

Job Applications and Labor Market Flows*

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Abstract

Job applications have risen over time yet job-finding rates remain unchanged. Meanwhile, separations have declined. We argue that increased applications raise the probability of a good match rather than the probability of job-finding. Using a search model with multiple applications and costly information, we show that when applications increase, firms invest in identifying good matches, reducing separations. Concurrently, increased congestion and selectivity over which offer to accept temper increases in job-finding rates. Our framework contains testable implications for changes in offers, acceptances, reservation wages, applicants per vacancy, and tenure, objects that enable it to generate the trends in unemployment flows.

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

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1 Introduction

The advent of the ICT revolution in the 1980s introduced significant improvements in search and communications technologies, enabling workers to submit more job applications over time. Despite this increase in the number of applications, the unemployment outflow (job finding) rate in the U.S. has not observed any long-run increase. Conversely, the unemployment inflow (job separation) rate has declined since the 1980s. Since unemployment flows are inextricably tied to job-search behavior, a natural question arises as to why an increase in applications has not led to any sustained rise in the outflow rate. We argue that the main benefit of increased applications has not been to increase the probability of finding a job, but rather to increase the probability of finding a good match, as evidenced by the substantial decline in the separation rate over time.

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

In our model, workers submit multiple applications to separate vacancies and costlessly observe the match quality drawn for each application. Match quality evolves over time but is persistent as future draws are correlated with current values and high-productivity matches are less susceptible to match quality shocks. Employment relationships endogenously dissolve if match quality falls below a reservation threshold. Firms can receive multiple applicants. 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 enables firms to minimize their rejection probabilities whenever they identify and 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 1976-1985.¹ We use our calibrated model to analyze how unemployment inflow and outflow rates change when *only* the number of applications that workers can send increases as observed in the data. Importantly, our model has testable implications for labor market outcomes that underlie the predicted changes in unemployment flows. We demonstrate that the model's predictions on application outcomes such as offer and acceptance rates, reservation wages, the tenure distribution, and the number of applicants per vacancy largely mimic patterns observed in the data. Crucially, we argue that any model that analyzes changes in inflow and outflow rates must also account for changes in the aforementioned factors which have a first order effect on unemployment flows.

Under our calibrated model, the inflow rate declines by 19 percent when applications increase, about 43 percent of the decline in data.² Why does the model predict that an increase in applications leads to a decline in the inflow rate? In our model, an increase in applications affects the inflow rate in two opposing ways. On one hand, a higher number of applicants per vacancy raises firms' incentives to acquire information and thus, the share of informed firms. More informed firms lead to a greater formation of high-productivity matches which – because of the persistence in match quality – are less susceptible to job destruction, reducing inflows. On the other hand, the ability to contact more vacancies elevates workers' outside options. This raises workers' selectivity, leading to a 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.

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

¹We calibrate our initial steady state to the period 1976-1985 for two reasons. First, this time period covers the EOPP survey where we have data on the number of applications in 1980. Second, we think one of the main reasons behind the increase in applications is the advent of the ICT revolution, which had its roots in the 1980s.

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

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

Turning to outflows, our model predicts that a rise in applications causes the outflow rate to decline by a marginal 3 percent. These results are consistent with the fact that the outflow rate has remained relatively unchanged over time in the data. Why does the model generate a muted response in the outflow rate despite a rise in applications? Similar to inflows, an increase in applications has an ambiguous effect on outflows. While an increased contact between job-seekers and vacancies contributes toward a higher outflow rate, whether the job-finding rate actually increases ultimately depends on the probability that these contacts are converted into offers and acceptances. The probability a single application yields an offer falls when there is increased competition amongst workers, while the probability that an offer is accepted falls when workers contact more vacancies and can select from more options. A fall in either of these probabilities contributes toward depressing outflow rates. In our calibrated model, and as in the data, the decline in offer and acceptance rates is sizable, and counteracts the direct effect of contacting more vacancies when applications increase. The decline in offer probabilities partially stems from the fact that the rise in applications in our model leads to an overall higher number of applicants per vacancy, consistent with the data. The decline in acceptance rates in our model is not solely driven by an increase in reservation match quality and hence, reservation wages. Holding fixed reservation match quality, acceptance rates still decline substantially as workers reject jobs more often when they submit more applications and can choose from more offers. This result concurs with our empirical findings that while acceptance rates have fallen by a large margin in the data, the coincident rise in reservation wages has not been to the same magnitude. In summary, our model predicts that the rise in applications has been accompanied by a decline in offer probabilities and acceptance rates.

Finally, we demonstrate why endogenizing the firm's information acquisition problem is necessary to understand how a rise in applications affects trends in unemployment flows. To do so, we consider two thought experiments: a case where information about a firm's applicants is free (full information) and a case where information is infinitely costly (no information). We find that both models predict changes in unemployment flows that are inconsistent with the data. Intuitively, the effective cost of job creation is invariant to the number of applications in either of these models as information is either free or no firm pays for information. Since the cost is constant but the benefit of a vacancy is increasing when the probability of zero applicants is lower, vacancy creation rises. This higher vacancy creation does not occur in our baseline model as the effective cost of job creation is rising with the share of informed firms. Thus, in the full information environment, the outflow rate rises by a non-trivial amount as higher vacancy 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, this contributes positively towards a worker’s job-finding rate. In contrast, the outflow rate declines substantially in the no information environment because the benefits of additional applications are negated when firms cannot identify high-quality matches. Although vacancy creation rises, it does not rise enough to keep the number of applicants per vacancy constant. As such, increased applications result in lower offer probabilities and a large decline in the outflow rate. In terms of inflows, both counterfactuals predict increases in the inflow rate, contrary to the data.

Overall, our results suggest that increased information acquisition by firms in response to a rise in applications is necessary to explain the joint dynamics in inflow and outflow rates. We find evidence from the data to support this result. Using data from the Quarterly Census of Employment and Wages (QCEW), we document a substantial growth in employment placement services industry over time.³ In addition, a recent survey on hiring managers reports that managers increasingly use staffing and recruiting firms to find skilled workers.⁴ These suggest that firms are increasingly willing to pay for information, underscoring the need to understand how increased information acquisition can affect labor market flows alongside the rise in applications.

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

³Specifically, we find that for the periods 1990-2007 and 2010-2019, average employment growth in employment placement services outpaced growth in total employment. During the Great Recession, growth in employment placement services lagged total employment growth. The share of total establishments that are establishments in the employment placement services industry has also grown steadily since the 1990s, with the share in 2019 being 61 percent higher than its level in 1990.

⁴See <https://prn.to/34uAXAk>

to long-run trends in unemployment flows.

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

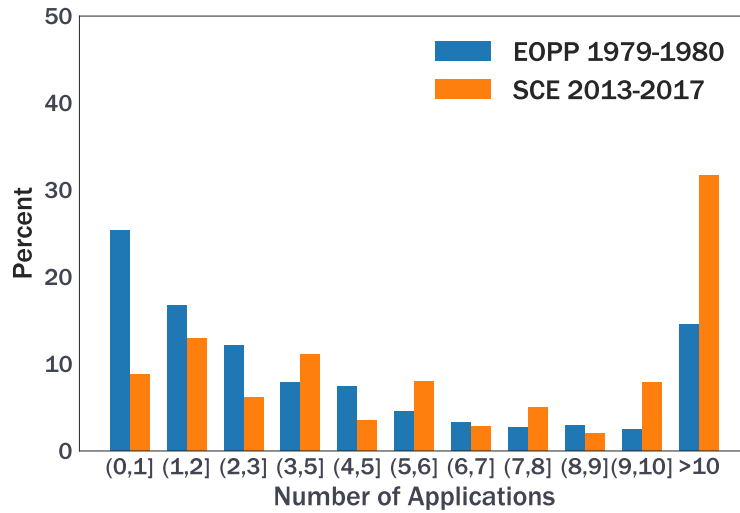
On the theoretical side, Engbom (2019) extends the labor search model to incorporate rich firm dynamics and entrepreneurial choice, and shows how an aging workforce contributes to the decline in worker dynamics over time. We focus on how changes in application behavior affect labor market flows through their effects on household search and firm hiring decisions. Mercan (2017) and Pries and Rogerson (2019) show that an exogenous reduction in uncertainty regarding a worker’s fit for a job is key to explaining the decline in worker turnover and job separations over the past four decades. In our paper, an improvement in information via a higher share of informed firms also affects labor market flows. However, the increase in the share of informed firms in our model is an *endogenous* response to rising applications. Separately, Martellini and Menzio (2020) study an economy with search frictions along a balanced growth path and show how *both* inflow and outflow rates can remain unchanged since the 1950s even if search technology improves. Our starting point is that improvements in search technology have led to an increase in applications and we focus on explaining how this rise since the 1980s can enable workers to find better matches and observe fewer separations, without triggering a simultaneous rise in job-finding probabilities. By focusing on the effects of increased applications, our model has testable implications for the changes in application outcomes such as offer probabilities, acceptance rates, reservation wages, tenure, and the number of applicants per vacancy – factors which we show have a first order effect on unemployment flows.

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 alternative formulations of our framework and their implications for 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.

Figure 1: Change in number of job applications over time



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

2.1 Job applications

Using information from the EOPP and SCE Labor Market Survey, we provide novel evidence on how the job 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 the unemployment spells and job search activities of unemployed workers that occurred between 1979 and 1980. Around 80 percent of the interviews occurred between May and September, and a total of 29,620 families were interviewed. The Federal Reserve Bank of New York's SCE survey is a household survey that is conducted annually with more than 1,000 respondents per year. We use information from the SCE for the years 2013 to 2017. Both datasets provide individual-level information on demographics, employment, wages, and regular hours of work. Appendix A provides a list of the variables we use, and explains how we calculate moments using these variables. To evaluate the comparability of these datasets with more widely used surveys, Table A1 and Table A2 in Appendix A compare the EOPP and SCE samples to the CPS over the same time period. Overall, the EOPP 1979-1980 and SCE 2013-2017 samples capture well the demographic changes observed in the CPS between the two time periods.

In both datasets, we consider a sample of unemployed individuals aged 25-65 who sent at least

one job application during their unemployment spell.⁵ Figure 1 highlights how the distribution of applications submitted per month by the unemployed has shifted rightward over time. Between the two surveys, the median number of applications per month increased from 2.7 to 6, implying that the median number of applications more than doubled between 1979-1980 and 2013-2017.⁶ To ascertain whether the rise in applications is due to prevailing aggregate economic conditions, Table A3 in Appendix A shows that this result continues to hold even after controlling for business cycle effects. Finally, Table A4 in Appendix A documents that the rise in applications is a common pattern across various demographic groups. Overall, our findings imply that the number of applications has increased over the past four decades.

2.2 Labor market flow rates

Turning now to unemployment flows, we use monthly data from the CPS on the total number of employed, unemployed, and short-term unemployed, i.e., respondents who are unemployed for at most five weeks, and calculate the outflow and the inflow rates over time using standard procedures found in the literature. Appendix A provides details on our data and methodology.⁷ Echoing previous studies, Figure 2 shows that the outflow rate exhibits no secular trend since the 1980s, while the inflow rate has fallen by 44 percent, from 4.1 to 2.3 percent.

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

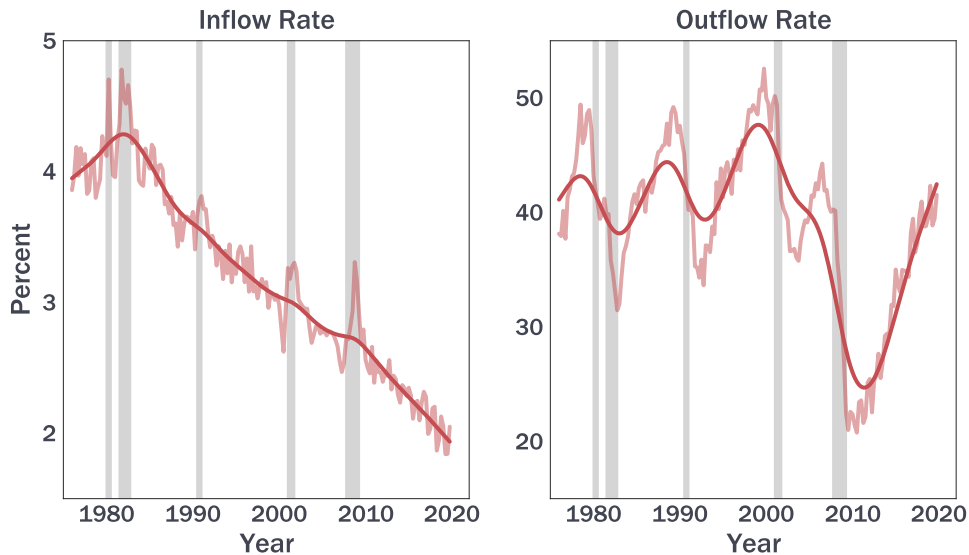
We focus on the behavior of inflow and outflow rates since the 1980s for two reasons. First, in order to quantitatively analyze the impact of increased job applications on these flow rates, we need data on the number of applications and application outcomes over time. This data is available in the EOPP survey that covers 1979-1980 and in the SCE that covers 2013-2017. Second, we argue that the advent of the ICT revolution in the 1980s enabled workers to submit

⁵While the SCE provides information on the number of job applications submitted by employed workers, the EOPP does not. For this reason, we focus only on applications submitted by unemployed workers.

⁶While the mean also more than doubled between the two time periods, we focus on the median as the mean is twice of the median as shown in Table A4, implying significant skewness in the distribution of applications.

⁷The 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. Moreover, in Figure A1, we exploit the panel nature of the CPS and present results based on monthly transition rates as well.

Figure 2: Unemployment outflow and inflow rates



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

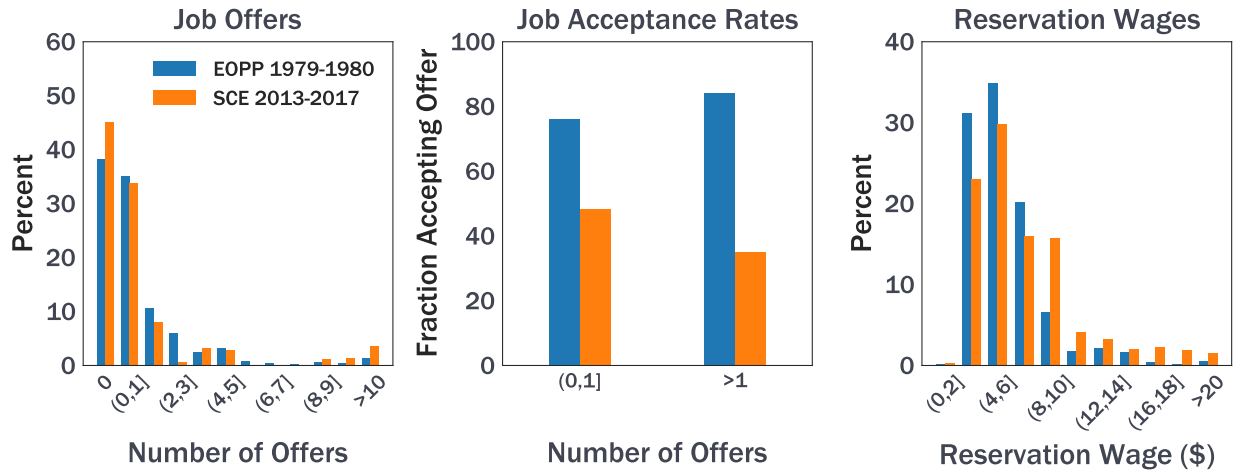
more applications and contact more firms over time. This phenomenon, in turn, had an impact on labor market flows through its effects on the hiring and match formation process. One may think that the inflow rate exhibits no secular trend once data prior to 1980 is considered. [Martellini and Menzio \(2020\)](#) study a search economy along a balanced growth path and argue that the inflow rate exhibits no secular trend between 1948 and 2018. We find evidence to the contrary. Using their data, we conduct two time-series tests. First, we conduct a [Kwiatkowski, Phillips, Schmidt, and Shin \(1992\)](#) (KPSS) test and reject the hypothesis that the inflow rate is stationary. Second, we conduct a Bai-Perron test ([Bai and Perron, 1998, 2003](#)) and reject the hypothesis that there are no break points in the inflow rate. Rather, we find that one of the break points occurs exactly in 1980, lending support to the fact that the inflow rate has trended downwards for the last 40 years. Overall, we find no evidence that the inflow rate is stationary.⁸

2.3 Offer arrival and acceptance rates and reservation wages

Flows out of unemployment are inextricably tied to job search behavior. 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

⁸While the outflow rate is also non-stationary, it does not exhibit any persistent increase or decrease since 1980 nor do we find evidence of a break point around 1980.

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



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

affect workers' acceptance decisions and reservation wages. Since these factors eventually affect job-finding rates, it is relevant to understand how these variables have changed over time. In Section 5.1, we discuss that these findings serve as testable implications for our model.

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

We highlight several results. First, the fraction of individuals with no offers increased from 38 percent to 45 percent over time, implying that the fraction of unemployed with offers declined. Second, offer acceptance rates also declined over time. For instance, among those who received more than one offer during a month of unemployment, the fraction of individuals who accept an offer decreased from 84 percent to 35 percent. Finally, the distribution of real hourly reservation wages shifted rightward across these two time periods. The mean real hourly reservation wage (in 1982-1984 dollars) increased from \$5.83 to \$6.94.⁹ While acceptance rates have fallen by a large margin, the coincident rise in reservation wages has not been to the same magnitude, suggesting that the increase in the latter only partially explains the sharp decline in the former.¹⁰

Thus, while the unemployed now submit more applications, they are less likely to receive and accept job offers. 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

⁹We use seasonally adjusted Consumer Price Index for All Urban Consumers: All Items (CPIAUCSL) where the unit is set to 100 between 1982 and 1984.

¹⁰In fact, the reservation wage grew less than the mean wage as shown in Appendix A.

labor flows should also jointly account for changes in application outcomes. We now develop a framework to examine how a rise in applications can affect labor flows and application outcomes.

3 Model

3.1 Environment

Time is discrete. The economy comprises a unit mass of infinitely-lived workers who are ex-ante identical. Workers are risk neutral and discount the future with factor β . Workers can either be employed or unemployed. Unemployed workers consume home production b . Employed workers consume their wages and are attached to firms that can employ at most one worker. The output from a matched firm-worker pair is equal to its match quality x , which is an iid draw at the time of meeting from a time-invariant distribution $\Pi(x)$ with support $[\underline{x}, \bar{x}]$. Match qualities can evolve over time. With probability $\rho(x)$, workers re-draw new match quality y from a conditional distribution $\Psi(y|x)$, where $d\Psi(y|x)/dx < 0$, implying that new draws of match quality y are positively correlated with previous values of x . We further assume that $\rho(x)$ is decreasing in x , implying that higher-productivity matches observe a lower frequency of match quality shocks. Employed workers endogenously exit into unemployment whenever their new match quality drawn 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 each period. The number of applications, a , that a worker can send each period is a random variable drawn from a Poisson distribution with parameter ξ . The probability that a worker draws a applications is given by¹¹:

$$p(a) = \frac{1}{a!} \xi^a \exp(-\xi).$$

A worker sends each application she draws to a separate vacancy. For each vacancy contacted, the worker observes her match quality x for that particular application.

The number of applicants at a vacancy, j , is also a random variable. Denote u as the measure of unemployed, v as vacancies, and $q(j)$ as the probability that a firm receives j applicants. Then, given that, on average, the probability that a worker applies to any one particular vacancy is ξ/v , the probability a firm has j applicants is:

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

where $\theta = v/u$ is the ratio of vacancies to unemployed job-seekers. Unlike workers, firms do

¹¹The probability that a worker draws a applications follows an urn-ball matching process as in [Butters \(1977\)](#).

not observe their applicants' match qualities. A firm, however, can choose to pay a fixed cost, κ_I , to learn its applicants' qualities.¹² While paying κ_I reveals to the firm information about its applicants' match qualities, it does not inform the firm about the number of applications and offers applicants have nor does it provide information about their match qualities at other jobs.¹³ As such, information is asymmetric as a worker knows her match qualities across all her a applications and her number of offers received, while a firm that acquires information only knows its applicants' match qualities at its own vacancy. We restrict our attention to symmetric equilibria in pure strategies; that is, all firms with j number of applicants employ the same information acquisition and hiring strategy. Finally, each vacancy costs κ_V to post.

Timing At the beginning of each period, firms post vacancies and unemployed workers realize the number of applications, a , that they can send for that period.¹⁴ Next, existing matches observe separation and match quality shocks. Newly separated workers must wait one period before searching for a job. Following this, unemployed workers submit applications and observe their match quality at each vacancy contacted. Firms receive applications and choose whether to acquire information. Firms then make offers to their chosen applicants, and workers decide whether to accept offers. Once an offer has been accepted, wage bargaining commences, where the worker's bargaining weight is given by $\eta \in [0, 1]$.¹⁵ At this stage, firms that did not acquire information learn about their worker's match quality. Wages are re-bargained every period. We assume that once a worker accepts an offer, she discards all other offers, implying that at the bargaining stage, the worker's unemployment value forms her outside option. Finally, production occurs. Having described the environment, we proceed to defining the worker's and firm's end-of-period value functions, i.e., after search and matching has occurred.

3.2 The firm's problem

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

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

where $x - w(x)$ represents the firm's current profits. With probability δ , the job is exogenously destroyed and the firm shuts down. Conditional on no exogenous separation, the match observes a match quality shock with probability $\rho(x)$, where the new match quality y is re-drawn from conditional distribution $\Psi(y | x)$, with $\psi(y | x)$ being the associated density. Let \tilde{x} be the reserva-

¹²In Section 6.1, we discuss how our model would change in an economy featuring a marginal cost of information. We then reproduce our key findings under this assumption.

¹³We assume that firms make offers simultaneously. Thus, no worker has an offer prior to firms making offers.

¹⁴In Section 6.3, we provide a sketch of how our model would vary with on-the-job-search and a discussion about its effects on our main results.

¹⁵Specifically, by accepting an offer, the worker agrees to engage in wage-bargaining with the firm.

tion match quality – an endogenously determined object to be formally defined below. As long as $y \geq \tilde{x}$, the match is preserved with continuation value $V^F(y)$. With probability $1 - \rho(x)$, the match observes no match quality shock and the firm continues with $V^F(x)$.

3.3 The firm’s information acquisition problem

No information acquisition Consider a firm that receives 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:

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

where $\pi(x)$ is the probability density from which the chosen applicant draws match quality x and $\Gamma(x) = \sum_{a=1}^{\infty} p(a) \Gamma(x, a)$ is the probability a worker accepts an offer of match quality x . Since firms do not know the number of applications submitted by their applicants and match qualities are also unknown, the expectation is taken over the number of possible applications and over the unconditional distribution of match qualities. Before we elucidate the derivation of $\Gamma(x, a)$, 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 pays cost κ_I to learn the match qualities of all its applicants. As we show in Section 3.6, wages are determined via surplus splitting and surplus $S(x)$ is increasing in quality x . Then the following lemma is true.

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

Proof. See Appendix B.1. □

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 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. As a result, the expected benefit from acquiring information is given by:

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

where $[\Pi(x)]^j$ is the distribution of the maximum order statistic. Given the expected benefit from acquiring information, the information acquisition problem for a firm with j applicants is:

$$\Xi(j) = \max \{V^I(j) - \kappa_I, V^{NI}\}. \tag{1}$$

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.1. □

As the number of applicants at a firm, j , increases, the likelihood that at least one of its applicants is a high-productivity match also increases. Thus, the expected benefit of information acquisition, $V^I(j)$, is strictly increasing in j , as only firms 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 high match quality is increasing in j , the firm with no information cannot take advantage of this because it makes offers randomly. Since the expected value of no information is a constant, the net value of information, $V^I(j) - \kappa_I$, crosses V^{NI} once from below. As such, for a finite and small enough κ_I , there exists j^* applications such that $V^I(j) - \kappa_I \geq V^{NI}$ for all $j \geq j^*$. Hence, for any number of applicants $j \geq j^*$, the firm always chooses to acquire information. Finally, it is clear that $j^* > 1$ because $V^I(1) - \kappa_I < V^{NI}$.

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

$$\kappa_V = \sum_{j=1}^{\infty} q(j)\Xi(j). \quad (2)$$

3.4 Employed workers

The value of an employed worker with match quality x is given by:

$$\begin{aligned} V^W(x) = & w(x) + \beta(1 - \delta)(1 - \rho(x))V^W(x) \\ & + \beta[\delta + (1 - \delta)\rho(x)\Psi(\tilde{x} | x)]U + \beta(1 - \delta)\rho(x) \int_{\tilde{x}}^{\bar{x}} V^W(y) \psi(y | x) dy, \end{aligned} \quad (3)$$

where $w(x)$ is the worker's current wage. With probability δ , the worker exogenously separates into unemployment. Jobs that are not exogenously destroyed are subject to a match quality shock with probability $\rho(x)$. If the new match quality drawn is above the reservation match productivity, i.e., $y \geq \tilde{x}$, the worker remains employed with continuation value $V^W(y)$. Otherwise, the worker endogenously exits into unemployment. With probability $1 - \rho(x)$, no match quality shock occurs and the worker continues with 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 who has submitted a applications. When the employment value, $V^W(x)$, is increasing in match quality, the worker always prefers to accept her highest match quality drawn so long as that value is above \tilde{x} . Consider a worker who draws match quality $x \geq \tilde{x}$ from one of her a applications and receives an offer for this draw. The worker will accept this offer of quality x if 1) it is her highest match quality, or 2) it is not her highest match quality but other applications with higher match quality failed to yield offers. Thus, the worker's probability of accepting an offer with match quality $x \geq \tilde{x}$ for a particular application is given by:

$$\Gamma(x, a) = [\Pi(x)]^{a-1} + \sum_{i=1}^{a-1} (a-i)[1 - \Pi(x)]^i [\Pi(x)]^{a-1-i} [1 - Pr(\text{offer} | y > x)]^i, \quad (4)$$

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

$$Pr(\text{offer} | y > x) = \int_x^{\tilde{x}} \sum_{\ell=1}^{\infty} \hat{q}(\ell) Pr(\text{offer} | y, \ell) \frac{\pi(y)}{1 - \Pi(x)} dy, \quad (5)$$

where

$$Pr(\text{offer} | y, \ell) = \mathbb{I}[\ell \geq j^*] [\Pi(y)]^{\ell-1} + (1 - \mathbb{I}[\ell \geq j^*]) \frac{1}{\ell}, \quad (6)$$

and $\hat{q}(\ell) = q(\ell) / \sum_{\ell=1}^{\infty} q(\ell)$.¹⁶ When $x < \tilde{x}$, the worker rejects the offer since the value of unemployment is larger. When $x \geq \tilde{x}$, the first term on the right-hand-side of Equation (4) depicts the case where the worker accepts an offer of match quality x because it is her highest match quality drawn. This occurs with probability $[\Pi(x)]^{a-1}$. The second term corresponds to the cases where the worker has drawn match quality $y > x$ in her i other applications for $i \in \{1, 2, \dots, a-1\}$, and match qualities less than x for her remaining $(a-1-i)$ applications. This occurs with probability $(a-i)[1 - \Pi(x)]^i [\Pi(x)]^{a-1-i}$. Since her i applications that drew match quality greater than x failed to yield an offer, she accepts her next best outcome which is x . Equation (5) represents the probability that a worker with match quality $y > x$ receives an offer for that application, while Equation (6) 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 (6) depicts the case where the worker meets a firm that chooses to acquire information because it received $\ell \geq j^*$ applicants.¹⁷ Since this firm observes its applicants' match qualities, the worker receives an offer only when she is the best applicant. This occurs

¹⁶The weights are given by $\hat{q}(\ell)$ 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.

¹⁷ ℓ is the number of applicants at the firm where the worker has drawn match quality y , and j is the number of applicants at the firm where the worker has drawn match quality x .

with probability $[\Pi(y)]^{\ell-1}$. The second term depicts the case where the worker meets a firm with $\ell < j^*$ applicants. Since the firm does not acquire information and randomly selects an applicant, the worker receives an offer with probability $1/\ell$. Summing across ℓ and conditioning on $y > x$ yields Equation (5).

The probability that a worker with a applications is hired with match quality x in one of her applications is:

$$\phi(x, a) = \Gamma(x, a)Pr(\text{offer} | x) = \Gamma(x, a) \sum_{j=1}^{\infty} \hat{q}(j)Pr(\text{offer} | x, j), \quad (7)$$

where $\phi(x, a)$ is the product of the expected offer probability, $Pr(\text{offer} | x)$, and the acceptance probability, $\Gamma(x, a)$. Given these probabilities, we can write the unemployed worker's value as:

$$U = b + \beta \left[p(0)U + \sum_{a=1}^{\infty} p(a)U(a) \right], \quad (8)$$

where

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

With probability $p(0)$, workers who draw $a = 0$ applications remain unemployed. Next, consider a worker who sends a applications. 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 $\phi(x, a)$. Since any of the worker's a applications could have yielded this outcome, the unemployed worker who submits a applications finds a job with probability $a \int_{\tilde{x}}^{\bar{x}} \phi(x, a)\pi(x)dx$. Ex-ante, workers do not know the number of applications they would draw. As such, they form expectations over all the possible a applications they could possibly draw.

3.6 Surplus and wage determination

Wages are determined by Nash bargaining only after the worker has accepted a job, and are re-bargained each period.¹⁸ In accepting an offer, the worker discards all other offers prior to bargaining. We assume that there is no recall: Firms, that have made an offer to a particular candidate, have rejected all their other applicants. The assumption of no recall is standard in the literature (see, for example, Albrecht, Gautier, and Vroman, 2006; Galenianos and Kircher, 2009; Gautier and Wolthoff, 2009; Gautier and Moraga-Gonzalez, 2018; and Albrecht, Cai, Gautier, and Vroman, 2020).¹⁹ Further, firms that did not acquire information learn about their worker's

¹⁸In Section 6.4, we discuss the implications of alternative wage protocols on our main results.

¹⁹Allowing for recall can raise the firm's job-filling probability by allowing them to contact other applicants when their chosen candidate rejects their offer. It can, however, also lower the worker's acceptance rate, $\Gamma(x)$, as workers are less likely to accept an offer of any match quality x when other applications have drawn higher match qualities. These competing forces suggest that the inclusion of recall need not guarantee higher job-finding rates.

match quality at this stage. Thus, at the bargaining stage, the firm's and worker's outside options are equal to their values from remaining unmatched. The wage for a job of quality x is:

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

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

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

with

$$(1-\beta)U = b + \beta\eta \sum_{a=1}^{\infty} p(a) a \int_{\tilde{x}}^{\bar{x}} \phi(x,a) \pi(x) S(x) dx.$$

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

3.7 Labor market flows

Unemployed The steady state unemployment rate is implicitly given by:

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

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

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

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

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

3.8 Equilibrium

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

Lemma 2 (Key equilibrium conditions). $\{\tilde{x}, \theta, j^*\}$ are determined by the free entry condition given by Equation (2) and the following conditions²⁰:

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

and

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

Equation (14) is derived by evaluating $S(x)$ at the reservation match quality, \tilde{x} , and represents the lowest match quality for which a match can be sustained. Equation (15) determines j^* which is the smallest number of applicants firms must have for them to acquire information. Finally, the free entry condition, Equation (2), provides information on θ .²¹

3.9 Forces at play

Before turning to our main results, it is useful to understand how the different components in the unemployment inflow and outflow rates respond when applications rise. One simple way to increase the number of applications sent in the model is to raise the parameter ξ that governs the Poisson distribution from which workers draw applications. As such, we ask how the factors affecting outflow and inflow rates would change with an increase in ξ , holding constant our key equilibrium objects, i.e., \tilde{x}, θ , and j^* .

Outflow from unemployment Recall that the outflow rate is given by:

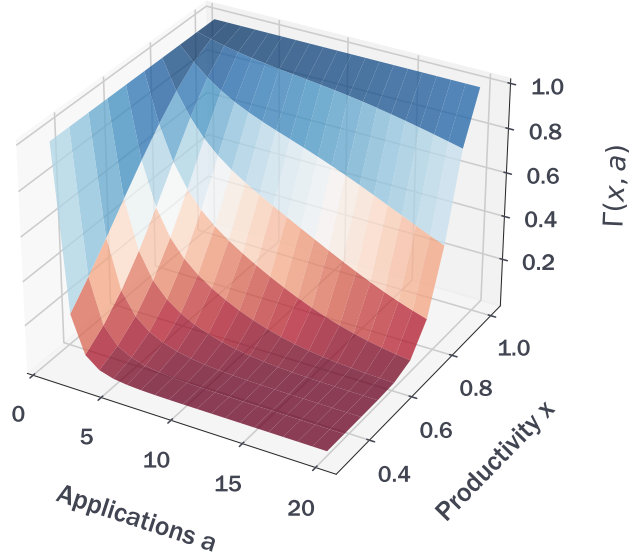
$$\text{outflow rate} = \underbrace{\sum_{a=0}^{\infty} p(a) a}_{\text{1) expected applications}} \int_{\tilde{x}}^{\bar{x}} \underbrace{\text{Pr}(\text{offer} | x)}_{\text{2) probability offer for } x} \times \underbrace{\Gamma(x, a)}_{\text{3) probability accept for } x} \pi(x) dx. \quad (16)$$

Notably, the unemployment outflow rate is a function of three components: 1) the expected number of applications a worker sends and conditional on the realized number of applications; 2) the probability she receives an offer; and 3) the probability she accepts an offer. The first component in Equation (16) represents the effect an increase in the expected number of applica-

²⁰Figure A3 in Appendix B.2 highlights the existence of a unique equilibrium in our calibrated model.

²¹Appendix B.2 discusses a more general setup of our problem with mixed strategies.

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



Note: This figure plots how $\Gamma(x, a)$ varies with the number of applications a and match productivity x .

tions, $\sum_{a=0}^{\infty} p(a)a = \xi$, has on the outflow rate. Holding all else constant, the ability to submit more applications and contact more vacancies has the *direct* effect of increasing the outflow rate.

While the effect from a higher ξ contributes positively towards the outflow rate, an increased average number of applications also *indirectly* affects the probability that a single application yields an offer. From Equation (7), the offer probability, $Pr(\text{offer} | x)$, depends on the distribution of applicants across vacancies $q(j)$, which in turn depends on ξ . To see this, observe that differentiating $q(0)$ with respect to ξ , we get:

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

The probability that a firm does not receive any applications, $q(0)$, is strictly declining in ξ , implying that the distribution, $q(j)$, shifts rightward away from zero applicants with an increase in ξ . When firms have more applicants on average, the probability that a single application yields an offer falls. Consider a worker who applies to a firm with j applicants and who draws match quality $x > \tilde{x}$. From Equation (6), the probability that a worker receives an offer for this application is weakly declining in j .²² Thus, as ξ increases, each applicant faces more competition at the same vacancy, reducing the probability of an offer for their match quality x .

The final component in the outflow rate in Equation (16) is the acceptance probability $\Gamma(x, a)$ for a given number of applications. Numerically, we show that holding all else constant, acceptance probability $\Gamma(x, a)$ 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

²² $[\Pi(x)]^{j-1}$ is weakly declining in j and $1/j$ is strictly declining in j .

one of their *other* applications draws a match quality greater than x . Since a higher ξ increases the average number of applications drawn by workers, it also has the *indirect* effect of lowering average acceptance probabilities, $\sum_{a=1}^{\infty} p(a) \int_{\tilde{x}}^{\bar{x}} \Gamma(x, a) \pi(x) dx$.

Ultimately, whether the unemployment outflow rate rises with ξ depends on the extent to which the direct effect of a higher contact rate is neutralized by the indirect effects of lower offer and acceptance probabilities. Notably, previous studies by [Albrecht, Gautier, and Vroman \(2003\)](#) and [Gautier and Moraga-Gonzalez \(2018\)](#) have also found the unemployment outflow rate to be non-monotonic in the number of applications. These papers, however, abstracted from match heterogeneity and how information choices affect offer probabilities. Our paper highlights how these two additional elements can act on acceptance rates and offer probabilities to weigh against the direct positive effect a higher number of applications has on the outflow rate. In [Section 6.2](#), we quantitatively study how the relative size of the direct and indirect effects on the outflow rate changes with increases in ξ . In particular, we show that these offsetting forces can lead to a muted and non-monotonic relationship between the outflow rate and the number of applications.

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

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

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

Thus far, we have limited our analysis to a partial equilibrium setting. In general equilibrium, however, \tilde{x} , θ , and j^* can vary in response to changes in ξ . Changes in these equilibrium objects in turn affect the factors underpinning labor market flows. As such, we use our calibrated model to understand the general equilibrium impact of a rise in applications on labor market flows.

4 Calibration

A period in our model is a month. We calibrate the initial steady state to the period 1976-1985 as this interval of time covers the period of the EOPP survey. Because we are interested in long-term trends, we treat the 10-year period around 1979-1980 as a steady-state. We set the

Table 1: Internally calibrated parameters

Parameter	Description	Value	Target	Model	Data
κ_V	Vacancy posting cost	0.50	Outflow rate	0.45	0.41
κ_I	Cost of information	0.73	Recruiting cost/mean wage	0.95	0.93
δ	Exog. separation rate	0.025	Inflow rate	0.042	0.041
λ	Persistence of x	4.77	EU_{20}/EU_{80}	4.22	4.05
A	Beta distribution	0.94	Fraction with no offers	0.35	0.38
B	Beta distribution	0.89	Fraction accept and > 1 offer	0.16	0.22
b	Home production	0.11	Reservation wage/mean wage	0.76	0.66

Note: This table provides a list of internally calibrated parameters. 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 and have more than one offer are obtained from the EOPP for 1979-1980. Finally, the reservation to 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.

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 median is approximated by $\xi + 1/3 - 0.02/\xi$. As such, we set $\xi = 2.38$ so that the median number of applications sent in the model is also equal to 2.7. We target the median rather than the mean because the mean is much higher than the median as shown in Table A4, suggesting that there are a few individuals who send many applications. We next discuss our strategy for model parameters that will be calibrated internally.

Evolution of match quality We assume that the unconditional distribution of initial match quality, $\Pi(x)$, follows a beta distribution with shape parameters (A, B) and support $x \in [0, 1]$. Because the shape and skewness of $\Pi(x)$ affects the expected benefit of creating a job and vacancy posting, it affects the individual's probability of receiving an offer. The shape of $\Pi(x)$ 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 who accept a job and received more than 1 offer. In our model, the fraction of job-seekers with zero offers is given by $\sum_{a=1}^{\infty} p(a) \left(\int_{\underline{x}}^{\bar{x}} [1 - Pr(\text{offer} | x)\pi(x)dx] \right)^a$, while the fraction of job-seekers who accept a job and received more than 1 offer is given by the joint probability of both outcomes. In our model, the probability an individual accepts a job and has more than 1 offer is affected by the reservation match quality. Clearly, if all offers are for match qualities below \tilde{x} , the worker rejects all offers. The level of \tilde{x} is affected by the likelihood of drawing high match quality values.

Within each period, a worker is subject to a match quality shock with probability $\rho(x) = \min\{\exp(x_{ref} - x), 1\}$, where x_{ref} is set equal to the mean of the unconditional distribution of match qualities, i.e. $x_{ref} = A/(A + B)$. This implies that workers who draw and accept job offers with match qualities below the mean of the distribution observe a match quality shock with probability 1. For matches with $x > x_{ref}$, the frequency of match quality shocks is strictly declining in x . This formulation allows us to reflect the fact that low wage jobs observe higher

unemployment risk.²³ Conditional on a match quality shock, individuals draw their new match qualities from the joint distribution $\Psi(x, x')$ which is constructed using a Gumbel copula:

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

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

Labor market We target the average inflow rate over the period 1976-1985 to pin down the exogenous separation probability δ . We choose the vacancy posting cost, κ_V , to match an average outflow rate in the data.²⁴ Since the fixed cost of information, κ_I , affects recruiting costs, we set κ_I to match a ratio of recruiting costs to average wages of 0.928, as reported by [Gavazza, Mongey, and Violante \(2018\)](#). In our model, the recruiting cost a firm expects to pay when choosing whether to create a vacancy is given by $\kappa_V + \sum_{j \geq j^*} q(j) \kappa_I$. Finally, the level of home production, b , is set to match the ratio of the reservation wage to the mean wage. 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 reasonably well.

5 Quantitative Results

5.1 Equilibrium response to an increase in applications

We now analyze how an increase in applications affects unemployment flows and application outcomes. In the data, the median number of applications increased from 2.7 to 6 between the 1979-1980 period and the 2013-2017 period. We ask how the same rise in the median number of applications affects labor market moments in our calibrated model, holding all other parameters fixed. To obtain this rise in the median number of applications, we increase ξ from 2.38 to 5.67.

We first document the changes in the equilibrium objects $\{\tilde{x}, \theta, j^*\}$. [Table 2](#) highlights our

²³Using social security data, [Karahan, Ozkan, and Song \(2019\)](#) estimate that workers with low lifetime earnings observe a higher risk of job loss than the median worker.

²⁴In the CPS, we calculate HP-filtered time series of average outflow and inflow rates. We target the average of the trend component between 1976 and 1985.

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

	$\xi = 2.38$	$\xi = 5.67$	Percent change
Information threshold j^*	4	6	
Fraction of firms informed	0.35	0.91	157
Labor market tightness θ	0.82	0.60	-26
Reservation match quality \tilde{x}	0.53	0.64	21

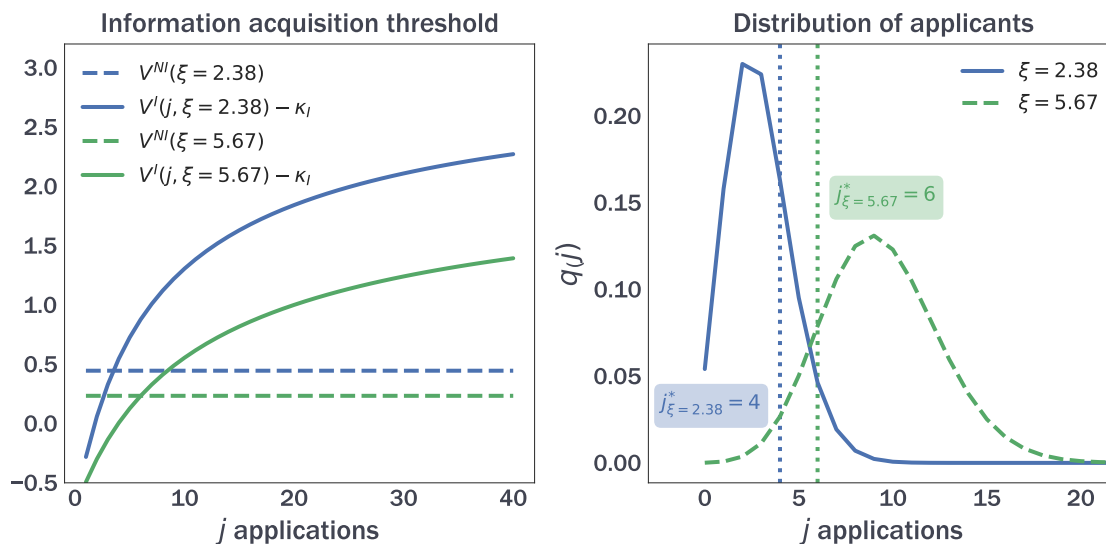
Note: This table summarizes the changes in equilibrium variables when ξ increases from 2.38 to 5.67, which corresponds to an increase in the median number of applications from 2.7 to 6.

results. First, an increase in ξ raises the share of firms acquiring information substantially, despite an increase in the information threshold, j^* . As foreshadowed in Section 3.9, acceptance probabilities are weakly declining in the number of applications sent. As such, j^* rises because the value of acquiring information, $V^I(j)$, falls by more than the value of not acquiring information, V^{NI} , when acceptance probabilities decline with more applications sent, as depicted by the left panel of Figure 5. Intuitively, for a given number of applicants j , information is less valuable if workers reject offers more often. Nonetheless, the right panel of Figure 5 shows that the increase in ξ causes the distribution of applicants per vacancy, $q(j)$, to shift right, resulting in a larger share of firms with $j \geq j^*$ applicants. Consequently, more firms acquire information when ξ is higher, and the share of informed firms increases from 35 percent to 91 percent.

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

Finally, reservation match quality, \tilde{x} , rises when ξ increases. There exists counteracting forces that mitigate the extent to which a rise in applications improves the worker's outside option. On the one hand, the ability to contact more vacancies raises the probability that at least one application draws a high match quality and yields an offer. This higher probability of finding a good match raises the worker's outside option and their selectivity over the minimum acceptable job quality. On the other hand, a greater number of applications and a decline in vacancy creation implies a higher average number of applicants at a vacancy. Increased competition in turn depresses the worker's ability to find a job and thus their outside option. Consequently, the rise in \tilde{x} is partially tempered by the rise in congestion.

Figure 5: Firms raise information acquisition threshold but receive more applicants as ξ rises



Note: The left panel shows how the information acquisition threshold j^* is determined when ξ increases from 2.38 to 5.67, which corresponds to an increase in the median number of applications from 2.7 to 6. The right panel shows how the distribution of applicants per vacancy, $q(j)$, changes with a rise in applications. The dashed vertical line represents the equilibrium j^* cutoff below which firms do not acquire information.

5.2 The response of inflow and outflow rates

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

5.2.1 Inflow rate

Table 3 highlights that a rise in applications alone causes the average inflow rate to decline by 19 percent, accounting for 43 percent of the decline in the data. This is despite an increase in reservation match quality. To explain how the effect of improved firm selection – i.e., a greater formation of high quality matches – causes a decline in separations, we show how the distribution of employed workers across match quality changes with a rise in ξ , and how this change affects the frequency of shocks and the likelihood that a match is severed given a shock.

Figure 6 illustrates how the match quality distribution of employed workers changes with a rise in applications. As more firms acquire information when ξ increases, a larger share of firms identify and hire highly productive applicants, giving rise to a greater formation of high

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

	Impact on unemployment flows					
	$\xi = 2.38$		$\xi = 5.67$		Percent change	
	Model	Data	Model	Data	Model	Data
Inflow rate	0.042	0.041	0.034	0.023	-19	-44
Outflow rate	0.448	0.408	0.434	0.318	-3	-22
direct effect					61	
indirect effect					-64	

Note: This table summarizes the model-predicted inflow and outflow rates when ξ increases from 2.38 to 5.67, which corresponds to an increase in the median number of applications from 2.7 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 a lower median number of applications and the latter period corresponds to the period with a higher median number of applications.

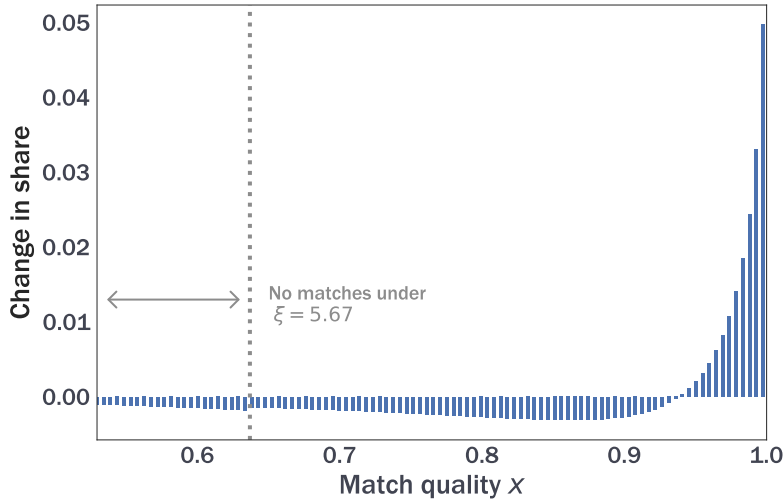
quality matches and a decline in the share of low-to-middling quality jobs. This larger share of high quality matches leads to greater job stability as the frequency of match quality shocks falls by 4.2 percent. Crucially, workers are less likely to separate from their job in the event of a match quality shock when the distribution of employed is concentrated amongst high quality matches. Conditional on a shock, the share of employed who draw a new match quality $x' < \tilde{x}$ and separate into unemployment falls by 41 percent when ξ increases.²⁵ The combined effects of a lower frequency of match quality shocks and a large decline in the likelihood of a match being severed conditional on a shock outweigh the effect of a higher reservation match quality \tilde{x} . Thus, the inflow rate in our model declines substantially as the effects from improved firm selection dominate the effects from increased worker selectivity.

Can the implications of improved firm selection and increased worker selectivity be tested against the data? In our model, variations in firm and worker selectivity have implications for the distribution of employed across match qualities, which in turn is informative about changes in the tenure distribution over time. As such, we compare changes in the model-implied tenure distribution against its data counterpart. In our model, the distribution of employed shifts towards higher quality matches. Accordingly, the share of short duration jobs declines significantly, while the share of jobs with longer duration falls by less. Table 4 shows that the share of workers employed in jobs lasting less than a quarter falls by 63 percent when ξ increases, while the share employed in jobs lasting between one and three years falls by a smaller 14 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. Using data from the CPS, [Molloy, Smith, and Wozniak \(2020\)](#) show that the median tenure has remained relatively unchanged over the last four decades, while the share of employed in jobs lasting more than a year and less than three years has declined 11 percent. Using data from

²⁵Conditional on a shock, the share of employed who draw match quality $x' < \tilde{x}$ is $\int_{\tilde{x}}^{\bar{x}} \Psi(\tilde{x} | x)g(x)dx$.

Figure 6: Realized match quality distribution improves as applications increase



Note: The figure shows how the share of employed workers across match quality x changes when ξ increases from 2.38 to 5.67, which corresponds to an increase in the median number of applications from 2.7 to 6. Specifically, for each bin, the figure shows the difference in the pmf $[G(x_2)_{\xi=5.67} - G(x_1)_{\xi=5.67}] - [G(x_2)_{\xi=2.38} - G(x_1)_{\xi=2.38}]$.

the Quarterly Workforce Indicators (QWI), Pries and Rogerson (2019) find that the share of employed in jobs lasting less than a quarter has fallen by 39 percent between 1999 and 2015. Importantly, these empirical findings are inconsistent with the predictions of an alternative model that posits a decline in exogenous separation rates over time. In such a model, the decline in exogenous separation rates would imply a uniform decline in the separation rates of all jobs, an increase in all tenure lengths, and a rise in median tenure. In contrast, our model would not only suggest a sharp decline in jobs of very short tenure length, but also that jobs of high match quality now observe slightly larger separation rates stemming from the increase in reservation match quality. To see this, note that the probability a match endogenously dissolves for a given x is given by $\rho(x)\Psi(\tilde{x} | x)$. Since \tilde{x} is higher when ξ increases, this raises $\Psi(\tilde{x} | x)$, implying that a match of given x quality is now more prone to separation. As such, median tenure remains unchanged in our model, a finding consistent with the data.

Taking stock The rise in applications in our model accounts for 43 percent of the empirical decline in the average inflow rate. The fall in our model-predicted inflow rate stems from a sharp drop in the share of low-quality jobs, while median tenure remains unchanged. Our model's predictions align with the empirical changes in the tenure distribution over time.

5.2.2 Outflow rate

Focusing on unemployment outflows, a rise in ξ causes the outflow rate in our model to decline a modest 3 percent. While the average outflow rate in the data is lower in the period 2010-2019 when compared to that in the period 1976-1985, this is largely due to the fact that the economy experienced a slow labor market recovery following the Great Recession. By 2019, the

outflow rate had returned back to its long-run average of about 0.41. Thus, the modest decline in our model-predicted outflow rate is 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 rise in applications? Recall from Section 3.9 that the extent to which the outflow rate varies with applications depends on whether the direct effect of submitting more applications outweighs its indirect effects on offer and acceptance probabilities. To quantify both effects, we decompose the percent change in the outflow rate between two time periods t_1 and t_2 as:

$$\frac{\text{outflow rate}_{t_2} - \text{outflow rate}_{t_1}}{\text{outflow rate}_{t_1}} = \underbrace{\frac{\sum_{a=1}^{\infty} \left\{ [p_{t_2}(a)a - p_{t_1}(a)a] \int_{\bar{x}}^{\infty} \phi_{t_2}(x, a) \pi(x) dx \right\}}{\text{outflow rate}_{t_1}}}_{\text{direct effect}} + \underbrace{\frac{\sum_{a=1}^{\infty} \left\{ p_{t_1}(a)a \int_{\bar{x}}^{\infty} [\phi_{t_2}(x, a) - \phi_{t_1}(x, a)] \pi(x) dx \right\}}{\text{outflow rate}_{t_1}}}_{\text{indirect effect}}.$$

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

The model's ability to reproduce the lack of a secular increase in the outflow rate as observed in the data emanates from its predicted declines in offer and acceptance rates. Crucially, the magnitudes of these changes in offer and acceptance rates upon a rise in applications in our model align with the data, as shown in Table 4. The fraction of the unemployed with offers declines by 24 percent and 11 percent in our model and in the data, respectively. The larger decline in our model stems from the fact that both a fall in vacancy creation and a higher number of applications contributes to increased congestion amongst workers. Notably, labor market tightness, θ , is only one component that affects the degree of competition amongst job-seekers when workers can submit multiple applications. A more relevant measure is the mean number of applicants per vacancy, ξ/θ . It should be noted that we do not target the mean number of applicants per vacancy, and only ensure that the median applications sent by workers in the model is equal to that observed in the data. In that regard, one should not expect the *levels* of applicants per vacancy to be exactly as observed in the data. Nonetheless, our model does predict a substantial *growth* in the mean number of applicants per vacancy. The mean number of applicants per vacancy rises by 223 and 146 percent in our model and in the data, respectively.²⁶

²⁶Using 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.

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

Panel A: Tenure distribution						
	$\xi = 2.38$		$\xi = 5.67$		Percent change	
	Model	Data	Model	Data	Model	Data
Share employed $t < 1$ quarter	0.015	0.080	0.005	0.049	-63	-39
Share employed $1 \leq t < 3$ years	0.17	0.18	0.15	0.16	-14	-11
Median tenure (years)	3.28	4	3.28	4	0	0

Panel B: Outflow rate components						
	$\xi = 2.38$		$\xi = 5.67$		Percent change	
	Model	Data	Model	Data	Model	Data
Mean applicants per vacancy ξ/θ	2.92	24.0	9.41	59.0	223	146
Fraction > 0 offer	0.65	0.62	0.50	0.55	-24	-11
Acceptance rate	0.42	0.80	0.26	0.43	-40	-46
Reservation wage	0.61	5.83	0.71	6.92	16	19

Note: This table summarizes the changes in the tenure distribution and outflow rate components (the average fraction > 0 offer, the average acceptance rate, and the average reservation wage) when ξ increases from 2.38 to 5.67, which corresponds to an increase in the median number of applications from 2.7 to 6. Data moments on the share of jobs that last $t < 1$ quarter is taken from Pries and Rogerson (2019) who use data from the QWI. Data moments on the share of jobs lasting $1 \leq t < 3$ years and median tenure are taken from Molloy, Smith, and Wozniak (2020) who use CPS data. Data moments on the mean applicants per vacancy are taken from Faberman and Menzio (2018) for 1980 and Marinescu and Wolthoff (2020) for 2011. Data moments on outflow rate components are computed 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 a lower median number of applications and the latter period corresponds to a period with the higher median number of applications. Reservation wages in the data are average hourly reservation wages in 1982-1984 dollars.

The decline in the fraction receiving offers is one of the outcomes serving to counteract the positive effect of a higher average number of applications on outflow rates. The other key variable that affects the outflow rate is the acceptance rate. We calculate the model's average acceptance rate as the expected probability of accepting an offer for a particular application, $\int_{\tilde{x}}^{\bar{x}} \sum_{a=1}^{\infty} p(a) \Gamma(x, a) \pi(x) dx$. In our model, a higher number of applications causes workers to be more selective over the minimum job they are willing to accept – as depicted by the increase in \tilde{x} . In addition, workers experience an increased probability that at least one of their other applications draws a higher match quality. This increased probability of drawing a higher match quality from another application leads the worker to more frequently reject a job offer of given quality x . As such, acceptance rates in our model decline by 40 percent, close to the 46 percent fall observed in the data. While these changes are not targeted, our model's predicted changes in offer and acceptance probabilities largely mimic the patterns observed in the data over time.

The decline in acceptance rates in our model does not solely stem from the increase in reservation wages. Across the two time periods, the reservation wages rises by 16 percent in the model, implying that the rise in selectivity only contributes to part of the decline in acceptance rates. We note that the *levels* of reservation wages in our model are not comparable to the

levels observed in data since we do not calibrate wages in the model to match dollar amounts in the data. However, even if it is not targeted, we emphasize that our model’s predictions on the *growth* in reservation wages aligns well with its empirical counterpart. This is in spite of our parsimonious exercise of only increasing ξ .

Reflecting patterns in the data, our model’s smaller increase in reservation wages in the data relative to the larger decline in acceptance rates suggest that changes in reservation match quality are not the main driver behind changes in the acceptance rate. To understand how much acceptance rates would instead decline by if reservation match qualities remained constant, we conduct the following comparative static exercise. Holding fixed \tilde{x} at its level when $\xi = 2.38$ and keeping all other equilibrium objects at their $\xi = 5.67$ levels, we find that acceptance rates still fall by 30 percent. Thus, acceptance rates decline in our model with higher applications not only because workers are more selective over the minimum quality job they are willing to accept, but also because workers are more likely to have drawn a high match quality offer in at least one of their other applications, reducing their need to accept the first offer they receive.

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

5.3 The role of costly information

The key insight delivered by our baseline model is that an increase in applications need not necessarily translate into higher job-finding rates but does instead precipitate the formation of better matches that are longer-lived. We now consider two thought experiments to uncover why the interaction of information acquisition with an increase in applications is crucial for this result. In the first experiment, we set $\kappa_I = 0$, and label this the “Full Information” (FI) model.²⁷ In the second experiment, we consider the other extreme and set $\kappa_I \rightarrow \infty$. 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.²⁸ In both models, the firm’s investment in information acquisition does not vary with the number of applications. Hence, comparing the results from the FI and NI models against our baseline model allows us to isolate how variations in the firm’s information decision in response to more applications would affect predictions of our model.

Equilibrium outcomes Table 5 details the results from our counterfactual exercises. Both the FI and NI models observe an increase in labor market tightness, θ , when applications rise. Unlike our baseline model which featured higher expected job creation costs whenever more firms

²⁷While we use the term “Full information”, it should be noted that firms only observe the match qualities of applicants at their vacancy. They cannot observe the applicants’ match qualities at other jobs, the applicants’ number and quality of competing offers, or the number of applications sent.

²⁸Details of our calibration strategy and model fit can be found in Appendix C.1.

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

	Full Information (FI)		No Information (NI)		Percent change			
	$\xi = 2.38$	$\xi = 5.67$	$\xi = 2.38$	$\xi = 5.67$	Data	Model	FI	NI
Labor market tightness θ	0.86	0.93	0.89	0.93	-26	8	4	
Reservation match quality \tilde{x}	0.54	0.66	0.44	0.41	21	22	-6	
Inflow rate	0.042	0.043	0.043	0.045	-44	-19	2	7
Outflow rate	0.47	0.57	0.46	0.37	-22	-3	21	-18
direct effect						61	64	50
indirect effect						-64	-43	-68

Note: This table summarizes the equilibrium outcomes and labor market flows when ξ increases from 2.38 to 5.67, which corresponds to an increase in the median number of applications from 2.7 to 6. Model refers to the baseline scenario in which there is a fixed cost κ_I of acquiring information. FI is the “Full Information” model in which $\kappa_I = 0$, and NI is the “No Information” model in which $\kappa_I \rightarrow \infty$. Data moments on labor market flows are computed as averages from the CPS, where the time periods 1976-1985 and 2010-2019 correspond to the periods with a lower and higher median number of applications, respectively.

acquired information, job creation costs do not vary with the number of applications in the FI and NI economies, as firms either obtain information for free or never acquire it. Since a higher number of applications lowers the probability of firms receiving zero applicants, this raises the expected benefit of creating a job. The rise in the expected benefit of a vacancy coupled with a constant cost of job creation causes vacancy creation and consequently, market tightness, θ , to rise with the increase in ξ in the FI and NI models.

Focusing on reservation match quality \tilde{x} , the FI model predicts a rise in \tilde{x} , while the NI model predicts a decline in \tilde{x} as applications increase. These differences stem from how workers’ outside options change with an increase in applications across the two models. In the FI model, firms always identify the highest quality applicant. When workers submit more applications, the probability that at least one application draws a high match quality and yields an offer increases. This strengthens the worker’s outside option, encouraging a rise in \tilde{x} . Conversely, in the NI model, firms randomly select candidates from their applicant pool. Thus, the increased probability of drawing a high match quality does not translate into more offers. Although labor market tightness improves in the NI model, the increase in mean applications, ξ , outweighs the increase in θ . The increased congestion among workers brought about by the rise in ξ worsens workers’ outside options and causes \tilde{x} to fall.

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 increases in the inflow rate, implying that FI and NI models fail to capture empirical patterns of inflow and outflow rates over time.

Focusing first on the FI model, the inflow rate rises by 2 percent, while the outflow rate rises by 21 percent, opposite to the large decline in the inflow rate and lack of change in the outflow rate observed in the data. While the FI model also exhibits a greater formation of high quality matches as in the baseline model, the effects from increased worker selectivity far outweigh the

effects from improved firm selection. Because firms in the FI model always identify the best applicant to hire, average match quality in the FI model improves by a mere 2 percent. Thus, even though the incidence of match quality shocks falls by 2 percent, the larger increase in worker selectivity implies that employed individuals of any given quality x now observe a larger probability of exiting into unemployment. Conditional on a shock, the share of employed who draw a new match quality $x' < \tilde{x}$ rises by 15 percent in the FI model. This higher probability of a match being severed causes the inflow rate to rise 2 percent. In summary, the effects from improved firm selection are small in this environment when there is no change in the share of informed firms. In contrast, the worker selectivity effect is stronger relative to our baseline model, because congestion effects arising from increased applications are partially mitigated by the contemporaneous rise in vacancy creation in the FI model.

Focusing on the outflow rate, note that in the FI model, the probability of receiving an offer for a given match quality x from a firm with j applicants is given by $Pr(\text{offer} \mid x, j) = [\Pi(x)]^{j-1}$. Since $dPr(\text{offer} \mid x, j)/dx \geq 0$, this probability is increasing in x . Because an increase in applications implies that workers face a higher likelihood of drawing a high match quality in at least one of their applications, their probability of receiving an offer from at least one of their applications is higher. Further, acceptance probabilities, $\Gamma(x, a)$ are 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 – which in turn raises the probability of receiving and accepting an offer for that high x – contribute towards increasing the outflow rate in the FI model.²⁹

Switching now to the NI model, the outflow rate declines by 19 percent, while the inflow rate rises by 7 percent. The rise in the inflow rate is largely driven by the fall in the reservation match quality \tilde{x} . Average match quality worsens as the distribution of employed shifts towards lower quality jobs which observe both a higher frequency of shocks and a larger probability of the match being severed. The frequency of match quality shocks increases by 2 percent, and conditional on a shock, the employed are 15 percent more likely to draw $x' < \tilde{x}$ and separate into unemployment. In contrast to our baseline model where higher worker selectivity is a force towards increasing the inflow rate, declining worker selectivity here is the main driver behind the rise in the inflow rate as there is now a larger share of low quality, high turnover jobs. Increased applications only serves to weaken the worker's outside option through increased congestion when firms cannot identify high quality matches.

Finally, to understand why the outflow rate declines by a large amount in the NI model, note that the worker's probability of receiving an offer for match quality x from a firm with j applicants is given by $Pr(\text{offer} \mid x, j) = 1/j$. Because firms are uninformed about their

²⁹Nonetheless, because the number of applicants per vacancy and total number of applications sent are increasing on average, the change in the indirect effect is still negative. To see this, recall that $\Gamma(x, a)$ and $Pr(\text{offer} \mid x, j) = [\Pi(x)]^{j-1}$ are decreasing in a and j . Since both $q(j)$ and $p(a)$ shift rightward, the increase in applications still weighs negatively on average acceptance and offer probabilities.

applicants' qualities, the probability of an offer depends only on the number of applicants at a firm, j . Since the increase in applications on average outweighs the increase in labor market tightness in the NI model, the distribution of applicants, $q(j)$, shifts rightward, with the mean number of applicants per vacancy, ξ/θ , rising by 128 percent. As a result, workers face more competition at each vacancy and observe a much lower probability of receiving an offer for a single application. Consequently, the unemployment outflow rate declines significantly.

Overall, our results highlight that the interaction between a firm's information acquisition decision and the number of applications sent is important for capturing the joint behavior in 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 main results.

6.1 Assuming a marginal cost of information acquisition

While our model nests both the FI and NI models, a natural question arises as to whether our model mechanisms would differ if we were to instead assume a marginal cost of information. We first note that our assumption of a fixed cost of information in our baseline model is motivated by recent evidence by [Davis and Samaniego de la Parra \(2020\)](#) who find that 67 percent of vacancy postings originate from recruitment firms and staffing firms. In addition, using data from the QCEW, we find that the average growth in employment in employment placement services outpaced the growth in total employment between the periods 1990-2007 and 2010-2019, implying that recruitment agencies are now used more often in the hiring process. Recruitment agencies in turn are paid placement fees which are typically some percentage of the worker's salary.³⁰ Given the prevalent use of recruiting and staffing agencies as well as their fee structures, we argue that our assumption of a fixed cost of information is *empirically relevant*. Nonetheless, in this section, we explore the consequences of assuming a marginal cost of information.

Consider an economy where firms pay a cost κ_I for *each* applicant it screens. Denote \hat{j} as the level such that for any $j > \hat{j}$, the firm observes that the marginal cost of information exceeds its marginal benefit; i.e., $\kappa_I > V^I(j+1) - V^I(j)$ for any $j > \hat{j}$. There still exists a lower bound $j^* > 1$ where for any $j < j^*$, the value of not acquiring information exceeds the net benefit of acquiring information; i.e., $V^{NI} > V^I(j) - \kappa_I j$ for $j < j^*$. Thus, for any $j^* \leq j \leq \hat{j}$, the firm acquires information on all of its applicants, and for any $j > \hat{j} \geq j^*$, the firm acquires information on a subset \hat{j} of its applicants. Appendix C.2 provides more details on such a setup.

Holding all else constant, an increase in ξ still raises the average number of applicants per vacancy in this environment. So long as the mean applicants per vacancy is not far above \hat{j} in

³⁰See <https://bit.ly/3HII3kv>, for example, on the cost structures of recruitment agencies.

Table 6: The effect of ξ on inflows and outflows

ξ	1	1.5	2	2.5	3	3.5	4	4.5	5	10
Inflow rate	0.038	0.040	0.042	0.042	0.040	0.041	0.038	0.038	0.036	0.031
Outflow rate	0.372	0.419	0.446	0.446	0.447	0.443	0.429	0.411	0.424	0.424

Note: This table presents the model-implied inflow and outflow rates under different values of mean applications ξ .

the initial steady state, the increase in applications still raises the share of informed firms and improves the distribution of realized match quality, contributing towards a lower inflow rate. As shown in Table A7, we find that the model is still capable of generating the differential trends observed for the inflow and outflow rate. The inflow rate falls by 10 percent in this environment, while the outflow rate does not change. In part, the more modest decline in the inflow rate in this model (10 percent) compared to our baseline model (19 percent) can be explained by the fact that, with marginal costs of information, there is now an upper bound on the benefits of information. Although more firms acquire information when applications increase, they only do so for a subset of their applicants. Hence, the improvement in the distribution of match qualities and the decline in the inflow rate are smaller in this model. Even then, the same mechanisms as in the baseline model remain: increased information acquisition by firms and the formation of better matches play a crucial role in reducing the inflow rate, while the indirect effects through lower offer arrival and acceptance probabilities result in negligible changes to the outflow rate.

6.2 Inflow and outflow rates across different levels of applications

In this section, we demonstrate how varying the number of applications results in a non-monotonic profile of inflow and outflow rates. To do this, we solve the model for $\xi \in [1, 10]$ and show how going from very low levels of applications to very high levels can affect flows.

The inflow rate initially rises at low levels of ξ , as seen in Table 6. When few applications are sent, a small increase in the number of applications greatly increases the worker's outside option, causing a larger increase in reservation match quality, \tilde{x} . This dominates the effects from improved firm selection, leading separations to initially rise. This rise in the inflow rate only occurs for values of $\xi < 2.38$, which is the value required to match the median number of applications in 1980. Past its peak around $\xi = 2$, the inflow rate declines significantly, as further improvements in workers' outside options with higher ξ are swamped by the effects from improved firm selection and an increasing concentration of high quality matches.

The outflow rate also exhibits a hump-shaped profile, initially increasing when ξ is low and eventually decreasing modestly at higher levels of ξ . This non-monotonic pattern is explained by changes in the relative size of the direct and indirect effects from a higher number of applications. Increasing ξ from a low starting point of 1 to 2 results in a net 20 percent increase in the outflow rate. Using the decomposition presented in Equation (17), the direct effect of being able to send

more applications contributes to a 63 percent increase in the outflow rate, while the indirect effect from reduced offers and acceptances contributes to 43 percent decline in the outflow rate. In contrast, raising ξ from 3 to 4 results in a direct effect of 21 percent which is more than offset by an indirect effect of 25 percent, leading to a net 4 percent decline in the outflow rate.

We find that the outflow rate is maximized around $\xi = 3$, which is slightly higher than the value $\xi = 2.38$ for the calibrated economy with a low median number of applications and lower than $\xi = 5.67$ which corresponds to the economy with a high median number of applications. Above $\xi = 5$, we find that variations in the outflow rate is largely limited as the direct and indirect effects offset each other. We emphasize that even though $\xi = 3$ generates the highest outflow rate, this is not necessarily the efficient number of applications as vacancy creation is costly in our model. Given our set-up, a planner would maximize the net lifetime output as opposed to the outflow rate. We leave this as a topic for future research.

6.3 On-the-job search

Thus far, we have focused on the effects an increased number of applications sent by unemployed workers on labor 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.3, we provide details for the model with on-the-job search. Intuitively, adding on-the-job search provides firms an additional reason to acquire information, as workers hired into high quality matches have a lower probability of quitting when there is less of a ladder to climb. In other words, retention probabilities are increasing in match quality. Holding all else constant, an increase in applications raises the ability of employed workers to search for better opportunities. This in turn strengthens the firm's incentive to acquire information to find high quality matches that are longer-lived. As a result, the inflow rate would still decrease. Furthermore, an increase in the share of informed firms and a greater concentration of high quality matches reduces the share of employed individuals transitioning between jobs. Thus, holding all else constant, our model would suggest a decline in job-to-job flows as applications increase.

6.4 Wage protocols

The Nash bargaining protocol in our model ensures that firms always extend offers to their highest quality applicant and workers always accept the offer with the highest match quality. This result would continue to hold even if one were to allow workers to use counteroffers in the bargaining process, as in [Postel-Vinay and Robin \(2002\)](#). In that case, workers use their second-best offer (if any) to bargain up the value they received in their preferred job. Suppose a worker receives an offer for an application that draws match quality y and an offer for a separate application that draws match quality x where $y < x$. When firms engage in Bertrand

competition for the worker, the worker always chooses to accept the job with the higher match quality – in this case x – because they can attain the entire surplus of their second-best match, $S(y)$. Since workers always accept an offer with the highest match quality, firms still strictly prefer to extend an offer to their highest quality applicant because this minimizes their rejection probability. Thus, all we require in our model for firms and workers to prefer their highest quality match is for surplus and acceptance probabilities to be increasing in match quality.

7 Conclusion

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

Quantitatively, our model predicts that the rise in applications accounts for about 43 percent of the empirical decline in the inflow rate, while the outflow rate remains relatively unchanged. Our model also contains several testable implications. Overall, we find that changes in our model-predicted job offer and acceptance rates, reservation wages, and tenure distribution in response to a rise in applications largely mimic patterns in their data counterparts.

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

Our model can be extended in several dimensions. First, the number of applications that the unemployed submit can vary over the business cycle. This, together with the fact that applications have increased over time could have implications for firms’ hiring behavior and the emergence of slow labor market recoveries following economic downturns. Second, incorporating ex-ante worker and firm heterogeneity into our model would be useful to understand why some firms receive relatively more applications and how this affects labor market power and earnings inequality over time. Finally, while increasing the number of applications can have non-monotonic effects on the job-finding rate, it also changes expected recruiting costs when firms alter their hiring behavior. This gives rise to a trade-off that would govern what the efficient number of applications is. We leave these considerations for future research.

References

- 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.
- ALBRECHT, J. W., P. A. GAUTIER, AND S. B. VROMAN (2003): “Matching with multiple applications,” *Economics Letters*, 78, 67–70.
- BAI, J. AND P. PERRON (1998): “Estimating and testing linear models with multiple structural changes,” *Econometrica*, 47–78.
- (2003): “Computation and analysis of multiple structural change models,” *Journal of Applied Econometrics*, 18, 1–22.
- BRADLEY, J. (2020): “Worker-firm screening and the business cycle,” Tech. rep., University of Nottingham.
- BUTTERS, G. R. (1977): “Equilibrium distributions of sales and advertising prices,” *Review of Economic Studies*, 44, 465–491.
- CRUMP, R. K., S. EUSEPI, M. GIANNONI, AND A. ŞAHİN (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. ŞAHİN (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. ŞAHİN, 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 KLAUW, 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.
- 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.
- KWIATKOWSKI, D., P. C. PHILLIPS, P. SCHMIDT, AND Y. SHIN (1992): “Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?” *Journal of Econometrics*, 54, 159–178.
- 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 oversampled low-income families, but this did not greatly weaken moments pertaining to the aggregate economy, as shown in Section A.3 below.

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

In our study, we analyze a sample of unemployed individuals aged 25-65 who are not self-employed and who submitted at least one job application during each unemployment spell that occurred in 1979 and 1980. This gives us 5410 unique individual-spell observations.³¹ For each of these individual-spell observations, we first calculate unemployment duration in months.³² Using data on the number of job applications for each mode of job search (e.g., private employment agencies, newspapers, labor unions, friends and relatives, etc), we obtain the total number of job applications for each spell. Then, we divide the total number of job applications sent during each spell by its duration to obtain the average monthly number of applications for that spell. Similarly, using information on the number of offers received through each mode of job search, we calculate the total number of offers received and the monthly number of offers received for each spell. The data also provides an indicator variable on whether the individual accepted any of the offers received. Using this variable, we also calculate the fraction of individuals who receive a certain number of job offers and accept an offer. Finally, the survey also contains information on the lowest hourly wage rate that the individual would accept during the unemployment spell.

³¹There 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.

³²To do so, we use variables named STLOOK16, ENDLOK16, STLOOK26, and ENDLOK26, which provide beginning and end dates (in mm/dd/yy format) of the first and second looking-for-work spells, respectively.

We use this information to measure the reservation wage of the individual.³³

A.2 SCE

The SCE Labor Market Survey was developed by the Federal Reserve Bank of New York.³⁴ The dataset provides information about respondents' demographics, job information if employed (i.e., earnings, hours, industry, employer size, etc), job search activities, and reservation wages.

We use the annual survey between 2013-2017. Because of the small sample size relative to the EOPP data, we pool the SCE observations across these years, as in Faberman, Mueller, Şahin, and Topa (2020). To maintain consistency with our EOPP analysis, we restrict the SCE sample to unemployed individuals aged 25-65 who are not self-employed and who submitted at least one application during each unemployment spell. This includes individuals who are unemployed at the time of the survey and individuals who, at the time of the survey, were employed for less than four months in their job and reported experiencing an unemployment spell prior employment. For both of these groups, we analyze their job search activities during each reported unemployment spell. For currently unemployed individuals, the survey provides the total number of job applications during the past four weeks, the total number of job offers received during the past four weeks; and, if no job offers were received in the past four weeks, the total number of job offers received in the last six months, where we use unemployment spell duration information to convert the latter to the average number of job offers received per month of unemployment. The survey also provides information on whether the individual accepted or will accept a job offer. For currently employed individuals with a previous unemployment spell, the survey also provides the total number of job applications and the total number of job offers received during the unemployment spell. Again, we use information on the duration of the unemployment spell to convert these numbers to the average number of job applications and job offers received per month of unemployment. Since these individuals found employment after an unemployment spell, we infer that they accepted a job offer. Then, using information about the offers and acceptance decisions in our sample, we calculate the fraction of individuals who accept job offers. The SCE also asks the lowest wage the individual would accept, which we use to measure the reservation wage.³⁵

³³APLYJOBS 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.

³⁴Source: Survey of Consumer Expectations, 2013-2019 Federal Reserve Bank of New York (FRBNY). The SCE data is available without charge at <http://www.newyorkfed.org/microeconomics/sce> and may be used subject to the license terms posted there. FRBNY disclaims any responsibility or legal liability for this analysis and interpretation of Survey of Consumer Expectations data.

³⁵For currently unemployed individuals, variables JS14, JS19, JS19b, JS23, and L7 give the total number of job applications during the past four weeks, the total number of job offers received during the past four weeks, the number of job offers received during the past six months, whether the individual accepted or will accept the job offer, and the duration of unemployment spells, respectively. For currently employed individuals who had an unemployment spell previously, JH13, JH14, and JH16 provide information on the duration of the unemployment

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

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

Note: This table compares demographics across 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 EOPP, SCE, and CPS samples

In this section, we compare the EOPP and SCE samples to the CPS samples over time. This comparison lends credence to the validity of linking empirical findings on the long-run changes in unemployment flows observed in the CPS to changes in job search outcomes observed between the EOPP and SCE. Our results reveal that the EOPP and the SCE samples capture well the changes in educational attainment, marital status, female labor force participation, age composition, as well as earnings and hours over time.³⁶

Table A1 compares demographics from samples across these three datasets. We highlight several results. First, the EOPP sample captures the education and age composition of the CPS 1980 sample almost exactly. Second, there has been a steady increase in the fraction of individuals with a college degree over time, as shown by the comparison between the CPS 1980 and the CPS 2015.³⁷ Importantly, the SCE and CPS 2015 have almost the same fraction of individuals with a college degree. This implies that the EOPP and the SCE samples capture the increase in educational attainment well. Third, the EOPP and SCE samples slightly overestimate the increase in older workers (age groups 45-54 and 55-64) in the working age population and underestimates the decline in the fraction of married individuals when compared to CPS.

Next, Table A2 compares labor market moments across the three datasets. Similar to the spell, the total number of job applications, and the total number of job offers received during the unemployment spell, respectively. The variable RW2h_rc provides the reservation wage information.

³⁶When comparing the EOPP and SCE samples with CPS samples, we focus on individuals (employed or non-employed) aged 25-65 who are not self-employed.

³⁷We also compared SCE and CPS samples for each year between 2013 and 2017. The results are very similar to the comparison made for 2015.

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

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

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

A.4 Job applications: Eliminating business cycle effects

In Section 2.1, we use data from the EOPP and SCE samples and show that the unemployed are now sending more applications than they used to in the 1980s. One concern may be that there are cyclical factors behind the differential outcomes observed between the 1979-1980 period and the 2013-2017 period. For example, unemployed individuals may send more applications during an expansion than during a recession. In order to ensure that this change is not driven by cyclical changes in the labor market, we now control for aggregate moments to eliminate these business cycle effects. In particular, we use the EOPP and the SCE samples to estimate the following regression equation:

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

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

Table A3: Eliminating the business cycle effects

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

Note: This table provides results on the 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.

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

A.5 Job applications: Demographic groups

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

A.6 CPS

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

The CPS provides monthly data on the number employed, the number unemployed, and the number unemployed with at most five weeks of unemployment duration (which we define as the short-term unemployed).³⁸ Let U_t , U_t^S , and L_t be the number of unemployed individuals, the

³⁸Importantly, 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

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

	EOPP 1979-1980		SCE 2013-2017		Percent change	
	Mean	Median	Mean	Median	Mean	Median
All	6.82	2.70	14.11	6.00	107	122
College	4.98	2.46	11.73	6.00	136	144
Non-college	7.36	2.82	15.11	7.00	105	148
Male	7.44	2.50	12.88	6.00	73	140
Female	6.13	2.86	15.11	6.00	146	110
Young	7.24	2.86	14.39	9.00	99	215
Old	4.27	1.67	13.94	6.00	226	259

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.

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

$$dU/dt = -f_t U_t + s_t (L_t - U_t). \quad (\text{A1})$$

Moreover, we can write

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

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

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

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

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

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

which defines the unemployment inflow rate s_t and probability $S_t = 1 - e^{-s_t}$, given data on

[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, Hobijn, and Şahin \(2010\)](#). [Shimer \(2012\)](#) finds similar results with alternative ways of correcting the data.

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 2.³⁹

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

Let subscript $k_g \in \{m, f\}$ denote gender where m and f indicate male and female workers; $k_a \in \{y, p, o\}$ denote age where y , p , and o stand for young workers (age 16-24), prime age workers (age 25-54), and old workers (age 55 and above); $k_e \in \{nc, c\}$ denote education where nc and c indicate workers without a college degree and with a college degree; and $k_i \in \{mf, nmf\}$ denote industry where mf and nmf mean workers in manufacturing and non-manufacturing industries, respectively. Further, let $\omega_{k_l, t}^l$ be the share of subgroup k_l in each group $l \in \{g, a, e, i\}$ at time t such that $\sum_k \omega_{k, t}^k = 1 \forall l, t$. 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

$$\begin{aligned}
S_{t_2} - S_{t_1} = & \sum_{k_e \in \{nc, c\}} \sum_{k_g \in \{m, f\}} \sum_{k_a \in \{y, p, o\}} \sum_{k_i \in \{mf, nmf\}} \omega_{k_e, t_1}^e \omega_{k_g, t_1}^g \omega_{k_a, t_1}^a \omega_{k_i, t_1}^i \Delta S_{k_e, k_g, k_a, k_i} \quad (A2) \\
& + \sum_{k_e \in \{nc, c\}} \sum_{k_g \in \{m, f\}} \sum_{k_a \in \{y, p, o\}} \sum_{k_i \in \{mf, nmf\}} \Delta \omega_{k_e}^e \omega_{k_g, t_1}^g \omega_{k_a, t_1}^a \omega_{k_i, t_1}^i S_{k_e, k_g, k_a, k_i, t+1} \\
& + \sum_{k_e \in \{nc, c\}} \sum_{k_g \in \{m, f\}} \sum_{k_a \in \{y, p, o\}} \sum_{k_i \in \{mf, nmf\}} \omega_{k_e, t_1}^e \Delta \omega_{k_g}^g \omega_{k_a, t_2}^a \omega_{k_i, t_2}^i S_{k_e, k_g, k_a, k_i, t+1} \\
& + \sum_{k_e \in \{nc, c\}} \sum_{k_g \in \{m, f\}} \sum_{k_a \in \{y, p, o\}} \sum_{k_i \in \{mf, nmf\}} \omega_{k_e, t_1}^e \omega_{k_g, t_1}^g \Delta \omega_{k_a}^a \omega_{k_i, t_2}^i S_{k_e, k_g, k_a, k_i, t+1} \\
& + \sum_{k_e \in \{nc, c\}} \sum_{k_g \in \{m, f\}} \sum_{k_a \in \{y, p, o\}} \sum_{k_i \in \{mf, nmf\}} \omega_{k_e, t_1}^e \omega_{k_g, t_1}^g \omega_{k_a, t_1}^a \Delta \omega_{k_i}^i S_{k_e, k_g, k_a, k_i, t+1},
\end{aligned}$$

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

³⁹We use monthly outflow probability F_t and inflow probability S_t instead of rates f_t and s_t , given that our model is in discrete time.

Table A5: Shift share decomposition exercise

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

Note: This table summarizes the results of the shift-share analysis for the change in the aggregate inflow and outflow probabilities between 1976-1985 and 2010-2019 (first two columns) as well as 1976-1985 vs 2019 for the outflow probability (last column). We report the total change over time as well as 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 age 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.

same equation for the change in the aggregate outflow probability between t_1 and t_2 as well.

Table A5 summarizes the results of this shift-share analysis for the inflow and outflow probabilities. The average inflow probability across groups decreased from 3.6 percent in 1976-1985 period to 2.2 percent in 2010-2019 period.⁴⁰ Out of this 1.40 percentage points decline, 1 percentage point decline in inflow probability is due to within-group changes, implying that declines in group-specific inflow probabilities account for 71 percent of the total decline of the aggregate inflow probability. The remaining 29 percent is jointly explained by the rise in the fraction of workers with a college degree and the fraction of older workers, while changes in gender and industry composition did not have much impact on the aggregate inflow probability. Similarly, Table A5 also shows that the average outflow probability across groups decreased by around 7.4 percentage points from 38 percent to 30.6 percent between the same two intervals. However, this decline is due to the slow recovery of the labor markets after the Great Recession, as we show in Figure 2. Looking at the group-specific outflows over time, we see that the slow recovery of the outflow probability after the Great Recession is observed across many groups. As such, Table A5 shows that the majority of the total change in outflows are explained by the within-group change. By 2019, outflow probabilities had returned back to their long-run average. This is evidenced by the last column of Table A5 where the total change in the outflow probability is only around 2.3 percentage points from 37.9 percent to 40.2 percent when we compare the average outflow probability in 1976-1985 period and in 2019. Demographic (between-group) changes actually result in close to a 1 percentage point decline in the outflow probability, while the within-group

⁴⁰Notice that average inflow and outflow rates reported in this section differ from those we reported in Table 3. This is because we obtain the data inputs to Equation (A2), i.e. group specific weights and flows, from micro level data. In the main text, however, aggregate inflow and outflow rates are obtained by using aggregate level data on labor market stocks as discussed in the previous section.

changes result in roughly a 3 percentage points increase. This result shows that even when we control for compositional changes between the two time periods, the outflow probability does not exhibit any sizeable change over the long-run. Overall, these results emphasize that the trend decline in inflows and lack of trend in outflows are not driven by changes in worker demographics over time but rather reflect a more fundamental change in each group’s labor market experience.

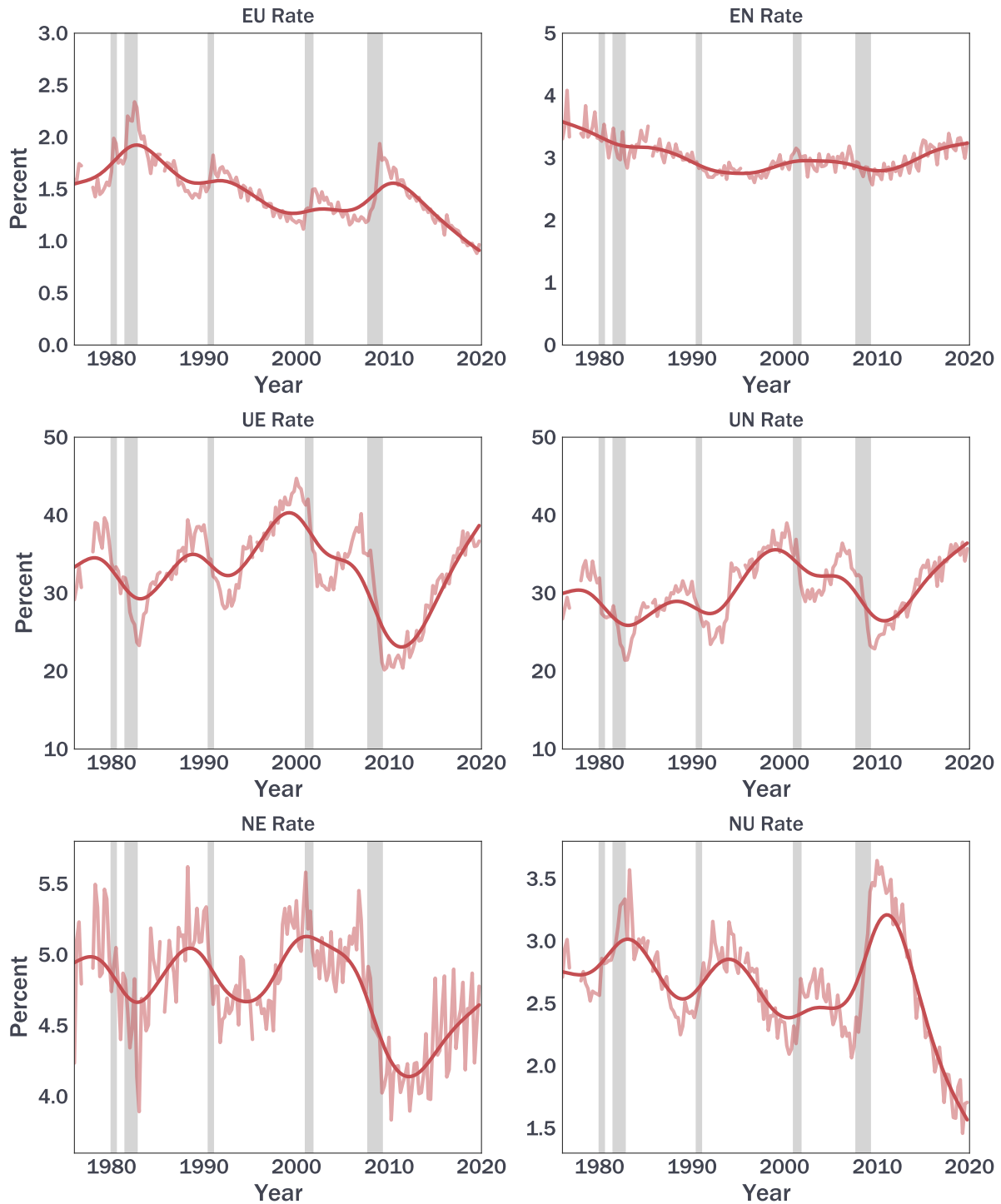
Calculating inflow and outflow rates from CPS panels The CPS underestimates the number of short-term unemployed workers is underestimated given that some workers who enter unemployment exit unemployment within the same month. However, the methodology outlined above accounts for this bias, which is referred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

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

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

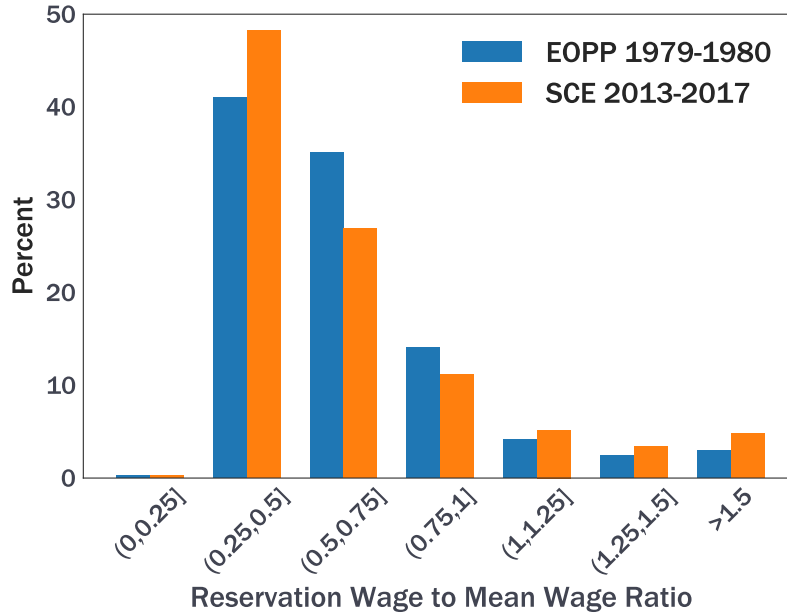
[Figure A2](#) plots the resulting distribution of the reservation wage to mean wage ratio over time. It shows that the distribution of the reservation wage to mean wage ratio has become more unequal over time. In particular, both the fraction of unemployed workers whose reservation wage is less than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

Figure A1: Transition rates using CPS panels



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

Figure A2: Reservation wage to mean wage ratio



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

B Model

In this appendix, we provide proofs for the propositions in the main text. We then discuss how the firm's information problem would be modified if they could instead play mixed strategies.

B.1 Proofs

Proof for Lemma 1 Consider a firm that has acquired information and that 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:

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

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

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

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

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

Can a pure strategy equilibrium where no firms acquire information exist? Suppose instead that all firms choose not to acquire information. So long as surplus is increasing in x , the worker always accepts the highest match quality offer. Thus, a firm 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 .

B.2 Information choice problem under mixed strategies

Here, we provide details on how the firm's information choice problem is modified if we instead allowed for mixed strategies.

Suppose that all firms with j applicants choose a probability ι to maximize their expected value from making an offer. In that case, the firm's information choice problem becomes:

$$\Xi(j) = \max_{\iota(j) \in [0,1]} \iota(j) [V^I(j) - \kappa_I] + [1 - \iota(j)] V^{NI},$$

where

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

and

$$V^{NI} = \int_{\tilde{x}}^{\bar{x}} \Gamma(x) V^F(x) d[\Pi(x)].$$

The firm's choice of whether to acquire information affects offer probabilities, which in turn, affect the probability that a worker accepts a particular offer with match quality x . As such, we can write the probability that a worker receives an offer from a firm with j applicants given that she has drawn x as:

$$Pr(\text{offer} \mid x, j) = \iota(j) [\Pi(x)]^{j-1} + [1 - \iota(j)] \frac{1}{j},$$

Summing across j , the probability of a worker getting an offer given that she has drawn match quality x is:

$$Pr(\text{offer} \mid x) = \sum_{j=1}^{\infty} \hat{q}(j) Pr(\text{offer} \mid x, j).$$

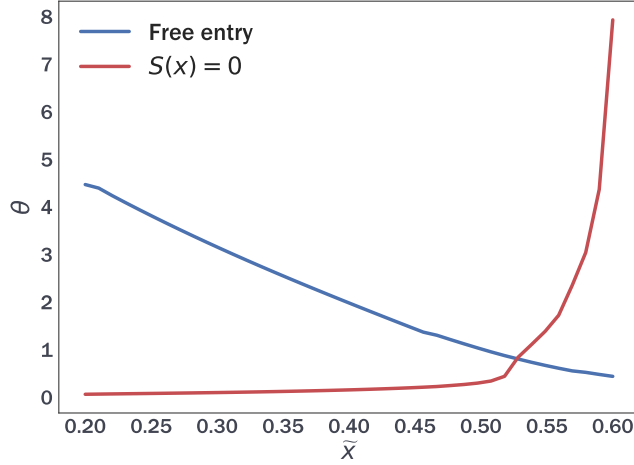
These offer probabilities affect the worker's acceptance probability which for ease of reference is copied below:

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

and $\Gamma(x) = \sum_{a=1}^{\infty} p(a) \Gamma(x, a)$.

Unique equilibrium in pure strategies To verify if a unique equilibrium exists under our calibration, we reformulate j^* to be a function of θ and \tilde{x} , i.e., $j^*(\theta, \tilde{x})$. Then, under our calibration, Figure A3 highlights that a unique equilibrium in pure strategies exists in (θ, \tilde{x}) space, implying that one of the mixed strategies equilibria is a pure strategies equilibrium. That is, for all $j \geq j^*$, $\iota(j) = 1$, and for all $j < j^*$, $\iota(j) = 0$.

Figure A3: Unique equilibrium in pure strategies exists



Note: This figure plots the equilibrium θ which satisfies the free entry condition (blue) and the zero-surplus condition (red) for any given level of reservation match quality \tilde{x} under the calibrated model. The intersection of the two lines represents the unique equilibrium in pure-strategies.

C Extensions

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

C.1 Calibration details of FI and NI models

Recall that we set $\kappa_I = 0$ in the FI model and $\kappa_I \rightarrow \infty$ in the NI model in Section 5.3. Given that κ_I is already set, we leave out the recruitment cost to mean wage ratio, which was used as a calibration target for κ_I in our calibration of the baseline model. For the rest of the parameters, we target the same moments as in the baseline model given in Table 1. Table A6 summarizes the calibration outcomes of the FI and NI models. Because we target the reservation wage to mean wage ratio in the data to pin down b , from Equation (14), the value of b is small when the continuation value from remaining unemployed is large relative to the continuation value of being employed at \tilde{x} . In other words, to make it attractive for workers to choose employment and to attain the reservation to mean wage ratio in the data, b must be small.

C.2 Marginal cost of information

We now elaborate on our discussion for the model with a marginal cost of information acquisition in Section 6.1. Suppose that κ_I is instead a marginal cost the firm pays for each applicant it acquires information on. Formally, the firm’s information problem takes the form of

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

Table A6: Calibration of FI and NI models

Parameter	Value		Target	Model		Data
	FI Model	NI Model		FI Model	NI Model	
κ_V	0.84	0.63	Outflow rate	0.47	0.46	0.41
δ	0.026	0.026	Inflow rate	0.042	0.043	0.041
λ	5.32	5.21	EU_{20}/EU_{80}	4.09	4.10	4.05
A	0.53	0.58	Fraction with no offers	0.34	0.32	0.38
B	0.73	0.53	Fraction accept and > 1 offer	0.17	0.17	0.22
b	0	0	Reservation wage/mean wage	0.77	0.70	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 and having 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.

where

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

and

$$V^I(n) = \int_{\bar{x}}^{\bar{x}} V^F(x) \Gamma(x) d[\Pi(x)]^n.$$

We assume that the firm decides on the optimal number of applicants, n , to acquire information on prior to learning the realizations of their match productivity. If the optimal number of applicants n is less than the number of applications received j , then the firm randomly acquires information on n of the j applicants. V^{NI} still takes the same form as in the baseline model:

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

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

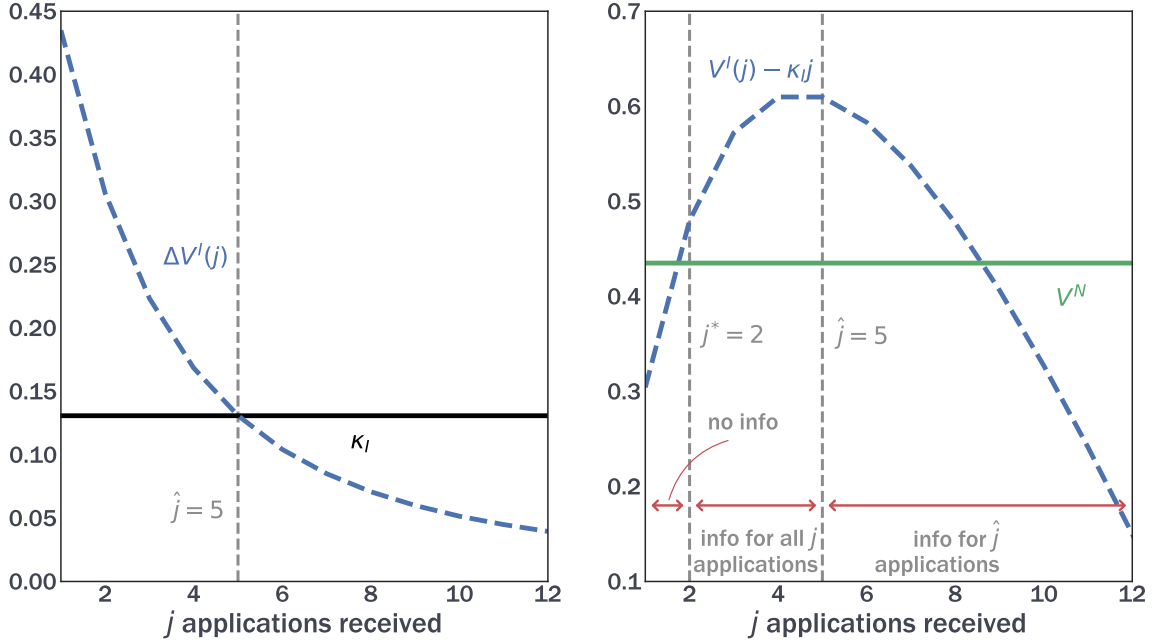
$$V^I(\hat{j}) - V^I(\hat{j} - 1) \geq \kappa_I,$$

and

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

The left panel of Figure A4 shows a numerical example where beyond \hat{j} applicants the marginal cost of information, κ_I , exceeds the marginal benefit of information, $\Delta V^I(j)$. Since the marginal cost of information exceeds the marginal benefit, the firm only acquires information on a random subset $\hat{j} < j$ of its applicants. We assume that any applicant the firm does not acquire information on is automatically rejected. A similar assumption is also made in Wolthoff (2018).

Figure A4: Upper bound on benefits of information rises with j with marginal cost of information



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

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

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

The right panel of Figure A4 shows how the firm would not acquire information for $j < j^*$ applicants since the value of not acquiring information is strictly greater. Given a choice of acquiring information on a subset of applicants vs. not acquiring information at all, the firm's value is maximized when it only acquires information on a subset $\hat{j} < j$ applicants for any applicant pool size j such that $j^* \leq \hat{j} < j$. The two thresholds (j^*, \hat{j}) , in turn imply the

following probability of receiving an offer of quality x from a firm with j applicants:

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

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

Table A7: Impact on labor market flows: baseline vs. marginal cost model

	Impact on unemployment flows					
	Baseline		Marginal cost		Percent change	
	$\xi = 2.38$	$\xi = 5.67$	$\xi = 2.38$	$\xi = 5.67$	Baseline	Marginal cost
Inflow rate	0.042	0.034	0.040	0.036	-19	-10
Outflow rate	0.448	0.434	0.380	0.378	-3	0
direct effect					61	78
indirect effect					-64	-78

Note: This table reports the model-predicted flow outcomes from our baseline model with a fixed cost of information against that from a model with marginal costs of information.

Numerical results While Figure A4 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 A7 shows that in the re-calibrated 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 subset of applicants for applicant pool size $j > \hat{j}$, 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 does not change. Thus, we conclude that the version of our baseline model with marginal cost of information acquisition also predicts a decline in the inflow rate, while no change in the outflow rate as the applications increase.

C.3 On-the-job search

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

1. Employed workers draw the number of applications from a Poisson distribution with pa-

parameter ξ_e and unemployed workers draw the number of applications from a Poisson distribution with parameter ξ_u every period.

2. Markets are segmented by employment status. Thus, unemployed workers do not search in the same market as employed workers.⁴¹
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 with the new firm. As such, the outside options of all job-seekers at the bargaining stage is equal to the value of unemployment.
4. We assume that the firm cannot observe the employed worker's match quality at their incumbent job.
5. Finally, for ease of exposition, we assume that $\rho(x) = 1$ for all x .

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

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

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

where $\int_z^{\bar{x}} \sum_{a=1}^{\infty} p^e(a) a \phi^e(y, z, a) \pi(y) dy$ is the probability the employed worker with current productivity z finds a job elsewhere through on-the-job search. If the match is exogenously destroyed or the worker quits for another job, the firm shuts down. Because match quality shocks are drawn prior to search and matching, the probability that workers quit to new jobs depends on the new match quality z that employed workers draw in their current match x . 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 $\Gamma^e(x, z, a)$ as the probability that an employed worker with match quality z at his current job, who draws a applications, accepts an offer of match quality x . Clearly if $x < z$, then $\Gamma^e(x, z, a) = 0$. 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

⁴¹This simplifies the problem given that the firm does not need to form expectation over the employment status of the worker.

offer. Thus, for a given $x \geq z$, we have:

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

Denote $\Gamma^e(x, z) = \sum_{a=1}^{\infty} p^e(a) \Gamma^e(x, z, a)$. For a firm that acquires no information, the firm takes expectation over i) the number of applications sent, ii) the possible match quality z that the employed worker might currently have, and iii) the new match quality they may have drawn at the firm's vacancy:

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

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

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

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

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

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

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

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

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:

$$\begin{aligned}
V^W(x) &= w(x) + \beta(1 - \delta) \int_{\tilde{x}}^{\bar{x}} \left[1 - \int_z^{\bar{x}} \sum_{a=1}^{\infty} p^e(a) a \phi^e(y, z, a) \pi(y) dy \right] V^W(z) \psi(z | x) dz \\
&+ \beta(1 - \delta) \int_{\tilde{x}}^{\bar{x}} \left[\int_z^{\bar{x}} V^W(y) \sum_{a=1}^{\infty} p^e(a) a \phi^e(y, z, a) \pi(y) dy \right] \psi(z | x) dz \\
&+ \beta [\delta + (1 - \delta) \Psi(\tilde{x} | x)] U,
\end{aligned}$$

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

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

$$\begin{aligned}
S(x) &= x + \beta(1 - \delta) \int_{\tilde{x}}^{\bar{x}} \left[1 - \int_z^{\bar{x}} \sum_{a=1}^{\infty} p^e(a) a \phi^e(y, z, a) \pi(y) dy \right] S(z) \psi(z | x) dz \\
&+ \beta(1 - \delta) \eta \int_{\tilde{x}}^{\bar{x}} \left[\int_z^{\bar{x}} S(y) \sum_{a=1}^{\infty} p^e(a) a \phi^e(y, z, a) \pi(y) dy \right] \psi(z | x) dz \\
&- (1 - \beta) U.
\end{aligned}$$

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

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

In steady state, the measure of unemployed is:

$$u = \frac{\delta + (1 - \delta) \int_{\tilde{x}}^{\bar{x}} \Psi(\tilde{x}_t | x) g(x) dx}{\int_{\tilde{x}}^{\bar{x}} \sum_{a=1}^{\infty} p^u(a) a \phi^u(x, a) \pi(x) dx + \left[\delta + (1 - \delta) \int_{\tilde{x}}^{\bar{x}} \Psi(\tilde{x}_t | x) g(x) dx \right]},$$

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

$$\begin{aligned}
G(x) &= (1 - \delta) \int_{\tilde{x}}^{\bar{x}} \int_{\tilde{x}}^x \left(1 - \int_x^{\bar{x}} \sum_{a=1}^{\infty} p^e(a) a \phi^e(h, z, a) \pi(h) dh \right) \psi(z | y) dz g(y) dy \\
&+ \int_{\tilde{x}}^x \sum_{a=1}^{\infty} p^u(a) a \phi^u(y, a) \pi(y) dy \frac{u}{1 - u}.
\end{aligned}$$

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