, in turn imply the following probability of receiving an offer of quality x from a firm with j applicants:

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

where in the final line of the above equation, $\widehat{j}/j$ refers to the probability that out of j applicants, the worker is among the subset $\widehat{j}$ of applicants to be interviewed. Apart from this change in offer probabilities, the rest of the set-up for the worker's problem remains similar to our baseline model.

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

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

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

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

C.4 On-the-job search

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

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

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

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

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

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

Operating firm The value of an operating firm is given by

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

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

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

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

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

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

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

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

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

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

Next, the firm's information problem in the market for employed workers is given by

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

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

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

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

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

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

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

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

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

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

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

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

In steady state, the measure of unemployed is

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

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

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

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