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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 technologies, enabling workers to submit more job applications over time. Despite this increase in 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. Because 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 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 more than doubling since the 1980s. Data from the Current Population Survey (CPS) highlight how the inflow rate has declined sharply since the 1980s, while the outflow rate remains relatively unchanged. Compositional changes and trends in temporary unemployment account for only a small share of these variations in inflow and outflow rates. Second, we build a tractable equilibrium labor search model to quantitatively analyze how rising applications can trigger a decline in the inflow rate without precipitating any trend increase in the outflow rate. We depart from the standard search model in two ways. First, workers can send multiple applications and vacancies can 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. Crucially, endogenous changes in firms' hiring behavior in response to higher applications are key for replicating the observed changes in unemployment flows over time. Our model also contains several testable implications on the changes in application outcomes, such as offer and acceptance probabilities, and reservation-to-median wage ratios. Using the EOPP and SCE, we provide new stylized facts about how these application outcomes have changed over time and show that our model can match both the levels and changes in these moments.

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. 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 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 can only exploit this benefit if they acquire information and are able to rank applicants.

We calibrate our model to match labor market moments and application outcomes for the period 1976-1985 and use it 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.[1] Importantly, our model has several testable implications for labor market outcomes that underlie the predicted changes in unemployment flows. Specifically, our model's predictions on offer and acceptance rates, reservation-to-median wage ratios, the tenure distribution, and the median number of applicants per vacancy largely mimic patterns observed in the data. We argue that any model that analyzes changes in inflow and outflow rates should also account for changes in these aforementioned factors, which have a first-order effect on unemployment flows.

Under our calibrated model, the inflow rate falls by 15 percent when applications increase, about one-third of the decline in data.[2] Why does our model predict that a rise in applications leads to a decline in the inflow rate? In our model, a rise 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. A higher fraction of informed firms leads 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 improved firm selection of workers 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. Our model generates a sharp fall in the share of individuals employed in low-quality high-turnover jobs, consistent with patterns observed in the data. When more firms acquire information in response to higher applications, fewer low-quality matches are formed, causing the share of short duration jobs to fall. Our model also predicts that median tenure remains unchanged, as in the data. Because each high-quality match now observes a marginally higher separation probability due to increased worker selectivity, median tenure remains unchanged despite fewer short duration jobs.

Turning to outflows, our model predicts almost no change in the outflow rate in response to a rise in applications, consistent with the data. Why does the model generate a muted response in the outflow rate despite a rise in applications? Similar to inflows, a rise in applications exerts

[1] We 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.

[2] Data moments are obtained for the periods 1976-1985 and 2010-2019, the latter of which covers the SCE.

two opposing forces on outflows. While increased contact between job-seekers and vacancies contributes to 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. Offer probabilities fall when there is increased competition amongst workers, while acceptance rates decline when workers contact more vacancies and can select from more options. A fall in either of these probabilities contributes to depressing outflow rates. In our calibrated model, and as in the data, the decline in offer and acceptance rates is sizable and counteracts almost exactly the direct effect of contacting more vacancies when applications increase.

The decline in offer probabilities stems from the fact that a 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 the increase in reservation match quality. 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 options. This result concurs with our empirical findings that while acceptance rates have fallen by a large margin in the data, the coincident rise in the reservation-to-median wage ratio has not been to the same magnitude. Overall, both the data and our model indicate that changes in workers' job acceptance behavior are strongly linked to changes in firms' offer rates.

This implies that the decline in acceptance rates in our model is not mechanical but depends critically on how offer probabilities respond to a rise in applications. If offer probabilities are constant or increasing, acceptance rates would decline in applications as workers receive more offers. Conversely, if offer probabilities fall to the extent that workers have fewer offers to choose from, acceptance rates would instead increase. In our model, acceptance rates decline not because offer probabilities do not fall, but because they fall by *less* than the increase in congestion, where the latter is measured by the median number of applicants per vacancy. Since more firms acquire information and workers are more likely to draw a high match quality in at least one of their applications when they contact more vacancies, the combined two events raise the probability that a worker receives an offer for her high match quality drawn. This mitigates the extent to which increased congestion can depress offer probabilities. Though offer probabilities fall in our model, they do not fall to the extent that they cause acceptance rates to rise.

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. In environments where firms do not adjust their information acquisition decision, either because there is full information (FI) when information is free or because there is no information acquisition (NI) when information is infinitely costly, we find changes in unemployment flows that are inconsistent with the data. In both these models, vacancy creation rises as the cost of job creation is constant but the benefit of a vacancy is increasing when firms expect more applicants. In the FI model, the outflow rate rises as higher vacancy creation mitigates the congestion arising from an increase in applications. In the NI model, the outflow rate declines substantially because the benefits of additional applications are negated when firms cannot identify high-quality matches. As such, vacancy creation does not rise enough to prevent increased congestion, and the outflow rate declines. In terms of inflows, both models predict increases in the inflow rate, contrary to the data. In the FI model, this occurs because the effects from improved firm selection are small relative to the rise in increased worker selectivity when firms can always identify the best applicant. In the NI model, lower outflow rates worsen workers' outside options and reservation match quality, leading to a greater formation of low-quality matches that are more susceptible to job destruction. Overall, these results suggest that variable information acquisition by firms in response to higher applications is key to explain the joint dynamics in inflow and outflow rates.

In our baseline model, we assume that firms pay a fixed cost of information but allow this cost to vary with the number of applications sent. Importantly, our findings do not depend on the cost structure assumed. We show that our results largely hold even if firms were to face a fixed cost that is constant over time or a marginal cost when deciding whether to acquire information. Our preferred cost structure — where the fixed cost of information varies with average applications sent — is a middle ground between the aforementioned alternatives and is motivated by the fact that firms increasingly use recruiting agencies to hire workers. Our cost structure reflects that most recruiting firms charge placement fees and allows for these placement fees to vary with the average applications sent. Empirically, we find evidence to support the growing importance of recruitment agencies. Data from the Quarterly Census of Employment and Wages (QCEW) show that the employment placement services industry has grown substantially over time.[3] Further, a recent survey for 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 as workers submit more applications over time.

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

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

[4]See https://tinyurl.com/yepw8pz5.

setup where firms pay a cost to reveal information about their applicants. Although Bradley (2020) allows firms to receive multiple applications, workers can send only 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 quantitatively explore how a rise in applications can explain 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 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 the number of job applications, and we explain how this rise since the 1980s has enabled 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 can explain the changes in application outcomes such as offer probabilities, acceptance rates, reservation wages, tenure, and the number of applicants per vacancy — factors that have a first-order effect on unemployment flows.

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, and Section 6 discusses alternative formulations of our framework and their implications. 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. In Section 2.2, we outline the trends in unemployment flows. Finally, in Section 2.3, we document how job application outcomes have changed over time.

2.1 Job applications

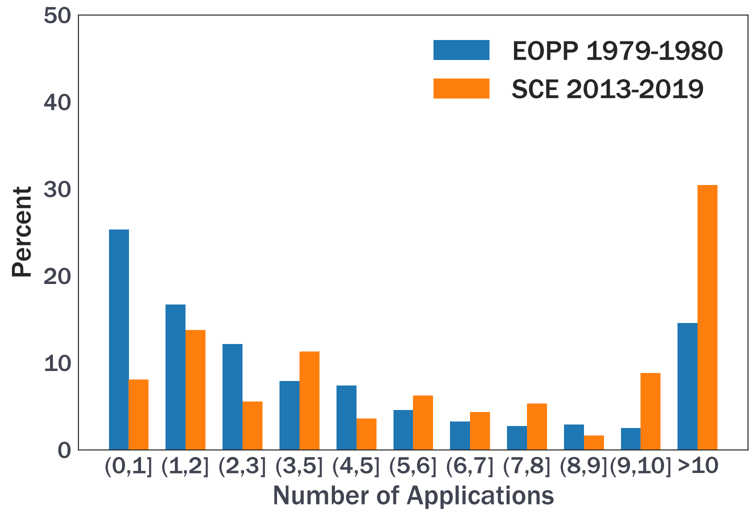
Using information from the EOPP and SCE Labor Market Survey, we provide novel evidence on how the job application behavior of unemployed workers has evolved over time. A unique feature of these datasets is that they offer insights into job search behavior and, unlike other household surveys, provide information on the job search 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 2019. 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 they are used to calculate moments. To evaluate the comparability of both the EOPP and SCE datasets with more widely used surveys, Tables A1, A2, and A3 in Appendix A compare sample demographics and outcomes from the EOPP and SCE to those from the CPS over the same time period. Overall, we show that the EOPP and SCE samples mostly capture the demographics, labor market outcomes, and labor earnings distributions observed in the CPS both in terms of levels and changes over time.

In both datasets, we consider a sample of unemployed individuals aged 25-65 who sent at least one job application during their unemployment spell. Figure 1 highlights how the distribution of applications submitted per month by the unemployed has shifted right over time. Between the two surveys, the median number of applications per month more than doubled between 1979-1980 and 2013-2019, rising from 2.7 to 7.[5] To ascertain whether the rise in applications is due to prevailing aggregate economic conditions, Table A4 in Appendix A shows that this result continues to hold even after controlling for business cycle effects. Finally, Table A5 in Appendix A documents that the rise in applications is a common pattern across various demographic groups.

[5]While the mean also roughly doubled between the two time periods, we focus on the median, as the mean is around twice of the median as shown in Table A5, implying significant skewness in the distribution of applications.

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 2013-2019 using the SCE data. In both datasets, our sample consists of unemployed individuals aged 25-65 who sent at least one job application during their unemployment spell.

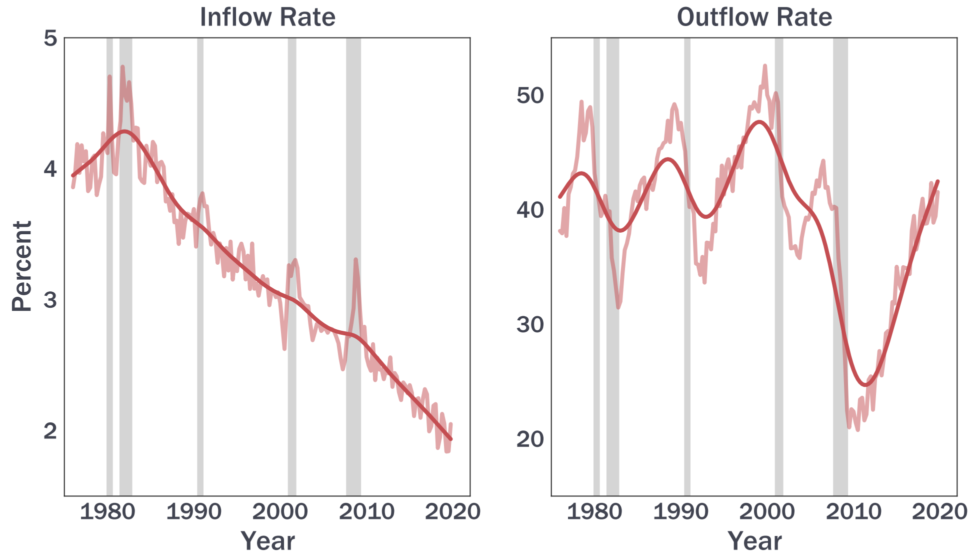
Overall, we find that the number of applications has increased over the past four decades.

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 inflow rates over time using standard procedures found in the literature. Appendix A provides details on our data and methodology. 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 percent to 2.3 percent.

We argue that this result is robust to an alternative way of measuring flow rates in the CPS and that neither changes in demographics over time nor trends in temporary unemployment largely contribute to this result. First, the CPS measure of short-term unemployed workers is underestimated since some workers enter and exit unemployment within the same month. In our baseline measurement of flow rates in the CPS, we follow Shimer (2012) to account for this bias. In Figure A1, we also use the matched micro-data from the CPS to present results based on raw monthly transition rates. In this case, we still find that the outflow rate does not exhibit any secular trend over the last four decades, while the inflow rate has fallen by about 30 percent. Second, since the U.S. labor force underwent significant demographic changes over 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 trend in the outflow rate. To answer these questions, we

Figure 2: Unemployment inflow and outflow rates



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

conduct a shift-share analysis on aggregate outflow and inflow rates in Appendix A. Table A6 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 trend remains true even after controlling for compositional shifts. Overall, changes in demographics explain little of the trends observed in unemployment flows. Third, changes in the fraction of temporarily unemployed over time may affect trends in inflow and outflow rates if this group has systematically different job-finding and job-separation rates. To ascertain whether this is the case, we re-calculate flow rates purged of the temporarily unemployed using the CPS micro-data. We still find no secular trend in the outflow rate, while the inflow rate declined by about 40 percent, as shown by Figure A2.

Finally, we note that our focus on the behavior of inflow and outflow rates since the 1980s stems from two reasons. First, to quantitatively analyze the impact of increased job applications on these flow rates, we need data on job applications and application outcomes over time. This data is available in the EOPP that covers 1979-1980 and in the SCE that covers 2013-2019. Second, we argue that the advent of the ICT revolution in the 1980s enabled workers to submit 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 are 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,

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 average acceptance rate of an offer; 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 2013-2019 using a pooled SCE sample. For both datasets, we use a sample of unemployed individuals aged 25-65 who sent at least one job application during their unemployment spell.

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 downward for the past 40 years. Overall, we find no evidence that the inflow rate is stationary.[6]

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 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 demonstrate how these findings serve as testable implications for our model.

We calculate the distribution of job offers received during a month of unemployment, the acceptance rate of an offer, and the distribution of real hourly reservation wages. We calculate these moments for 1979-1980 using the EOPP sample and for 2013-2019 using a pooled SCE sample. Figure 3 summarizes the results.

We highlight several results. First, the fraction of individuals with no offers increased from

[6]While 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.

38 percent to 43 percent over time, implying a decline in offer probabilities. Second, conditional on an offer, the average acceptance rate also declined over time. Among those who received at most one offer during a month of unemployment, the fraction of individuals who accept the offer declined from 76 percent to 58 percent.[7] Similarly, among those who received more than one offer during a month of unemployment, the average acceptance rate of an offer — calculated as the average ratio of a dummy variable indicating whether any offer is accepted to the number of offers received — declined from 39 percent to 20 percent.[8] Finally, the distribution of real hourly reservation wages shifted rightward over time. The median real hourly reservation wage (in 1982-1984 dollars) increased from \$7.81 to \$8.44.[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 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 be either unemployed or employed. 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 $[\underline{x}, \overline{x}]$. Match qualities can evolve over time. Every period, 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. 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 enter unemployment with probability δ.

[7] Because the monthly number of offers received are typically measured using information on total number of offers received during the entire unemployment spell, some individuals observe receiving, on average, less than one offer within a month. For this reason, we calculate the acceptance rate for individuals who receive at most one offer, as well as the acceptance rate for those who receive more than one offer in a month separately.

[8] This definition follows that of Blau and Robins (1990).

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

[10] In fact, the median reservation wage to median hourly wage ratio has only increased by 3 percent over the last four decades as shown in Table 4 and in Figure A3 in Appendix A.

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 by[11]:

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

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 not observe their applicants' match qualities. A firm, however, can choose to pay a cost, κ_I, to learn its applicants' qualities. While paying κ_I reveals to the firm information about its applicants' match qualities, it does not inform the firm about the number of applications and offers applicants have, nor does it provide information about their match qualities at other jobs.[12] 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 knows only 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.[13] 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 $\eta \in [0, 1]$. At this stage, firms that did not acquire

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

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

[13] In 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.

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 define 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:

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

where $x - w(x)$ represents current profits. With probability δ, the job is exogenously destroyed and the firm shuts down. If the match is not exogenously dissolved, it observes a match quality shock with the new match quality y drawn from conditional distribution $\Psi(y \,|\, x)$, with $\psi(y \,|\, x)$ being the associated density. Denote $\widetilde{x}$ as the reservation match quality – an endogenously determined object to be formally defined below. As long as $y \geq \widetilde{x}$, the match is preserved with continuation value $V^F(y)$. Otherwise, the worker endogenously separates from the firm.

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 based on their match qualities 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:

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

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 To acquire information, firms must pay a fixed cost κ_I to learn the match qualities of all its applicants. We assume that the cost takes the following form:

$$\kappa_I = \kappa_1^I + \kappa_2^I \xi.$$

The first term, κ_1^I, represents the base cost firms must pay if they choose to acquire information. The second term κ_2^I is a cost that varies with the expected number of applications sent, ξ. The term κ_1^I can be likened to a fee one must pay to employ a recruiting agency, while the term $\kappa_2^I \xi$ captures the notion that the recruiting agency may charge higher fees if it expects to screen more applications. Importantly, our results do not rely on this particular cost structure. In Section 6.1, we show that even if the fixed cost was independent of the number of applications sent, or the cost was instead a marginal cost per applicant, our results remain mostly unchanged.[14]

Given this cost structure, consider a firm with j applicants. As outlined in Section 3.6, wages are determined via surplus splitting and surplus is increasing in x. Then the following 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:

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

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:

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

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

[14]Our baseline cost structure where the fixed cost of information changes with average applications sent is a middle ground between a constant fixed cost and a marginal cost structure. Further, modeling the information cost as a fixed cost reflects the fact that firms have increasingly relied on recruiting agencies to fulfill their hiring needs. Recruitment agencies in turn are paid a fee for when they fill a position. Under this fee structure, we view fixed costs of information as being the empirically relevant information costs firms face.

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. 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:

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

3.4 Employed workers

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

$$V^W(x) = w(x) + \beta\left[\delta + (1-\delta)\Psi(\widetilde{x} \mid x)\right]U + \beta(1-\delta)\int_{\widetilde{x}}^{\overline{x}} V^W(y)\,\psi(y \mid x)\,dy, \tag{3}$$

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. If the new match quality drawn is below the reservation match productivity, i.e., $y < \widetilde{x}$, the worker endogenously exits into unemployment. This occurs with probability $\Psi(\widetilde{x}|x)$. For any new match quality $y \geq \widetilde{x}$, the worker remains employed with continuation value $V^W(y)$.

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

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

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

$$Pr(\text{offer} \mid y > x) \;\; = \;\; \int_x^{\overline{x}} \sum_{\ell=1}^{\infty} \widehat{q}(\ell)\, Pr(\text{offer} \mid y, \ell) \frac{\pi(y)}{1-\Pi(x)} dy, \tag{5}$$

where

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

and $\widehat{q}(\ell) = q(\ell)/\sum_{\ell=1}^{\infty} q(\ell)$.[15] When $x < \widetilde{x}$, the worker rejects the offer since the value of unemployment is larger. When $x \geq \widetilde{x}$, the first term on the right-hand side of Equation (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 $i \in \{1, 2, \ldots, a-1\}$, and match qualities less than x for her remaining $(a-1-i)$ applications. This occurs with probability $(a-i)[1-\Pi(x)]^i[\Pi(x)]^{a-1-i}$. If all of her i applications that drew match quality greater than x fail to yield an offer, which happens with probability $[1-Pr(\text{offer} \mid y > x)]^i$, 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.[16] Since this firm observes its applicants' match qualities, the worker receives an offer only when she is the best applicant. This occurs with probability $[\Pi(y)]^{\ell-1}$. The second term depicts the case where the worker meets a firm with $\ell < j^*$ applicants. Since the firm does not acquire information and randomly selects an applicant, the worker receives an offer with probability $1/\ell$. Taking expectations over 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:

$$\phi(x,a) = \Gamma(x,a) Pr(\text{offer} \mid x) = \Gamma(x,a) \sum_{j=1}^{\infty} \widehat{q}(j) Pr(\text{offer} \mid x, j), \tag{7}$$

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

[16] ℓ in Equation (5) or (6) is the number of applicants at the firm where the worker has drawn match quality y, and j in Equation (7) is the number of applicants at the firm where the worker has drawn match quality x.

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

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

where

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

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 $a \int_{\widetilde{x}}^{\overline{x}} \phi(x,a)\pi(x)dx$. 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.[17] Upon 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 also rejected all their other applicants. The no recall assumption is standard in the literature (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).[18] Further, firms that did not acquire information learn about their worker's 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:

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

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

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

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

[18] Allowing 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.

with

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

The surplus of a match is given by current output plus the expected value from a match 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:

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

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

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

$$g\,(x)\,(1-u) \quad = \quad (1-\delta)\int_{\widetilde{x}}^{\overline{x}} \psi\,(x \mid y)\,g\,(y)\,dy(1-u) + \sum_{a=1}^{\infty} p(a)a\phi\,(x,a)\,\pi\,(x)\,u. \tag{13}$$

The left-hand side denotes outflows from employed workers with match quality x. Because all employed individuals are *either* exogenously separated from their job *or* subject to a match quality shock, the measure of employed workers with quality x who flow out of this group is equal to $g(x)(1-u)$.[19] The right-hand side of Equation (13) represents the inflows into the measure of employed with quality x. The first term describes the inflows from the employed who drew new match quality x, while the second term represents inflows from unemployment.

3.8 Equilibrium

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

Lemma 2 (Key equilibrium conditions)**.** $\{\widetilde{x}, \theta, j^*\}$ *are determined by the free-entry condition*

[19] With continuous distributions, the probability of exactly drawing x again is zero.

given by Equation (2) and the following conditions[20]*:*

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

and

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

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

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

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

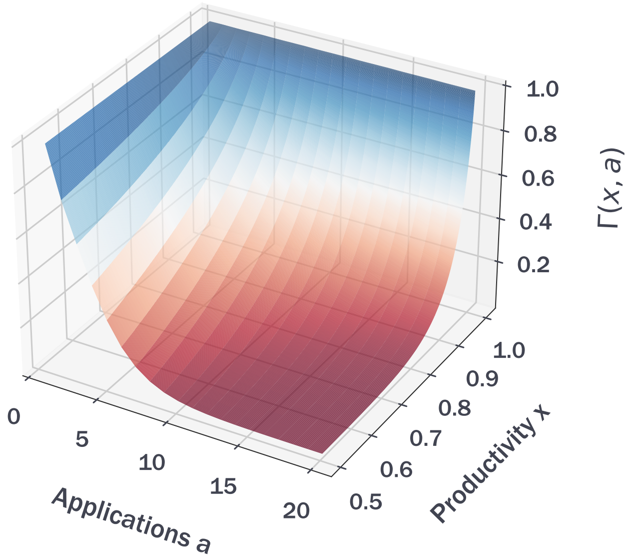
The unemployment outflow rate is a function of three components: 1) the expected number of applications a worker sends and conditional on the realized number of applications; 2) the probability she receives an offer; and 3) the probability she accepts an offer. The first component in Equation (16) represents the effect an increase in the expected number of applications, $\sum_{a=0}^{\infty} p(a)a = \xi$, 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 toward the outflow rate, an increased number of applications also *indirectly* affects the probability an application yields an offer. From Equation (7), the offer probability, $Pr(\text{offer} \mid x)$, depends on the distribution of applicants across

[20] Figure A4 in Appendix B.2 highlights the existence of a unique equilibrium in our calibrated model.

[21] Appendix 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.

vacancies $q(j)$, which in turn depends on ξ. 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 when ξ increases. 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 $x > \widetilde{x}$. 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 one of their *other* applications draws a match quality greater than x. Since a higher ξ increases the number of applications drawn by workers, it also has the indirect effect of lowering average acceptance probabilities, $\sum_{a=1}^{\infty} p(a) \int_{\widetilde{x}}^{\overline{x}} \Gamma(x, a)\pi(x)dx$.

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. Previous studies by Albrecht, Gautier, and Vroman (2003)

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

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 and offer probabilities to weigh against the direct effect of contacting more vacancies. In Section 6.2, we quantitatively study how the relative size of the direct and indirect effects on the outflow rate changes with ξ, and we highlight how these offsetting forces can lead to a non-monotonic relationship between the outflow rate and the number of applications.

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

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

The first term captures exogenous separations, while the second term captures endogenous separations. Holding $\theta, \widetilde{x}$, and j^* constant, an increase in 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 as the persistence in match quality implies that individuals with a high x are less susceptible to low quality draws in the future. More firms acquiring information in response to a higher ξ therefore improves the distribution of realized match quality and lowers the inflow rate.

Thus far, we have limited our analysis to a partial equilibrium setting. In general equilibrium, however, $\widetilde{x}, \theta$, and j^* can vary in response to changes in 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. As we are interested in long-term trends, we treat the 10-year period around 1979-1980 as a steady state. We set the discount factor $\beta = 0.993$ and the worker's bargaining power $\eta = 0.5$, as is standard in the literature. The median number of applications per month in the EOPP is 2.7. Accordingly, we set $\xi = 2.7$.[23] We target the median rather than the mean in the data because the mean is much higher than the median, as shown in Table A5, implying that there are a few individuals

[23] We assume that the central limit theorem applies, i.e., as the sample size gets larger, the sampling distribution approaches that of a normal distribution. This implies a mean that is equivalent to the median and hence $\xi = 2.7$. We thank the referee for this suggestion.

Table 1: Internally calibrated parameters

Parameter	Description	Value	Target	Model	Data
κ_V	Vacancy posting cost	0.74	Outflow rate	0.45	0.41
κ_1^I	Cost of information	0.22	Recruiting cost/mean wage	1.21	0.93
κ_2^I	Cost of information	0.026	Growth of vacancy rate	-21.5	-16.8
δ	Exog. separation rate	0.023	Inflow rate	0.041	0.041
λ	Persistence of x	4.53	Variance of income growth	0.10	0.08
A	Beta distribution	0.76	Fraction with no offers	0.43	0.38
B	Beta distribution	0.84	Average acceptance rate	0.37	0.37
b	Home production	0.08	Reservation wage/median wage	0.73	0.62

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 average acceptance rate are obtained from the EOPP for 1979-1980. The ratio of recruiting costs to average wages in the data is reported by Gavazza, Mongey, and Violante (2018). We calculate the vacancy rate as the ratio of vacancies (using data on vacancies from the composite Help-Watend Index by Barnichon 2010) to sum of vacancies and employment. We then calculate the average of trend component (logged and HP-filtered with smoothing parameter 1600) of the vacancy rate between 1976 and 1985 and between 2010 and 2019 and report the percent change between these two time periods. The variance of annual income growth in the data is calculated by Blundell, Pistaferri, and Preston (2008). Finally, the reservation to median wage ratio represents the ratio of median hourly reservation wage of the unemployed in the EOPP to the median hourly wage of the employed in the CPS.

who send many applications. Next, we 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 $\Pi(x)$ affect the expected benefit of creating a job and vacancy posting, they affect 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 empirical fraction of job-seekers with zero offers and the average acceptance rate conditional on receiving offers. In the data, we calculate the average acceptance rate among all individuals with non-zero offers as the weighted average of acceptance rates among individuals with at most one offer and those with more than one offer.[24] In our model, $\sum_{a=1}^{\infty} p(a) \left(\int_{\underline{x}}^{\overline{x}} [1 - Pr(\text{offer} \mid x)\pi(x)dx] \right)^a$ represents the fraction of job-seekers with zero offers, while the average acceptance rate is given by $\int_{\widetilde{x}}^{\overline{x}} \Gamma(x)\pi(x)dx$. In our model, the acceptance rate is affected by the number of offers received as well as the reservation match quality. Clearly, if all offers are for match qualities below $\widetilde{x}$, the worker rejects all offers. The level of $\widetilde{x}$ is affected by the likelihood of drawing high match quality values, which in turn is affected by the distributional properties of $\Pi(x)$.

A worker is subject to match quality shocks every period. Individuals draw their new match

[24]The average acceptance rate for each of these groups is documented in Figure 3 in Section 2.3. To obtain the economy-wide average acceptance rate, we calculate the weighted sum of these group-level acceptance rates. Appendix A.1 and A.2 provide more details on how we calculate this moment in the EOPP and the SCE.

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

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

This implies a conditional distribution of match quality re-draws of the form $\Psi(x' \mid x)$, where the parameter $\lambda \in [1, \infty)$ controls the degree of dependence between draws. When $\lambda = 1$, x and x' are independent, and when $\lambda \to \infty$ there is perfect positive dependence between x and x'. The functional form of $\Psi(x' \mid x)$ for $\lambda > 1$ implies that matches with high x are less likely to observe an endogenous separation. Because the persistence in draws affects the growth rate of wages, we use λ to match the variance of the *change* in annual income.[25] A large dispersion in income growth rates would suggest less dependence between match quality draws. Similarly, complete independence between match quality draws would imply large volatility in income growth, as even high-wage earners can be easily displaced into unemployment next period. Conversely, a low variance of income growth suggests a high λ, as future draws are concentrated around the neighborhood of current match quality values. We target λ with a variance of annual income growth of 0.08, as reported by Blundell, Pistaferri, and Preston (2008).[26] Separately, we set the level of home production, b, to match the ratio of the median reservation wage to the median wage. We calculate the median hourly reservation wage of the unemployed in the EOPP and the median hourly wage of the employed in the CPS and find a ratio of 0.62.[27]

Labor market We target the average inflow rate for the period 1976-1985 to pin down the exogenous separation probability δ. We choose the vacancy posting cost, κ_V, to match the average outflow rate in the data. As presented in Section 3, we allow the fixed cost of acquiring information to vary with the expected number of applications such that $\kappa_I = \kappa_1^I + \kappa_2^I \xi$. Our specification implies that the fixed cost of information is increasing in ξ. Changes in the fixed cost stemming from the term $\kappa_2^I \xi$ would change the cost of job creation and hence impact the growth in the vacancy rate. Thus, we use κ_2^I to target the growth in the average vacancy rate between 1976-1985 and 2010-2019. To obtain this moment, we use data on the level of vacancies from the composite Help-Wanted Index by Barnichon (2010) and employment levels from the Bureau of Labor Statistics (BLS) and calculate the vacancy rate as vacancies divided by the sum of vacancies and employment.[28] In the data, we observe vacancy rates declining by 16.8 percent.

[25] We simulate our model and time-aggregate to derive the model-implied variance of annual income growth.

[26] Specifically, Blundell, Pistaferri, and Preston (2008) compute this moment as $\mathrm{var}(\Delta y_t)$, where y_t is the log of annual income net of predictable individual characteristics. We use the value reported for the year 1980.

[27] Similar to the data on applications, the mean reservation wage and mean wage far exceed their median counterparts, suggesting that a few individuals demand high reservation wages and earn high wages.

[28] We seasonally adjust the time series of the vacancy rate and compute the averages of the trend component for 1976-1985 and 2010-2019 separately. We target growth in the trend component between these two time periods. The trend component is obtained by HP-filtering the log of the quarterly vacancy rate series with smoothing parameter 1600.

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

	$\xi = 2.7$	$\xi = 7$	Percent change
Information threshold j^*	3	4	
Percent of firms informed	79.8	99.8	25
Labor market tightness θ	0.65	0.59	-10
Reservation match quality $\widetilde{x}$	0.51	0.61	20

Note: This table summarizes the changes in equilibrium variables when ξ increases from 2.7 to 7, which corresponds to an increase in the median number of applications from 2.7 to 7.

To calibrate κ_1^I in the model, we use the fact that the fixed cost of information affects overall recruiting costs. Thus, we use κ_1^I to target the ratio of recruiting costs to average wages of 0.93 in the data, as reported by Gavazza, Mongey, and Violante (2018). In our model, the expected recruiting cost is given by $\kappa_V + \sum_{j \geq j^*}^{\infty} q(j)\kappa_I$.

Table 1 shows that our calibrated model fits the data moments reasonably well. While we have largely targeted information that either relates to or underpins the flows in and out of unemployment, our model is also able to match several untargeted moments. For example, while we target the *growth* in the vacancy rate to pin down the component of information costs that varies with the expected number of applications, our calibrated model actually predicts a vacancy rate level of 5.5 percent, close to the empirical average vacancy rate of 4 percent observed between 1976 and 1985. Because the persistence in match quality affects not only the volatility of income but also the separation rates of different earnings groups, our model also matches the ratio of the inflow rate of those employed in the first quintile of the real hourly wage distribution to that of those employed in the fifth quintile. Using data from the CPS for 1976-1985, we find this ratio to be 4.05. Our model also predicts that those in the first quintile of the real hourly wage distribution are 4.18 times more likely to separate into unemployment compared with those at the fifth quintile. Finally, our model matches the levels of several important untargeted data moments presented in Table 4, which we discuss in Section 5.2.

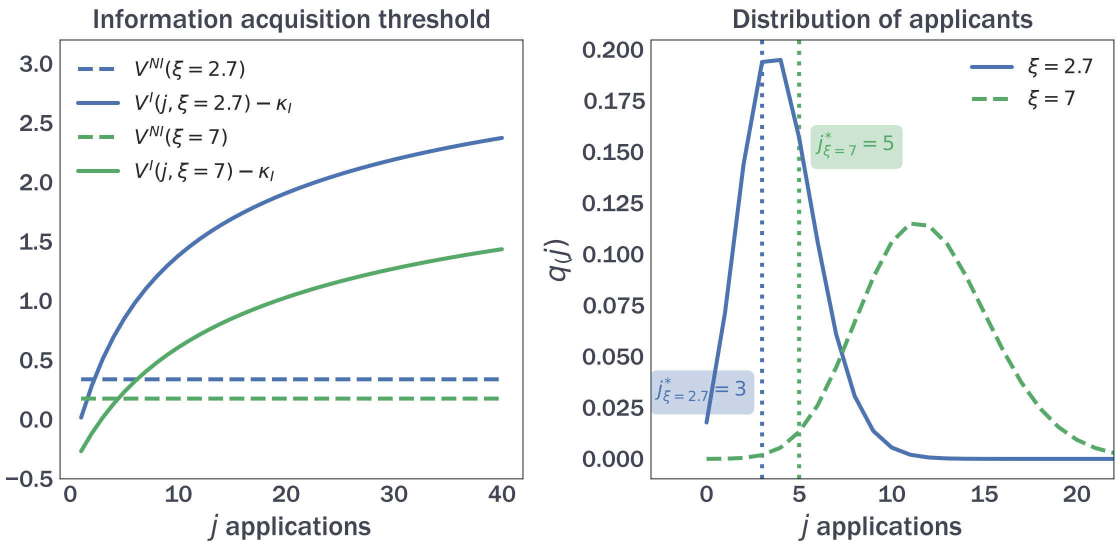
5 Quantitative Results

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 7 between the 1979-1980 period and the 2013-2019 period. We ask how this rise in the number of applications affects labor market moments in our calibrated model, holding all other parameters fixed. To obtain the rise in applications, we increase ξ from 2.7 to 7.

We first document the changes in the equilibrium objects $\{\widetilde{x}, \theta, j^*\}$. Table 2 highlights our results. First, an increase in ξ raises the share of firms acquiring information, despite an increase

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 is 2.7 and 7, separately. The right panel shows how the distribution of applicants per vacancy, $q(j)$, changes when ξ rises from 2.7 to 7. The dashed vertical line represents the equilibrium j^* cutoff below which firms do not acquire information.

in the information threshold, j^*. As foreshadowed in Section 3.9, acceptance probabilities are weakly declining in the number of applications sent. A higher offer rejection rate causes the value of acquiring information, $V^I(j)$, to fall by more than the value of not acquiring information, V^{NI}. Intuitively, information becomes less valuable when workers reject offers more often. In addition to acceptance probabilities falling, the cost of information, $\kappa_I = \kappa_1^I + \kappa_I^2\xi$, is also rising in applications sent. As such, the net value of acquiring information falls by more than the value of not acquiring information, as depicted by the left panel of Figure 5. Consequently, j^* rises in equilibrium as applications increase. 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. As a result, more firms acquire information when ξ is higher, with the share of informed firms rising by 25 percent.

Second, an increase in ξ causes labor market tightness, θ, to fall for three reasons. First, the fixed cost of information is increasing in ξ. Second, more firms acquiring information on average implies that the expected cost of recruitment is also larger. Both these factors imply that recruiting expenditures increase when ξ is higher. Third, 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 firms and receive offers. This in turn reduces their likelihood of accepting an offer of any match quality x. Both higher recruiting costs and lower acceptance rates depress vacancy creation. Consequently, θ declines despite firms contacting applicants at a higher rate.

Finally, reservation match quality, $\widetilde{x}$, rises when ξ increases. There exist 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 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 $\widetilde{x}$ is partially tempered by the rise in congestion.

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 1976-1985 and 2010-2019, as these two intervals cover the EOPP (1979-1980) and the SCE (2013-2019). For inflow and outflow rates, we take 10-year averages of the trend components because 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:Q1, however, the average outflow rate had recovered to its long-run average of around 0.41. Table 3 lists our results.

5.2.1 Inflow rate

Table 3 highlights that a rise in applications alone causes the inflow rate to decline by 15 percent in the model, accounting for around one-third of the decline in the data. This is in spite of the rise 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 likelihood that a match is severed.

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 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; workers are less likely to separate from their jobs when the distribution of employed is concentrated around high quality matches. The share of employed who draw a new match quality $x' < \widetilde{x}$ and separate into unemployment falls by 35 percent when ξ increases.[29] This large decline in the likelihood of a match being severed outweighs the effect of a higher reservation match quality $\widetilde{x}$. Thus, the inflow rate declines 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

[29] The share of employed who draw match quality $x' < \widetilde{x}$ is $\int_{\widetilde{x}}^{\overline{x}} \Psi(\widetilde{x} \mid x) g(x) dx$.

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

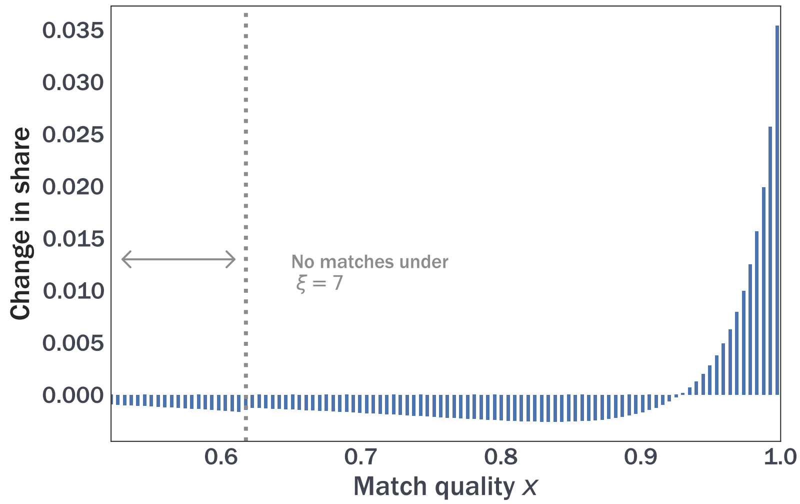
	$\xi = 2.7$		$\xi = 7$		Percent change	
	Model	Data	Model	Data	Model	Data
Inflow rate	0.041	0.041	0.035	0.023	-15	-44
Outflow rate	0.454	0.408	0.450	0.318	-0.9	-22
Outflow rate (2019)	0.454	0.408	0.450	0.409	-0.9	0.2
direct effect					67.5	
indirect effect					-68.4	

Note: This table summarizes the model-predicted inflow and outflow rates when ξ increases from 2.7 to 7 and compares these results with their empirical counterparts. Data moments are obtained as averages of trend components of logged and HP-filtered (with a smoothing parameter of 1600) inflow and outflow rates from the CPS for 1976-1985 and 2010-2019, where the median number applications was 2.7 in the former period and 7 in the latter period. The third row in the table repeats the same information as in the second row except that it presents the outflow rate in the data from the first quarter of 2019 to illustrate that the trend outflow rate has recovered to its long-run average in 2019 after the slow recovery following the Great Recession. Finally, the last two rows represent the impact of rise in applications on the model-predicted outflow rate due to the change in the expected number of applications submitted by workers (direct effect) and changes in offer arrival and offer acceptance probabilities (indirect effect).

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 with its data counterpart. In our model, the distribution of employed shifts toward 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 48 percent when ξ increases, while the share employed in jobs lasting between one and three years falls by a smaller 11 percent.

Our results concur in sign and magnitude with empirical findings on how the tenure distribution changed over time. Empirically, short tenure employment relationships have observed the sharpest decline. Using data from the Quarterly Workforce Indicators (QWI), Pries and Rogerson (2019) find that the share of employed in jobs lasting less than a quarter fell by 39 percent between 1999 and 2015. Using data from the CPS, Molloy, Smith, and Wozniak (2020) show that the share of employed in jobs lasting more than a year and less than three years declined 11 percent, while the median tenure remained relatively unchanged over the past four decades. 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 $\Psi(\widetilde{x} \mid x)$. Since $\widetilde{x}$ is higher when ξ increases, this raises $\Psi(\widetilde{x} \mid x)$, implying that

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 2.7 to 7. Specifically, for each bin, the figure shows the difference in the pmf $[G(x_2)_{\xi=7} - G(x_1)_{\xi=7}] - [G(x_2)_{\xi=2.7} - G(x_1)_{\xi=2.7}]$.

a match of given x quality is now more prone to separation. As such, median tenure remains relatively unchanged in our model, a finding consistent with the data.

Taking stock The rise in applications in our model accounts for around one-third of the empirical decline in the 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

In our model, a rise in ξ causes the outflow rate to decline a minute 0.9 percent. While the average outflow rate in the data is lower for 2010-2019 when compared with that for 1976-1985, this is largely because the economy experienced a slow labor market recovery following the Great Recession. By 2019:Q1, the outflow rate had returned to its long-run average of about 0.41, as shown by Table 3, which is in line with the lack of any long-run trend in the empirical outflow rate, as documented by Figure 2. Thus, the negligible change in our model-predicted outflow rate is consistent with the lack of a long-run change in the empirical outflow rate.

Why does our model predict such a negligible change 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

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

Panel A: Tenure distribution

	$\xi = 2.7$		$\xi = 7$		Percent change	
	Model	Data	Model	Data	Model	Data
Share employed $t < 1$ quarter	0.015	0.080	0.008	0.049	-48	-39
Share employed $1 \leq t < 3$ years	0.17	0.18	0.15	0.16	-11	-11
Median tenure (years)	3.60	4	3.60	4	0	0

Panel B: Outflow rate components

	$\xi = 2.7$		$\xi = 7$		Percent change	
	Model	Data	Model	Data	Model	Data
Median applicants per vacancy	4.67	5.21	12.5	14.5	168	178
Fraction > 0 offer	0.57	0.62	0.47	0.57	-17	-8
Acceptance rate	0.37	0.37	0.22	0.25	-41	-33
Reservation-to-median wage ratio	0.73	0.62	0.79	0.64	8	3

Note: This table summarizes the changes in the tenure distribution and outflow rate components (the fraction > 0 offer, the average acceptance rate, and the ratio of median reservation wage to median wage) when ξ increases from 2.7 to 7. Data moments on the share of jobs that last $t < 1$ quarter are 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 data from the CPS. Data moments on the median applicants per vacancy are calculated using data on vacancies from Barnichon (2010), data on unemployment from the BLS, aand data on median applications from EOPP and SCE surveys. Data moments on outflow rate components are computed as averages from the EOPP for 1979-1980 and from the SCE for 2013-2019, 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.

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

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

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 number of applications. In fact, the effects from lower offer and acceptance probabilities totally dominate the effect of contacting more vacancies, causing the outflow rate to be almost unchanged.

The model's ability to reproduce the lack of a secular increase in the empirical outflow rate emanates from its predicted declines in offer and acceptance rates. Crucially, our model-predicted changes in offer and acceptance rates in response to a rise in applications align with the data, as shown in Table 4. The fraction of the unemployed with offers declines by 17 percent in our model and 8 percent in the data. The larger decline in our model arises because both lower vacancy creation and a higher number of applications increases 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 median number of applicants per vacancy. In the data, we calculate this as the ratio of the median number of applications to labor market tightness.[30] To make the model comparable with the data, we compute the same ratio in the model.[31] Note that we do not target the median number of applicants per vacancy in our calibration and only ensure that ξ is equal to the median number of applications sent by workers in the data for each time period. Further, in disciplining κ_2^I, the component of information costs that varies with ξ, we target the growth in the vacancy rate, leaving vacancy rate levels untargeted across both time periods. As the level of unemployment is also untargeted in the second time period, our model-predicted levels and growth in median applicants per vacancy are not by construction pegged to the data. Despite being untargeted, our model still generates levels close to their empirical counterparts. More crucially, our model-predicted *growth* in the median number of applicants per vacancy closely mimics patterns in the data, with median applicants per vacancy rising by 168 percent in our model and 178 percent in the data.[32] These results suggest that the rise in applications over time has been accompanied by more competition at a vacancy.

The decline in the fraction receiving offers is only one of the outcomes serving to counteract the positive effect of a rise in applications on outflow rates. The other key variable that affects outflows is the acceptance rate. We calculate the model's average acceptance rate as the expected probability of accepting an offer for a particular application, $\int_{\widetilde{x}}^{\overline{x}} \sum_{a=1}^{\infty} p(a)\Gamma\left(x,a\right)\pi\left(x\right)dx$. In our model, a higher number of applications allows workers to be more selective over the minimum job they are willing to accept — as depicted by the rise in $\widetilde{x}$. 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, the acceptance rate in

[30] In particular, we first use data on the level of vacancies from the composite Help-Wanted Index of Barnichon (2010) and data on unemployment levels to obtain a time series of labor market tightness. We then seasonally adjust the data and obtain the trend component by HP-filtering the log of the quarterly series with smoothing parameter 1600. We compute averages of the trend component for the two time periods. Next, we use data on the median number of applications from the EOPP and SCE, and compute median applicants per vacancy as the ratio of median applications to labor market tightness for the two time periods.

[31] Since the number of applications sent are drawn from a Poisson distribution, its median is approximated by $\xi + \frac{1}{3} - \frac{1}{50\xi}$. See Choi (1994) for more details.

[32] Our results are similar if we were to instead compute the median from the distribution $q(j)$ in the model. In this case, the parameter that governs the Poisson distribution for applicants per vacancy is given by ξ/θ. As such, the median of the distribution $q(j)$ would be approximated by $\xi/\theta + \frac{1}{3} - \frac{1}{50\xi/\theta}$. Under this measure, the median of the distribution $q(j)$ increases by 172 percent between the two time periods, close to what is reported in Table 4. We note that this calculation is not feasible in the data given that we do not observe the actual number of applications at each vacancy.

our model declines by 41 percent, close to the 33 percent fall in the empirical acceptance rate. While untargeted, our model's predicted changes in offer and acceptance probabilities largely mimic the patterns observed in the data over time.

The decline in the acceptance rate in our model does not stem solely from an increase in reservation wages. Relative to the large decline in the acceptance rate, our model generates a smaller 8 percent rise in the reservation to median wage ratio, implying that the rise in reservation match quality contributes to only part of the decline in the acceptance rate.[33] Similarly, the median reservation wage to median wage ratio rises by a comparable 3 percent in the data, suggesting that the increase in reservation wages alone is also not the main factor behind the large empirical decline observed in workers' acceptance rates.

Decomposing the decline in the acceptance rate To understand how much the acceptance rate would instead decline if reservation match qualities remained constant, we hold fixed $\widetilde{x}$ at its level when $\xi = 2.7$ and keep all other equilibrium objects at their $\xi = 7$ levels. In this scenario, the acceptance rate still falls by 31 percent, suggesting that most of the decline in the acceptance rate is not because workers are more selective over the minimum quality job they are willing to accept, but because they are more likely to have drawn a higher match quality in at least one of their other applications, reducing their need to accept any offer of given quality x.

The decline of the acceptance rate in our model is not mechanical. More applications need not beget a lower acceptance rate, as offer probabilities are also changing when applications increase. To see this, we decompose the acceptance rate into two terms. We first focus on $\Gamma(x, a)$. The first term in Equation (4) reflects the fact that as a worker sends more applications, the probability that a particular job offer of match quality x is her best match quality drawn is smaller. While the first term in Equation (4) monotonically declines with a, the second term does not. In particular, the second term in Equation (4) highlights that in the event that x is not her best match quality, a worker still accepts an offer of quality x if her other applications that are of higher match qualities did not yield any offers. This underscores the fact that $\Gamma(x, a)$ cannot be divorced from offer probabilities, the latter of which are also endogenous objects. If offer rates declined significantly, individuals would have fewer options to choose from, making it more likely for a worker to accept an offer of quality x. Thus, it is not guaranteed that a rise in applications must trigger a decline in the acceptance rate in general equilibrium. In fact, the acceptance rate is only guaranteed to fall if offer rates are constant or increasing in equilibrium since the second term in Equation (4) is decreasing in $Pr(\text{offer}|y > x)$.[34]

[33] The *levels* of reservation wages in our model are not comparable with the levels observed in the data, since we do not calibrate wages in the model to match dollar amounts in the data. Further, match qualities in our model are bounded between 0 and 1. Thus, a more useful statistic we present here that addresses differences in scale due to dollar amounts is the ratio of reservation wages to median wages of employed.

[34] In Section 5.3.1, we show in a simpler model that even when there are no differences in match qualities, the change in the average acceptance rate when applications increase still depends on changes in offer probabilities.

Table 5: Decomposing the decline in the average acceptance rate

	$\xi = 2.7$	$\xi = 7$	Change
Average acceptance rate	0.37	0.22	-0.15
$\Gamma_{\mathcal{A}}$	0.33	0.15	-0.18
$\Gamma_{\mathcal{B}}$	0.04	0.07	0.03

Note: This table shows the percentage point change in different components of the average acceptance rate when applications increase.

While the above discussion focused on $\Gamma(x, a)$, the same decomposition can be applied to the average acceptance rate in our model. The average acceptance rate is:

$$\Gamma = \int \sum_a p(a)\Gamma(x, a)\pi(x)dx = \Gamma_{\mathcal{A}} + \Gamma_{\mathcal{B}},$$

where

$$\Gamma_{\mathcal{A}} = \int \sum_a p(a)[\Pi(x)]^{a-1}\pi(x)dx,$$

and

$$\Gamma_{\mathcal{B}} = \int \sum_a p(a) \sum_{i=1}^{a-1}(a-i)[1-\Pi(x)]^i[\Pi(x)]^{a-1-i}[1-Pr(\text{offer} \mid y > x)]^i\pi(x)dx.$$

In our model, a rise in ξ from 2.7 to 7 causes a decline in $\Gamma_{\mathcal{A}}$ to more than counteract the increase in $\Gamma_{\mathcal{B}}$, as shown in Table 5. Notably, $\Gamma_{\mathcal{B}}$ can only increase if it becomes less likely to receive offers; that is, $\partial\Gamma_{\mathcal{B}}/\partial Pr(\text{offer}|y > x) < 0$. This is precisely the case in our model, which observed the fraction of individuals with offers declining with a rise in applications. The contrasting behavior of $\Gamma_{\mathcal{A}}$ and $\Gamma_{\mathcal{B}}$ highlights the role of general equilibrium effects. While our comparative static results in Section 3.9 highlighted how the average acceptance rate can decline with ξ *holding all else constant*, our quantitative results highlight how in equilibrium, offer probabilities play a role in affecting the change in the average acceptance rate as well.

Finally, we look at offer probabilities to understand why $\Gamma_{\mathcal{B}}$ increases by less than the decline in $\Gamma_{\mathcal{A}}$. In our model, offer probabilities do not decline by the same amount as the rise in median applicants per vacancy. This is because offer probabilities in our model are also affected by two components, as depicted by Equation (6). The first component concerns the match quality, x, of an applicant, and the second component concerns the amount of competition at a vacancy or, in other words, the number of applicants, j. Offer probabilities are increasing in x and decreasing in j. When individuals submit more applications, they sample more of the distribution of match qualities, making it more likely that at least one of their applications is of very high match quality and would thus yield an offer. This partially mitigates increased congestion, causing offer probabilities to fall by less than the increase in median applicants per vacancy. Thus,

$\Gamma_{\mathcal{B}}$ rises by less, and the average acceptance rate declines. Importantly, the smaller decline in offer probabilities is due to the endogenous change in firms' information acquisition behavior in response to a higher number of applications. The increased probability of drawing high match quality x when workers send more applications can only translate to higher offer probabilities if firms actually identify their best applicant. The fact that more firms acquire information, which increases the likelihood that a worker receives an offer for her high match quality drawn, is a mitigating force (against increased congestion) on offer probabilities.

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 Understanding model mechanisms

Thus far, we have shown how our baseline model can generate a decline in the inflow rate and no change in the outflow rate in response to rising applications. A natural question that arises is whether a simpler model could have generated these same results. In this section, we shut down key features of the model, namely worker heterogeneity and information frictions, and demonstrate how results would differ if any of these elements are missing.

5.3.1 A model with homogeneous match quality

We begin with a simple model featuring no heterogeneity in match quality. To do this, we assume all workers have match quality $x = 1$. As all workers have the same quality, firms do not need to acquire any information. We provide a detailed outline of this model in Appendix C.1.

When there are no differences in match qualities across workers, the only exits into unemployment that occur are exogenous separations. As such, the first way such a simplified model fails to match the data is that it cannot replicate the secular decline in the unemployment inflow rate, unless one appeals to a declining exogenous separation rate over time. Neither can this model capture differential changes across the tenure distribution over time (as seen in Table 4).

Even if one were to allow for a declining exogenous separation rate over time, the model without heterogeneous match qualities still fails to match the lack of change in the outflow rate. Calibrating this model to the data, Table A7 in Appendix C.1 shows the outflow rate rising by 7 percent when applications increase and separation rates exogenously decline. In terms of our model's language, the outflow rate increases because the direct effect of contacting more vacancies outweighs the indirect effect stemming from the changes in offer and acceptance rates. Because offer probabilities fall by a significant 57 percent, workers do not have that much more options to choose from despite submitting more applications. Consequently, acceptance rates barely decline in this model with homogeneous match quality. The lack of a decline in acceptance rates in turn contributes towards a weaker counteracting indirect effect on the outflow rate. As such,

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

	Full Information (FI)		No Information (NI)		Percent change		
	$\xi = 2.7$	$\xi = 7$	$\xi = 2.7$	$\xi = 7$	Model	FI	NI
Labor market tightness θ	0.54	0.61	0.72	0.80	-10	14	11
Reservation match quality $\widetilde{x}$	0.45	0.54	0.44	0.40	20	20	-8
Inflow rate	0.042	0.044	0.043	0.044	-15	3	3
Outflow rate	0.46	0.47	0.37	0.27	-0.9	5	-28
direct effect					67.5	69	57
indirect effect					-68.4	-64	-85

Note: This table summarizes the equilibrium outcomes and labor market flows when ξ increases from 2.7 to 7, which corresponds to an increase in the median number of applications from 2.7 to 7. Model refers to the baseline scenario in which there is a time-varying fixed cost $\kappa_I = \kappa_1^I + \kappa_2^I \xi$ of acquiring information. FI is the "Full Information" model in which $\kappa_I = 0$, and NI is the "No Information" model in which $\kappa_I \to \infty$.

the direct effect of contacting more vacancies dominates and the outflow rate rises. These results differ from our baseline model, which predicted non-trivial declines in both offer probabilities *and* acceptance rates, as observed in the data. Overall, the simple model featuring no heterogeneity in match quality cannot match the joint dynamics in unemployment outflow and inflow rates, even when one appeals to an exogenously declining inflow rate.

5.3.2 The role of costly information

Having highlighted why heterogeneity in match quality is a necessary element of our model, we next examine the role of costly information. We consider two thought experiments to uncover why the interaction of information acquisition with an increase in applications is crucial for our main results. In the first experiment, we set $\kappa_I = 0$ and label this the "Full Information" (FI) model.[35] In the second experiment, we consider the other extreme and set $\kappa_I \to \infty$. We label this the "No Information" (NI) model. We re-calibrate the FI and NI models to match the same targets as our baseline model.[36] In both models, by construction, a firm's information acquisition choice does not vary with the number of applications. Comparing the results from the FI and NI models to 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 6 details the results from these two 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 acquired information, job creation costs do not vary with 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

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

[36]Details of our calibration strategy and model fit can be found in Appendix C.2.

the firm's probability receiving zero applicants, this raises the expected benefit of a vacancy. The rise in the expected benefit 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.

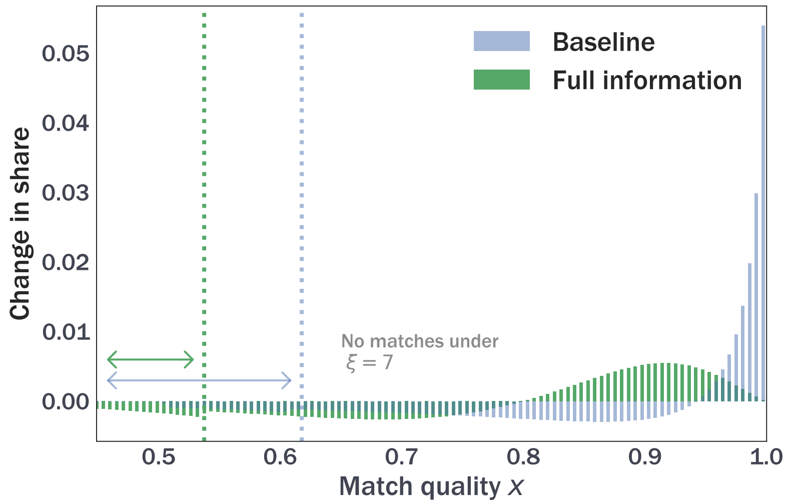
Focusing on reservation match quality, $\widetilde{x}$ rises in the FI model and falls in the NI model when applications increase. These differences stem from how workers' outside options change with a rise in applications across the two models. In the FI model, firms always identify the highest quality 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 $\widetilde{x}$. 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 rise in ξ outweighs the rise in θ, resulting in more competition at a vacancy. Increased congestion worsens workers' outside options and causes $\widetilde{x}$ 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 both models fail to capture the empirical patterns in inflow and outflow rates over time.

Focusing first on the FI model, the inflow rate rises by 3 percent, while the outflow rate rises by 5 percent, opposite to the large decline in the inflow rate and lack of change in the outflow rate observed in the data. To understand these results, it is useful to recall that a rise in applications has two opposing effects on the inflow rate. In our baseline model, a rise in applications prompted more firms to acquire information, resulting in a large increase in the formation of high quality matches. The greater formation of high-quality matches stems from the fact that additional applications represent additional opportunities for the worker to sample from the distribution, and more firms, by acquiring information, identified these high quality applicants. This is the effect we termed as improved firm selection, which works toward reducing the separation rate. The second effect that we termed as increased worker selectivity works as a force toward raising the separation rate. Sending more applications improves the worker's outside option, and raises the worker's reservation match quality. As a result, new match qualities drawn must now pass a higher threshold for the match to be sustained.

Importantly, both the improved firm selection effect and increased worker selectivity effect also operate in the FI model, but to different degrees. While the FI model also exhibits an improvement in average match quality as in the baseline model, the effects from increased worker selectivity far outweigh the effects from improved firm selection. In fact, the rise in the average match quality largely stems from the improvements at the bottom end of the distribution of realized match quality rather than at the top. Because FI firms can always identify and hire the best applicant, the effect of improved firm selection is diminished relative to that observed in

Figure 7: Change in distribution of realized match qualities: Baseline model vs FI model



Note: This figure shows how the share of employed workers across match quality x changes when ξ increases from 2.7 to 7. Specifically, for each bin, the figure shows the difference in the pmf $[G(x_2)_{\xi=7} - G(x_1)_{\xi=7}] - [G(x_2)_{\xi=2.7} - G(x_1)_{\xi=2.7}]$. Green bars represent the change for the FI model, while blue bars represent the change under our baseline model.

the baseline model; the increase in applications leads to only a small improvement at the upper end of the realized match quality distribution. Conversely, increased worker selectivity causes the bottom end of the distribution to be truncated rightward with a rise in $\widetilde{x}$. Consequently, improvements in the average match quality in the FI model largely stem from this truncation in the bottom end of the distribution. In contrast, under the baseline model, the endogenous increase in information acquisition serves as a multiplier for raising the quality of matches, the effects of which ultimately outpace the effects of increased worker selectivity on inflows. This multiplier is not present in the FI model. Figure 7 shows how a larger part of the improvement in the distribution of realized match qualities stems from the disappearance of matches around the bottom in the FI model (green bars) rather than from improvements and shifts occurring near the top, as in the baseline model (blue bars).[37]

Because most of the rise in the average match quality stemmed from a rise in worker selectivity, the probability that a worker is endogenously separated from his job, $\int_{\widetilde{x}}^{\overline{x}} \Psi(\widetilde{x}|x)g(x)dx$, actually rises 7 percent in the FI model. In contrast, when the effect from improved firm selection predominates — as is the case in our baseline model — the probability an employed worker endogenously separates from their job fell 35 percent. Again, this larger fall in our baseline model arises precisely because a stronger improved firm selection effect implies that there is a larger improvement in the the distribution of realized match qualities at the top.

In summary, the effects from improved firm selection are small in the FI model when there

[37]To show that our effects are not driven by differences in the unconditional distributions from which workers draw match qualities, Figure A5 in Appendix C.3 verifies that this occurs even when we impose that workers draw match qualities from the same unconditional distribution. In this case, the inflow rate still rises by 1 percent because the effects of improved firm selection are small relative to the effect of increased worker selectivity.

is no change in the share of informed firms. In comparison, the worker selectivity effect is stronger relative to our baseline model, as congestion effects arising from increased applications are partially mitigated by the rise in vacancy creation in the FI model and by the fact that when workers sample more of the distribution of match qualities, they are more likely to draw a high match quality in at least one of their applications and receive an offer.

Focusing on the outflow rate, the probability of receiving an offer for a given match quality x from a firm with j applicants is given by $Pr(\text{offer} \mid x, j) = [\Pi(x)]^{j-1}$ in the FI model. Since $dPr(\text{offer} \mid x, j)/dx \geq 0$, this probability is increasing in x. Because an increase in applications raises the worker's 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 also higher. This combined with higher vacancy creation causes offer probabilities in the FI model to decline by a mere 1 percent. Further, acceptance probabilities, $\Gamma(x, a)$, are also increasing in x. The milder increase in congestion due to the rise in θ, and the greater 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 — all contribute toward increasing the outflow rate in the FI model.[38]

Switching now to the NI model, the inflow rate rises by 3 percent, while the outflow rate declines by 28 percent. The rise in the inflow rate is largely driven by a greater formation of low quality matches which are more susceptible to job destruction. In response to a rise in applications, the employed are 6 percent more likely to draw $x' < \widetilde{x}$ and separate into unemployment despite a fall in $\widetilde{x}$. In contrast to our baseline model, which featured a large rise in the share of high quality matches, deterioration in the distribution of realized match quality is the main driver behind the rise in the inflow rate in the NI model.

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 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. 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.[39]

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.

[38] Nonetheless, 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.

[39] The direct effect on the outflow rate computed across the three models need not line up in terms of magnitude, since the computed $\phi_{t2}(x, a)$ is not equivalent across the three models.

6 Discussion

6.1 Different cost structures

While our model nests both the FI and NI models, a natural question arises as to whether our results would differ if 1) we assumed a fixed cost but did not allow it to vary with the number of applications and 2) we instead assumed a marginal cost of information. In what follows, we show that key model predictions hold even under alternative cost structures. In both variations, we assume that the cost of information is constant across time. We re-calibrate all models to match the data in the first time period and as such have comparable starting points.

6.1.1 Assuming a constant fixed cost of information acquisition

In this version of the model, we assume that the fixed cost of information does not vary with the expected number of applications, i.e. $\kappa_2^I = 0$, and information costs are instead governed by a single parameter $\kappa_I = \kappa_1^I$. Since we have one parameter less to calibrate, we drop the moment that κ_2^I was used to target in our baseline calibration: the growth in the vacancy rate over time.[40] Table A11 in Appendix C.4 shows our calibration results.

Table A12 in Appendix C.4 shows that our model results remained largely unchanged under a constant fixed cost of acquiring information.[41] This is because the forces in our model remain the same: When workers submit more applications, firms anticipate they will receive more applicants for their vacancy, increasing the likelihood of a high-quality applicant. A higher share of informed firms in turn raises the formation of high quality matches, which are less susceptible to job destruction. At the same time, higher expected recruiting costs drive down vacancy creation, tampering the effects from a rise in worker selectivity via an increase in $\widetilde{x}$. Overall, the effects from improved firm selection dominate and cause the inflow rate to decline by 15 percent.

Similarly, the model with a constant fixed cost of information predicts the outflow rate declining by a mere 1 percent. This occurs as the fall in offer probabilities and acceptance rates more than counteracts the effect from contacting more vacancies. As in the baseline model, increased congestion weakens offer probabilities while increased selectivity reduces acceptance rates when applications increase and information costs are held constant.

6.1.2 Assuming a marginal cost of information acquisition

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

[40] Notably, the growth in the vacancy rate is affected by $\kappa_2^I \xi$. Dropping this target means we are minimizing the distance between a smaller set of model-generated and data moments. Since the minimization problem in our calibration is different from the baseline model, estimated parameters can also then differ.

[41] A previous version of this paper that calibrated the model to different moments also found a similar result. The rise in applications prompts a large decline in inflow rates and no significant change in outflow rates.

from the QCEW, we find that the average growth in employment from employment placement services outpaced the growth in total employment between the periods 1990-2007 and 2010-2019, underscoring the increasing importance of recruitment agencies. Recruitment agencies in turn are paid placement fees, which are typically some percentage of the worker's salary.[42] 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 $\widehat{j}$ as the level such that for any $j > \widehat{j}$, the firm observes that the marginal cost of information exceeds its marginal benefit; i.e., $\kappa_I > V^I(j+1) - V^I(j)$ for any $j > \widehat{j}$. There still exists a lower bound $j^* > 1$ where for any $j < j^*$, the value of not acquiring information exceeds the net benefit of acquiring information; i.e, $V^{NI} > V^I(j) - \kappa_I j$ for $j < j^*$. Thus, for any $j^* \leq j \leq \widehat{j}$, the firm acquires information on all of its applicants, and for any $j > \widehat{j} \geq j^*$, the firm acquires information on a subset $\widehat{j}$ of its applicants. Appendix C.5 provides more details on such a setup.

Holding all else constant, an increase in ξ leads to more applicants per vacancy. So long as the average number of applicants per vacancy is not far above $\widehat{j}$ in the initial steady state, the increase in applications still raises the share of informed firms and improves the distribution of realized match quality, lowering the inflow rate. As shown in Table A14, the model is still capable of generating the differential trends observed for the inflow and outflow rates; the inflow rate falls by 11 percent while the outflow rate does not change. In part, the more modest decline in the inflow rate in this model (11 percent) compared with our baseline model (15 percent) can be explained by the fact that, with a marginal cost 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 are key in reducing the inflow rate, while lower offer arrival and acceptance probabilities lead to a negligible change in 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 $\xi \in [1, 16]$ and show how variations in ξ can affect flows. Figure A7 in Appendix C.6 shows our results.

The inflow rate initially rises at low levels of ξ, as seen in Figure A7. When few applications are sent, a small increase in ξ greatly strengthens the worker's outside option, causing a larger increase in reservation match quality, $\widetilde{x}$. This dominates the effects from improved firm selection,

[42]See https://tinyurl.com/3skzkpa4, for example, on the cost structures of recruitment agencies.

leading separations to initially rise. This rise in the inflow rate occurs only for values of $\xi < 2.7$, where 2.7 was the median number of applications in the EOPP. Past $\xi = 2.5$, the inflow rate declines significantly, as the effects of increased worker selectivity 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 22 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 64 percent increase in the outflow rate, while the indirect effect from reduced acceptance probabilities contributes to a 42 percent decline in the outflow rate. In contrast, raising ξ from 4 to 5 results in a direct effect of 15 percent, which is more than offset by an indirect effect of 16 percent, leading to a net -1 percent decline in the outflow rate.

We find that the outflow rate is maximized around $\xi = 4$, which implies that the outflow rate in our calibrated at $\xi = 2.7$ is to the left of this peak, while the outflow rate of our counterfactual economy at $\xi = 7$ is to the right of this peak. We emphasize that even though $\xi = 4$ generates the highest outflow rate, this does not necessarily constitute the efficient number of applications. As vacancy creation is costly in our model and expected information costs are also affected by the number of applications, a planner would choose to maximize lifetime output net of resource costs as opposed to the outflow rate. We leave this analysis for future work.

6.3 On-the-job search

Thus far, we have focused on the effects of an increased number of applications sent by unemployed workers on labor flows. Nonetheless, our model can be extended to include on-the-job search. In Appendix C.7, 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 can instead lead to a decline in the unemployment inflow rate through the increased formation of longer-lived matches. The extent to which the outflow rate changes in response to a rise in applications depends on how much the direct effect of contacting more vacancies is mitigated by endogenous declines in offer and acceptance probabilities. Meanwhile, the counteracting forces of improved firm selection and increased worker selectivity determine how much the inflow rate declines when applications increase. Quantitatively, our model predicts that the rise in applications can explain around one-third of the empirical decline in the inflow rate while simultaneously accounting for an unchanged outflow rate. Our model also contains several testable implications. Specifically, changes in our model-predicted job offer and acceptance rates, reservation wage to median wage, and tenure distribution in response to a rise in applications match the patterns observed in the data.

Crucially, 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, because information is either free or infinitely costly, these alternative models fail to jointly generate the declining trend in the inflow rate and lack of a long-run change 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 hiring behavior and the emergence of slow labor market recoveries following economic downturns. Second, incorporating ex-ante worker and firm heterogeneity into our model could provide insights as to why some firms receive relatively more applications and how this affects labor market power. 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 affect the efficient number of applications. We leave these for future research.

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Appendix

A Data

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

A.1 EOPP

The goal of the EOPP was to help participants find a job in the private sector during an intensive job search assistance program. Individuals had to be unemployed and meet income eligibility requirements to be able to participate in this program. The survey was created to analyze the effects of the program on the labor market outcomes of participants. As a result, by design, the survey oversampled low-income families. To alleviate concerns about the representativeness of the survey, the section on survey weights contained in the EOPP survey documentation explains that "*the final sample design included an oversample of low-income families with children, but not to the extent that it seriously weakened statistics pertaining to the general population.*" In Section A.3 below, we provide evidence in support of this claim.

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.

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 between 1979 and 1980. This gives us 5410 unique individual-spell observations.[43] For each of these individual-spell observations, we calculate the unemployment duration in months.[44] 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. We divide the total number of job applications sent during each spell by its duration to obtain the average monthly number of applications. 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 provide an indicator variable on whether the individual accepted any of the offers received. Because we measure the monthly number of offers received by dividing the total number of of-

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

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

fers received during the entire unemployment spell by the duration of the unemployment spell, some individuals observe receiving less than one offer within a month. For this reason, we first calculate the average acceptance rate among individuals with at most one offer and with more than one offer during a month of unemployment separately, using information on the monthly number of offers and an indicator variable on whether the individual accepted any of the offers received. For the group of individuals with at most one offer during a month of unemployment, we calculate the fraction of individuals that accept an offer. For individuals with more than one offer during a month of unemployment, we first calculate the ratio of the dummy variable indicating whether the individual accepted any offer to the number of offers received by the individual. We then calculate the weighted average of this ratio across individuals to obtain the average acceptance rate of an offer among individuals with more than one offer during a month of unemployment. This definition is identical to the conditional acceptance rate reported in Blau and Robins (1990). These are the moments provided in the middle panel of Figure 3. To obtain the economy-wide average acceptance rate, we calculate the weighted sum of these group-level acceptance rates, where the weights for each group are the fractions of individuals with at most one offer and more than one offer, respectively. This is the average acceptance rate in the data reported in Table 1 and Table 4. Finally, the survey also contains information on the lowest hourly wage rate that the individual would accept during the unemployment spell. We use this information to measure the reservation wage of the individual.[45]

A.2 SCE

The SCE Labor Market Survey was developed by the Federal Reserve Bank of New York.[46] 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 for 2013-2019. 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 to employment. For both groups, we analyze job search activities conducted during each reported

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

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

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 offers were received in the past four weeks, the total number of offers received in the last six months, where we use unemployment spell duration information to convert the latter to the average number of offers received per month of unemployment. The survey also provides information on whether the individual accepted or will accept an offer. For currently employed individuals with a previous unemployment spell, the survey also provides the total number of applications and the total number of offers received during the unemployment spell. We use information on the duration of the unemployment spell to convert these numbers to the average number of applications and offers received per month of unemployment. Since these individuals found employment after an unemployment spell, we infer that they accepted an offer. Then, using information about the offers and acceptance decisions in our sample, we calculate the average acceptance rate among individuals with at most one offer in a month and with more than one offer in a month, as well as the economy-wide average acceptance rate as in the EOPP. The SCE also asks about the lowest wage the individual would accept, which we use to measure the reservation wage.[47]

A.3 Comparison of outcomes between EOPP, SCE, and CPS samples

In this section, we compare outcomes between the EOPP and SCE samples to the CPS samples, both contemporaneously and 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. We find that the EOPP and the SCE samples capture well both the levels of and the changes in demographics, including educational attainment, marital status, female labor force participation, age composition, and labor market outcomes, such as the average, median, and standard deviation of annual earnings and weekly hours, and the distribution of annual earnings over time.[48]

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

[47] For currently unemployed individuals, variables JS14, JS19, JS19b, JS23, and L7 give the number of applications during the past four weeks, the number of offers received during the past four weeks, the number of offers received during the past six months, whether the individual accepted or will accept the offer, and the duration of unemployment spells, respectively. For currently employed individuals who had an unemployment spell previously, JH13, JH14, and JH16 provide information on the duration of the unemployment spell, the number of applications, and the number of offers received during the unemployment spell, respectively. The variable RW2h_rc provides the reservation wage information.

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

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
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.

CPS 2015.[49] 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 the share of older workers (age groups 45-54 and 55-64) in the working-age population and underestimate the decline in the fraction of married when compared with the CPS.

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

Finally, we compare the distributions of annual earnings across the three datasets. This exercise is especially useful as it allows us to evaluate whether oversampling of low-income households in the EOPP led to significantly lower values of percentiles of the earnings distribution in the EOPP relative to that in the CPS. Table A3 shows that percentiles of the weighted annual earnings distribution in the EOPP are quite comparable with that in the CPS. However, percentiles of the *unweighted* distribution in the EOPP are lower than their counterparts in the CPS. For example, the 25th, 50th, and 80th percentiles of the unweighted EOPP distribution are lower than the 20th, 40th, and 75th percentiles of the CPS distribution, respectively. Weighting of observations in the EOPP allows the survey outcomes to be more comparable with outcomes

[49]We also compared SCE and CPS samples for each year between 2013 and 2019. 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 ($)	15,727	17,290	85,298	97,074
Median annual earnings ($)	13,520	15,600	68,000	77,777
Std. dev. of annual earnings ($)	14,062	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 the sample of employed individuals and the values are in nominal terms.

Table A3: Comparison of EOPP, SCE, and CPS samples: Earnings distribution

	p5	p10	p20	p25	p40	p50	p60	p75	p80	p90	p95
EOPP 1980 - unweighted	2.9	4.6	6.7	7.8	10.4	12.5	14.7	19.3	20.8	26.0	31.2
EOPP 1980	2.9	4.8	7.3	8.3	11.4	13.5	16.0	20.8	22.4	27.6	33.3
CPS 1980	4.2	6.2	8.8	10.1	13.0	15.6	18.2	22.6	25.0	31.2	37.4
SCE 2015	21.0	34.0	45.0	48.5	60.0	68.0	76.0	100.0	113.0	150.0	180.0
CPS 2015	22.5	31.5	43.2	48.1	65.4	77.8	95.0	125.0	144.0	192.3	250.0

Note: This table compares various percentiles of annual labor earnings distributions from the EOPP, SCE, and CPS. In all datasets, the sample consists of employed individuals aged 25-65 who are not self-employed. The values reported are in units of $1000 and in nominal terms.

from the CPS. This result further supports the claim in the EOPP documentation: The oversampling of low-income households did not greatly weaken the survey's representativeness given the weights of observations. In addition, we also show that the annual earnings distribution in the SCE is not largely far from that in the CPS.

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 2013-2019 period. For example, unemployed individuals may send more applications during an expansion than during a recession. To ensure that the rise in applications over time 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:

$$y_{it} = \alpha + \beta_1 X_{it} + \beta_2 d_{t2} + \beta_3 \log(UR)_{cycle,t} + \beta_4 \log(GDP)_{cycle,t} + \beta_5 \log(v/u)_{cycle,t} + \epsilon_{it},$$

where i indexes individuals with at least one job application during an unemployment spell, t indexes quarter-year of the job search spell, 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 quarter-year t of the observation is between 2013 and 2019 and 0 otherwise, $\log(UR)_{cycle}$, $\log(GDP)_{cycle}$, and $\log(v/u)_{cycle}$ are the cyclical components of logged and HP-filtered (with smoothing parameter 1600) series of the quarterly unemployment rate, real GDP, and labor market tightness, measured as the ratio of vacancies to unemployment, respectively.[50]

The EOPP provides the beginning and end day, month, and year of each job search spell. Using this information, we obtain the quarter and year of each spell. When a job search spell is longer than a quarter, we pick the quarter in which the majority of days of the spell lies as the quarter of this job search spell. When a job search spell is longer than two full quarters, we pick the first full quarter of unemployment as the quarter of this job search spell.[51]

The SCE Job Search Supplement survey is implemented in October. Given that it asks questions about the job search activities for the last month, we assign all job search spells of individuals who report as currently unemployed to the third quarter of the year. For currently employed individuals with a previous unemployment spell, we use information on the starting month of their current job to obtain the quarter of the job search spell.

To control for business cycle effects, we first obtain quarterly data on the unemployment rate and real GDP from the BLS. We compute monthly data on market tightness using vacancy data from the composite Help-Wanted Index by Barnichon (2010) and unemployment levels from the BLS and aggregate our data into a quarterly series by taking monthly averages. To obtain the cyclical component, we HP-filter the log of these series with smoothing parameter 1600. We use these cyclical components in our regression and denote them by $\log(UR)_{cycle}$, $\log(GDP)_{cycle}$, and $\log(v/u)_{cycle}$, respectively. We also run separate regressions with quarterly growth rates of these series as independent variables. That is, instead of using the HP-filtered cyclical components, we first-difference the log of the quarterly unemployment rate, real GDP, and market tightness.

[50] Our goal in this section is to estimate this regression at a higher frequency to eliminate the business cycle effects and, at the same time, minimize the mismeasurement of the timing of each spell given that spells typically span more than a month. For this reason, we present results when we estimate this regression at the quarterly frequency. Results remain similar when we estimate the regression at the annual frequency.

[51] We pick the first full quarter because the literature shows that job-finding rates decline as the unemployment spell becomes longer, suggesting that the majority of job applications are sent in the early stages of an unemployment spell. However, we also run the same regressions where we instead assign the middle quarter to be the quarter of a job search spell. This means that, for example, if there are three full quarters for a job search spell, then the second quarter is assigned as the quarter of the spell. In this case, results in Table A4 remain similar.

Table A4: Eliminating the business cycle effects

Dependent variable: Number of job applications per month

	(1)	(2)	(3)	(4)	(5)	(6)
d_{t2}	6.19	5.87	5.26	5.63	6.82	6.78
	(1.61)	(1.51)	(1.94)	(2.04)	(1.87)	(1.84)
$\log(UR)_{cycle}$			-61.26	-230.7		
			(36.70)	(140.6)		
$\log(GDP)_{cycle}$			-482.5	-440.2		
			(222.1)	(212.8)		
$\log(v/u)_{cycle}$				-78.87		
				(59.20)		
$\Delta\log(UR)$					9.93	39.12
					(28.7)	(81.6)
$\Delta\log(GDP)$					-38.07	-113.9
					(174.3)	(199.3)
$\Delta\log(v/u)$						19.50
						(42.6)
Constant	6.82	8.47	7.59	6.55	8.03	8.60
	(0.59)	(1.24)	(1.53)	(1.59)	(1.04)	(1.41)
Controls	No	Yes	Yes	Yes	Yes	Yes

Note: This table provides results on the differential number of job applications between the 1979-1980 period and the 2013-2019 period, controlling for the cyclical components or growth rates of the quarterly unemployment rate, real GDP, and labor market tightness, measured as the ratio of vacancies to unemployment, as well as individual characteristics including gender and education. We obtain quarterly data on unemployment rate and real GDP from the BLS and monthly data on market tightness using the composite Help-Wanted Index by Barnichon (2010) and unemployment level from the BLS, which we aggregate into quarterly series by taking monthly averages. These series are then logged and HP filtered with smoothing parameter 1600 to obtain their cyclical components. We also create quarterly growth rates of these series, which are obtained by log first-differences of these quarterly series. Values in parentheses denote the standard errors.

These are denoted by $\Delta\log(UR)$, $\Delta\log(GDP)$, and $\Delta\log(v/u)$, respectively.

Table A4 summarizes the results. When we use log-deviations from HP-filtered aggregate data to control for business cycle effects, we find that, from the 1979-1980 period to the 2013-2019 period, the average monthly number of job applications significantly increased (an increase of 5.26 and 5.63, as shown by the third and fourth columns). When we use growth rates of aggregate data to control for business cycle effects, we find an even larger increase in the average monthly number of job applications between the two episodes (an increase of 6.82 and 6.78, as shown by the fifth and sixth columns).

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 (2013-2019). Here, we explore changes in the number of applications across various demographic groups using the two datasets. Table A5 summarizes the results. It shows that the number of applications increased significantly across all demographics groups.

Table A5: Number of job applications over time across demographic groups

	EOPP 1979-1980		SCE 2013-2019		Percent change	
	Mean	Median	Mean	Median	Mean	Median
All	6.82	2.70	13.01	7.00	91	159
College	4.98	2.46	12.07	6.00	142	144
Non-college	7.36	2.82	13.39	7.00	82	148
Male	7.44	2.50	10.04	6.00	35	140
Female	6.13	2.86	14.76	7.00	141	145
Young	7.24	2.86	13.08	9.00	81	215
Old	4.27	1.67	12.95	6.00	203	260
Reservation wage - below median	7.26	3.00	11.04	6.67	52	122
Reservation wage - above median	4.57	2.27	13.20	7.00	189	208

Note: This table summarizes the mean and median monthly number of job applications for all individuals, individuals with a college degree, individuals without a college degree, males, females, young individuals (age 25-45), old individuals (age 46 and above), individuals whose reservation wage is below the median of the reservation wage distribution, and individuals whose reservation wage is above the median of the distribution, using data from the EOPP 1979-1980 and the SCE 2013-2019.

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

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

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

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

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

which defines the unemployment inflow rate s_t and probability $S_t = 1 - e^{-s_t}$, given data on unemployment, the labor force, and the unemployment outflow rate f_t. Following these steps, we obtain outflow probability F_t and inflow probability S_t.[53] We then seasonally adjust these series and aggregate them into quarterly series by taking monthly averages. We then take the log of these series and HP-filter them with smoothing parameter 1600 to obtain their trend components. Figure 2 in Section 2 plots quarterly series and trend components of inflow and outflow rates obtained with this procedure.

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 $\sum_k \omega_{k,t}^{l} = 1 \;\forall\, l, t$. Finally, let S_{t_1} and S_{t_2} denote the aggregate inflow probability at t_1 and t_2; $S_{k_e,k_g,k_a,k_i,t}$ 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

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

Table A6: Shift share decomposition exercise

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

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

the time period between 2010 and 2019. Then, we can write the change in the aggregate inflow probability over the two time periods as

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

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

Table A6 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 the 1976-1985 period to 2.2 percent in the 2010-2019 period.[54] 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 A6 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 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 A6 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 A6 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 the 1976-1985 period and in 2019. Demographic (between-group) changes actually result in close to a 1 percentage point decline in the outflow probability, while the within-group changes result in roughly a 3 percentage points increase. This result shows that even when we 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.

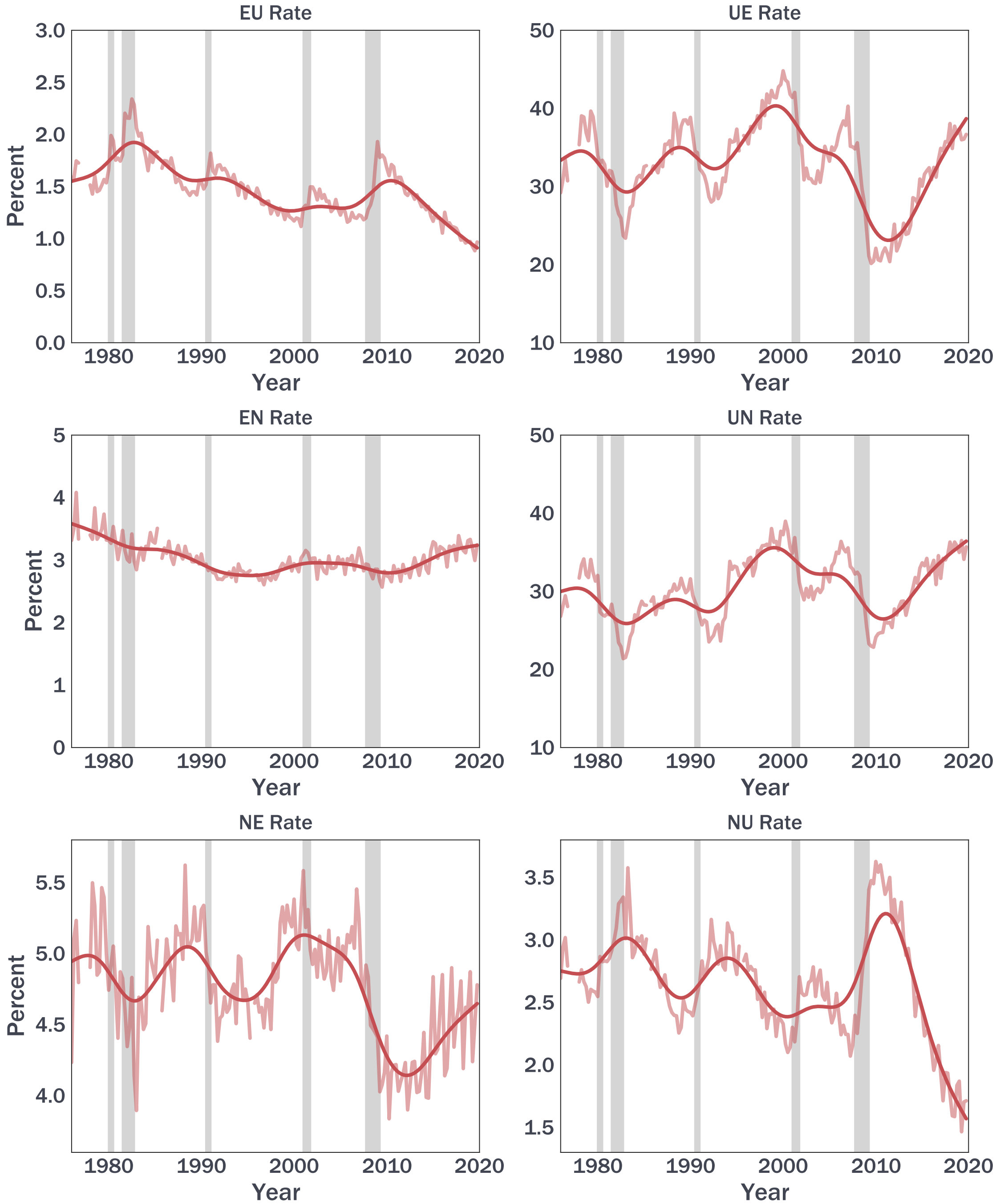
Calculating inflow and outflow rates from CPS micro data The CPS underestimates the number of short-term unemployed workers given that some workers who enter unemployment exit unemployment within the same month. However, the methodology outlined above accounts for this bias, which is referred to as time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

We now compare our findings from this method with those from an alternative method of calculating transition rates. The alternative method calculates raw transition rates using the matched micro-data from the CPS by following individual employment transitions.[55]

[54]Notice that average inflow and outflow rates reported in this section differ from those reported in Table 3. This is because we first calculate inflow and outflow rates for each group using group-level data on labor market stocks. We then obtain the average inflow and outflow rates at each time period by calculating the weighted average of inflow and outflow rates across groups. 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.

[55]Elsby, Hobijn, Şahin, and Valletta (2011) show that transition rates under the Shimer (2012) methodology and transition rates obtained through matched micro-data begin to deviate from each other near the end of the Great Recession. For this reason, it is useful to check whether our main conclusions about trends in unemployment outflow and inflow rates hold when we instead measure transition rates using the CPS micro data.

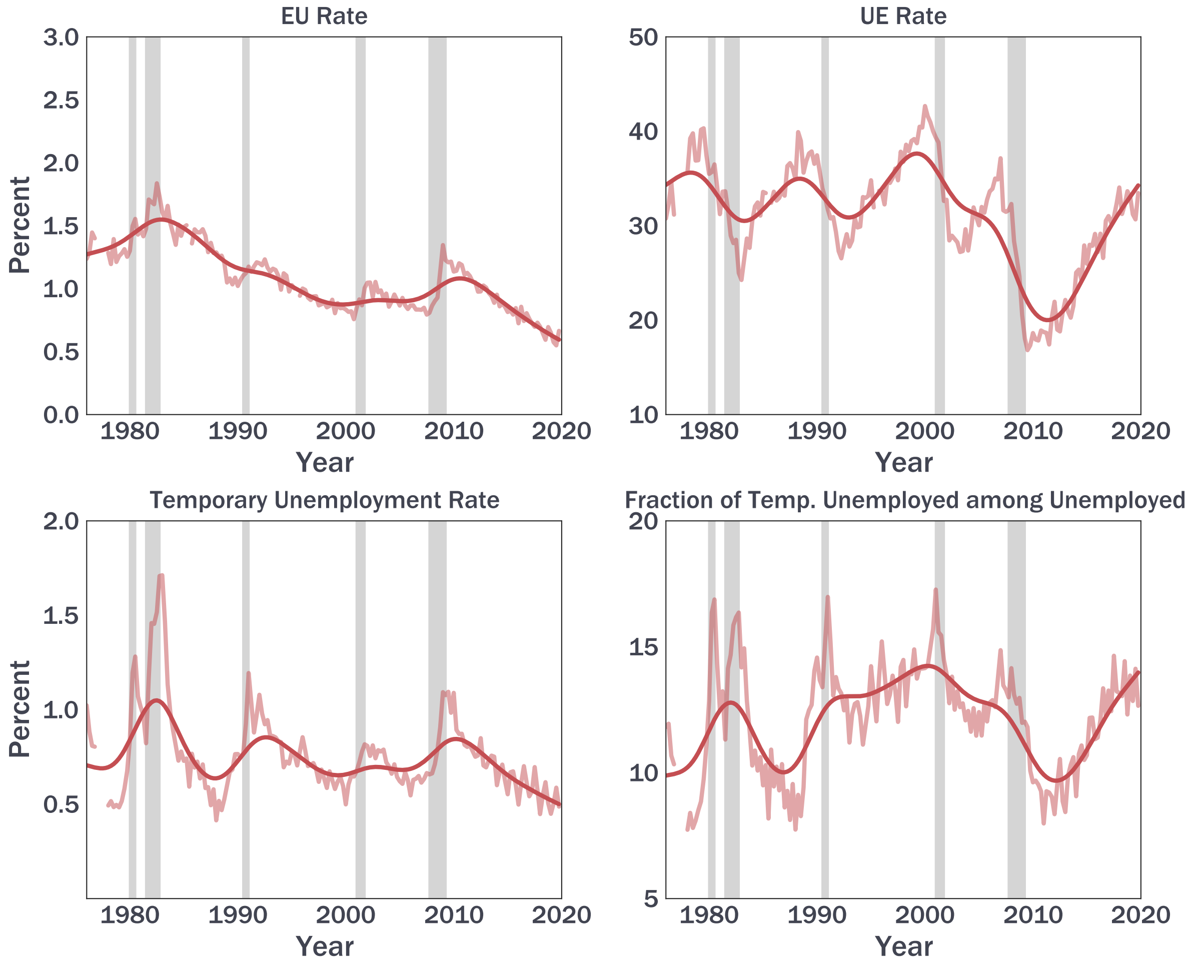
Figure A1: Transition rates using CPS micro data



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 for 1976:Q1 - 2019:Q4. These transition rates are obtained by using the matched micro-data from the CPS by following individual employment transitions. Quarterly time series are averages of monthly rates. Dark lines represent the trends, which are logged and HP-filtered quarterly data with smoothing parameter 1600. Gray shaded areas indicate NBER recession periods.

The results are summarized in Figure A1. It shows that the inflow (EU) rate exhibits a secular decline over time, while the outflow (UE) rate does not exhibit any long-run trend.

Figure A2: Transition rates using CPS micro data: Role of trends in temporary unemployment

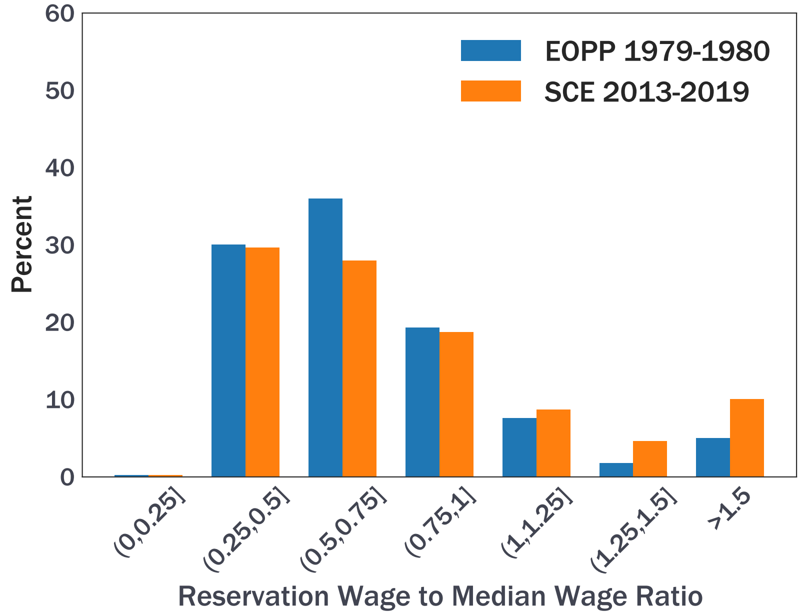


Note: The top panels of this figure show the unemployment inflow rate (EU) and outflow rate (UE) purged of temporarily unemployed by focusing only on transitions that do not lead to or originate from temporary unemployment, respectively. The bottom panels of this figure show the temporary unemployment rate, measured as the fraction of temporarily unemployed individuals within the labor force, and the fraction of temporarily unemployed among all unemployed. These results are obtained by using the matched micro-data from the CPS by following individual employment transitions. Quarterly time series are averages of monthly series. Dark lines represent the trends, which are logged and HP-filtered quarterly data with smoothing parameter 1600. Gray shaded areas indicate NBER recession periods.

In particular, the average EU rate declined 28 percent between the 1976-1985 and 2010-2019 episodes. This is similar to our results in Figure 2. Moreover, the decline in the inflow rate over time is not mostly 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 a strong trend increase or decrease over time.

Role of trends in temporary unemployment on inflow and outflow rates Finally, changes in the fraction of temporarily unemployed over time may also affect trends in outflow and inflow rates if these rates are systematically different for the temporarily unemployed compared with the unemployed who do not have an option to return to their previous jobs. To verify whether this is the case, we use the matched micro-data from the CPS as in the previous section. The CPS micro-data provides information on the reason of unemployment, which allows

Figure A3: Reservation wage to median wage ratio



Note: This figure shows the distribution of reservation wage to median wage ratio over time using data from the EOPP, SCE, and CPS. The EOPP and SCE samples incorporate unemployed individuals aged 25-65 with at least one job application during their unemployment spell. These two samples are used to calculate the distribution of hourly reservation wages for the 1979-1980 period and the 2013-2019 period, respectively. The CPS sample includes employed individuals aged 25-65 who are not self-employed. We use this sample to calculate the median hourly wages of the employed for the two time periods.

us to identify temporarily unemployed individuals.[56] Using this information, we calculate the inflow (EU) and the outflow (UE) rates purged of the temporarily unemployed, and focus solely on transitions that do not lead to or originate from temporary unemployment, respectively. We also calculate the temporary unemployment rate, measured as the fraction of temporarily unemployed individuals within the labor force, and the fraction of unemployed who are temporarily unemployed.

The results are summarized in Figure A2. We find that the trend inflow rate purged of the temporarily unemployed exhibits a decline over time, while the trend outflow rate purged of temporarily unemployed remains mostly unchanged. In particular, the average inflow rate in this case declined 38 percent between the 1976-1985 and 2010-2019 episodes. This is similar to our results in Figure 2. Figure A2 also shows that while the fraction of temporarily unemployed within the labor force was elevated during recessions in early 1980s, it quickly returned to its late 1970s level and has since remained roughly unchanged.

Distribution of reservation wage to median wage ratio over time Figure 3 in Section 2.3 shows the distributions of reservation wages over time using the EOPP and SCE samples. In Figure 3, when comparing reservation wages between different time periods, we adjust the

[56]The WHYUNEMP variable in the IPUMS CPS code 1, which refers to "job loser/on layoff", includes only those who are on temporary layoff. This is explained in Section 2C of Unemployment Concepts documentation of the CPS Interviewer Manual, which can be found at the following link: https://tinyurl.com/3kfw69sm.

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 median hourly wage of the employed for both the 1979-1980 and 2013-2019 periods. To do so, we use the CPS data to calculate the median 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 the unemployed obtained from the EOPP and SCE data by the median real hourly wage. Figure A3 plots the resulting distribution of the reservation wage to median wage ratio over time. It shows that the fraction of unemployed workers whose reservation wage is more than the median wage of the employed has slightly increased over time. Overall, we find that the median reservation wage to median hourly wage ratio has increased by only 3 percent between the two episodes, as presented in Table 4.

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, $V^F(x) = \eta S(x)$ 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 $V^W(x) - U$ 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 acquires 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. It is then clear that for a given x, $[\Pi(x)]^j$ is weakly declining as j increases, implying that:

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

In other words, the distribution $[\Pi(x)]^{j+1}$ has more concentration at higher x values than the distribution $[\Pi(x)]^j$. 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, $[\Pi(x)]^j$. Since the distribution $[\Pi(x)]^{j+z}$ FOSD $[\Pi(x)]^j$ for $z > 0$, it must be that

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

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

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

As per the discussion in Section 3.3, so long as the net expected value of acquiring information, $V^I(j) - \kappa_I$ cuts the value of not acquiring information, V^{NI}, once from below, our model features a unique j^* in terms of pure strategies.

We acknowledge that given our focus on pure strategies only, we do not allow for other equilibria to exist in terms of mixed strategies. This occurs whenever $V^I(j) - \kappa_I = V^{NI}$ for some j. As such, we outline below the firm's information choice problem if we instead allow 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:

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

where

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

and

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

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

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

Summing across j, the probability a worker receives an offer given her draw of x is:

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

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

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

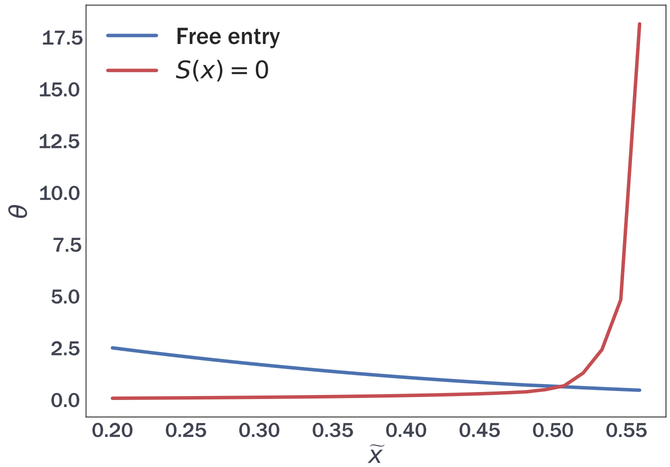
and $\Gamma(x)=\sum_{a=1}^{\infty}p(a)\Gamma(x,a)$.

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 $\widetilde{x}$, i.e., $j^{*}(\theta,\widetilde{x})$. Then, under our calibration, Figure A4 highlights that a unique equilibrium in pure strategies exists in $(\theta,\widetilde{x})$ 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 $j<j^{*}$, $\iota(j)=0$.

C Extensions

In this appendix, we provide details and results for the model with homogeneous match quality as well as the "Full Information" (FI) and "No Information" (NI) models. We also discuss the details and results for versions of our baseline model with alternative assumptions or extensions.

Figure A4: 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 $\widetilde{x}$ under the calibrated model. The intersection of the two lines represents the unique equilibrium in pure strategies.

C.1 A model with homogeneous match quality

We start with providing the details of the model with homogeneous match quality, which is presented in Section 5.3.1. To do so, we assume that all applicants have match quality $x = 1$. In other words, $\Pi(x)$ is degenerate. Since there are no match quality differences, firms are indifferent across all applicants and workers are indifferent across all vacancies. This in turn implies that firms do not need to acquire information on workers' productivities, and workers exit into unemployment only if they suffer an exogenous separation shock.

Next, we outline the value and policy functions of this model before discussing its results.

C.1.1 Value and policy functions

Firms' values When x is degenerate, the operating firm's value simplifies to:

$$V^F = x - w + \beta \left(1 - \delta\right) V^F,$$

where $x = 1$. So long as jobs are not exogenously destroyed, firms continue with value V^F.

For a vacant firm with j applicants, the value of creating a vacancy is given by

$$\Xi\left(j\right) = \Gamma V^F = \Xi,$$

where Γ is the acceptance rate of the worker and given by $\Gamma = \sum_{a=1}^{\infty} p\left(a\right) \Gamma\left(a\right)$, and $\Gamma(a)$ is the acceptance rate of the worker who has sent a applications. In this environment, all workers, if hired, bring the firm value V^F. Conditional on an offer, workers accept with probability Γ.

Accordingly, the free-entry condition is given by:

$$\kappa_V = \sum_{j=1}^{\infty} q(j)\, \Xi = \sum_{j=1}^{\infty} q(j)\, \Gamma V^F.$$

Workers' values and policy functions The employed worker's value is given by:

$$V^W = w + \beta(1-\delta)V^W + \beta\delta U.$$

Turning to conditional acceptance probabilities, the events that lead a worker who has submitted a applications to accept a particular offer are as follows: 1) it is her only offer, and 2) it is not her only offer, in which case she randomly accepts an offer out of all offers received. Thus, we can write $\Gamma(a)$ as:

$$\Gamma(a) = [1 - Pr(\text{offer})]^{a-1} + \sum_{i=1}^{a-1} \frac{1}{i+1} (a-i)\, Pr(\text{offer})^i [1 - Pr(\text{offer})]^{a-1-i}.$$

The first term on the right-hand-side corresponds to the event that it is her only offer out of a applications. The second term corresponds to the event that she has i other offers, and with probability $1/(i+1)$ she randomly picks this offer to accept. The average conditional acceptance rate is then given by $\Gamma = \sum_{a=1}^{\infty} p(a)\, \Gamma(a)$.

We next describe what offer probabilities look like. Consider a worker who sends an application to a vacancy with j applicants. The probability that the worker receives an offer is:

$$Pr(\text{offer}|j) = \frac{1}{j}.$$

Note that $Pr(\text{offer}|j)$ is strictly declining in j. Accordingly, the average offer probability of a given application that contacts a vacancy, averaged across all possible j applicants a vacancy might receive, is given by $Pr(\text{offer}) = \sum_{j=1}^{\infty} \widehat{q}(j) \frac{1}{j}$ where $\widehat{q}(j) = q(j)/(1-q(0))$. Average offer probabilities are a function of $q(j)$. As aforementioned in Section 3.9, the distribution of applicants per vacancy shifts rightward with an increase in ξ. Thus, if applications increase, holding all else equal, offer probabilities fall. Lower offer probabilities increase the likelihood that the individual has only one offer to choose from, as exemplified in $\Gamma(a)$.

The probability a worker who has sent a applications finds a job in one of her applications is given by:

$$\phi(a) = \Gamma(a)\, Pr(\text{offer}),$$

and the overall job-finding probability is given by $\phi = \sum_{a=1}^{\infty} p(a)\, a\phi(a)$.

Table A7: Impact on labor market flows: Homogeneous match quality

	Baseline		$x = 1$		Percent change	
	$\xi = 2.7$	$\xi = 7$	$\xi = 2.7$	$\xi = 5.7$	Baseline	$x = 1$
Inflow rate	0.042	0.035	0.041	0.023	-15	-44
Outflow rate	0.454	0.450	0.410	0.438	-0.9	7
direct effect					67.5	56
indirect effect					-68.4	-49

Note: This table reports the model-predicted flow outcomes from our baseline model with a time-varying fixed cost $\kappa_I = \kappa_1^I + \kappa_2^I \xi$ of acquiring information and from a model with homogeneous match quality, where $x = 1$

Thus, the unemployed worker's value becomes:

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

where

$$U\left(a\right) = a\phi\left(a\right) V^W + \left(1 - a\phi\left(a\right)\right) U.$$

Closing the model, we assume that workers and firms engage in Nash-bargaining, implying that they split surplus according to bargaining weights. Overall, surplus is given by $S = \frac{x-(1-\beta)U}{1-\beta(1-\delta)}$ and wages are given by $w = \left[1 - \beta\left(1 - \delta\right)\right] \eta S + \left(1 - \beta\right) U$.

C.1.2 Numerical results

We re-calibrate the simple model with homogeneous match quality to show how its model predictions compare with that of our baseline model. We set $\xi = 2.7$ and continue to assume that b, the value of home production, is the same as in our baseline model. Since all separations are exogenous in this model, we set $\delta = 0.041$ as in the data for the first time period. Finally, because match quality is degenerate, and thus firms do not need to acquire any information on workers' qualities, this leaves us with only one parameter to calibrate, κ_V, the vacancy posting cost. As in our baseline model, we target the unemployment outflow rate to pin down κ_V. This gives us a value of 0.92 for κ_V for an unemployment outflow rate of 0.41 in the first time period.

We then repeat the same exercise as in our baseline model and raise $\xi = 7$ for the second time period. To allow for the inflow rate to fall in this version of the model, we set $\delta = 0.023$ as observed in the data. Table A7 presents key labor market outcomes for the simplified model with homogeneous match quality. By construction, the decline in the exogenous unemployment inflow rate matches the data perfectly. The outflow rate, however, rises by 7 percent with the rise in applications, as changes in offer and acceptance rates only partially mitigate the direct positive effect of contacting more vacancies. Unlike our baseline model, which featured a stronger indirect effect, here, the significant 57 percent decline in the probability of an offer causes the

Table A8: Impact on offer and acceptance rates: Homogeneous match quality

	$\xi = 2.7$	$\xi = 7$	Percent change
Pr(offer)	0.20	0.09	-57
Average acceptance rate	0.77	0.76	-1

Note: This table presents changes in offer and acceptance outcomes rates when applications increase from a simplified version of the model where all applications have match quality $x = 1$.

acceptance rate to observe only a minute change, as shown in Table A8. Because the offer probability observes such a sharp decline, individuals do not have many more options to choose from despite submitting more applications. Consequently, acceptance rates barely fall.

C.2 Calibration details of FI and NI models

In this section, we provide details on the calibration of FI and NI models. Recall that we set $\kappa_I = 0$ in the FI model and $\kappa_I \to \infty$ in the NI model in Section 5.3.2. Given that κ_I is already set, this implies that relative to our baseline model, we have two fewer parameters. Accordingly, we leave out the moments that were used to pin the information cost parameters in our baseline model, namely the growth in the vacancy rate and the recruitment cost to mean wage ratio. For the rest of the parameters, we target the same moments as in the baseline model given in Table 1. Table A9 summarizes the calibration outcomes of the FI and NI models.

Table A9: Internally calibrated parameters: FI and NI models

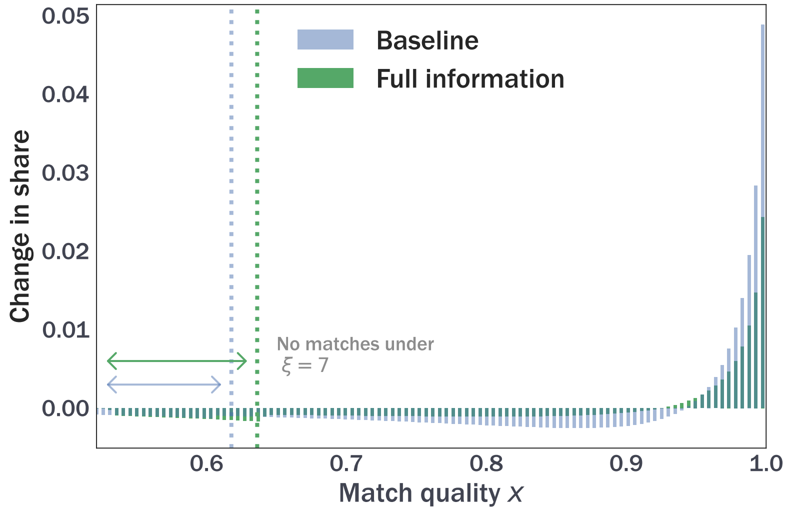
Parameter	Value		Target	Model		Data
	FI Model	NI Model		FI Model	NI Model	
κ_V	0.86	0.58	Outflow rate	0.45	0.38	0.41
δ	0.024	0.023	Inflow rate	0.042	0.043	0.041
λ	3.67	5.59	Variance of income growth	0.07	0.11	0.08
A	1.91	0.93	Fraction with no offers	0.50	0.39	0.38
B	2.20	1.06	Average acceptance rate	0.42	0.45	0.37
b	0.11	0.08	Reservation wage/median wage	0.73	0.70	0.67

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 1976-1985. The fraction of workers with no offers and the average acceptance rate are obtained from the EOPP for 1979-1980. The variance of annual income growth in the data is calculated by Blundell, Pistaferri, and Preston (2008). Finally, the reservation to median wage ratio represents the ratio of median hourly reservation wage of the unemployed in the EOPP to the median hourly wage of the employed in the CPS.

C.3 FI model under same calibration as baseline model

In this section, we show that even under the same calibrated parameters as our baseline model, the effect of increased worker selectivity continues to dominate the effect from improved firm selection when applications increase in the FI model. This is an exercise that we use in our discussion in Section 5.3.2.

Figure A5: Change in distribution of realized match qualities: FI model with baseline parameters



Note: This figure shows how the share of employed workers across match quality x changes when ξ increases from 2.7 to 7. Specifically, for each bin, the figure shows the difference in the shares $[G(x_2)_{\xi=7} - G(x_1)_{\xi=7}] - [G(x_2)_{\xi=2.7} - G(x_1)_{\xi=2.7}]$. Green bars represent the change for the full information (FI) model using the same calibrated parameters as our baseline model. Blue bars represent the change under our baseline model.

Table A10: Impact on labor market flows: FI model using parameters from baseline model

	Baseline		FI		Percent change	
	$\xi = 2.7$	$\xi = 7$	$\xi = 2.7$	$\xi = 7$	Baseline	FI
Inflow rate	0.045	0.035	0.044	0.045	-15	1
Outflow rate	0.454	0.450	0.527	0.601	-0.9	14
direct effect					67.5	59
indirect effect					-68.4	-45

Note: This table summarizes the labor market flows when ξ increases from 2.7 to 7, which corresponds to an increase in the median number of applications from 2.7 to 7. FI refers to the "Full Information" model in which $\kappa_I = 0$, and Baseline refers to our benchmark model where there is a time-varying fixed cost $\kappa_I = \kappa_1^I + \kappa_2^I \xi$ of acquiring information. The flows reported for both the FI and baseline models are generated using the calibrated parameters as detailed in Table 1.

We show that, even when workers draw match qualities from the same underlying distribution, we still see that most of the improvements in average match quality for the FI model — relative to our baseline model — stem from improvements from the bottom (disappearance of low-quality matches) and not from the top of the match quality distribution, as depicted by the green bars in Figure A5. Table A10 shows that even under the same calibrated parameters as the baseline model, the FI model features a rise in the separation rate, as the effect from improved firm selection is weaker when firms can always identify the best applicant. Since the FI model is not re-calibrated here but rather we impose the parameters from our baseline model's calibration, the inflow and outflow rates in this version of the FI model need not match levels of flow rates observed in the data.

Table A11: Internally calibrated parameters: Constant fixed cost model

Parameter	Description	Value	Target	Model	Data
κ_V	Vacancy posting cost	0.75	Outflow rate	0.45	0.41
κ_1^I	Cost of information	0.33	Recruiting cost/mean wage	1.26	0.93
δ	Exog. separation rate	0.024	Inflow rate	0.041	0.041
λ	Persistence of x	4.15	Variance of income growth	0.09	0.08
A	Beta distribution	0.59	Fraction with no offers	0.46	0.38
B	Beta distribution	0.60	Average acceptance rate	0.42	0.37
b	Home production	0.09	Reservation wage/median wage	0.69	0.62

Note: This table provides a list of internally calibrated parameters for the model where the cost of information is independent of the expected number of applications. The moments relating to unemployment flows are obtained from the CPS and are presented as averages for 1976-1985. The fraction of workers with no offers and the average acceptance rate are obtained from the EOPP for 1979-1980. The ratio of recruiting costs to average wages in the data is reported by Gavazza, Mongey, and Violante (2018). The variance of annual income growth in the data is calculated by Blundell, Pistaferri, and Preston (2008). Finally, the reservation to median wage ratio represents the ratio of median hourly reservation wage of the unemployed in the EOPP to the median hourly wage of the employed in the CPS.

Table A12: Impact on labor market flows: Constant fixed cost model

	Baseline		Constant		Percent change	
	$\xi = 2.7$	$\xi = 7$	$\xi = 2.7$	$\xi = 7$	Baseline	Constant
Inflow rate	0.041	0.035	0.041	0.035	-15	-15
Outflow rate	0.454	0.450	0.448	0.443	-0.9	-1.0
direct effect					67.5	65
indirect effect					-68.4	-66

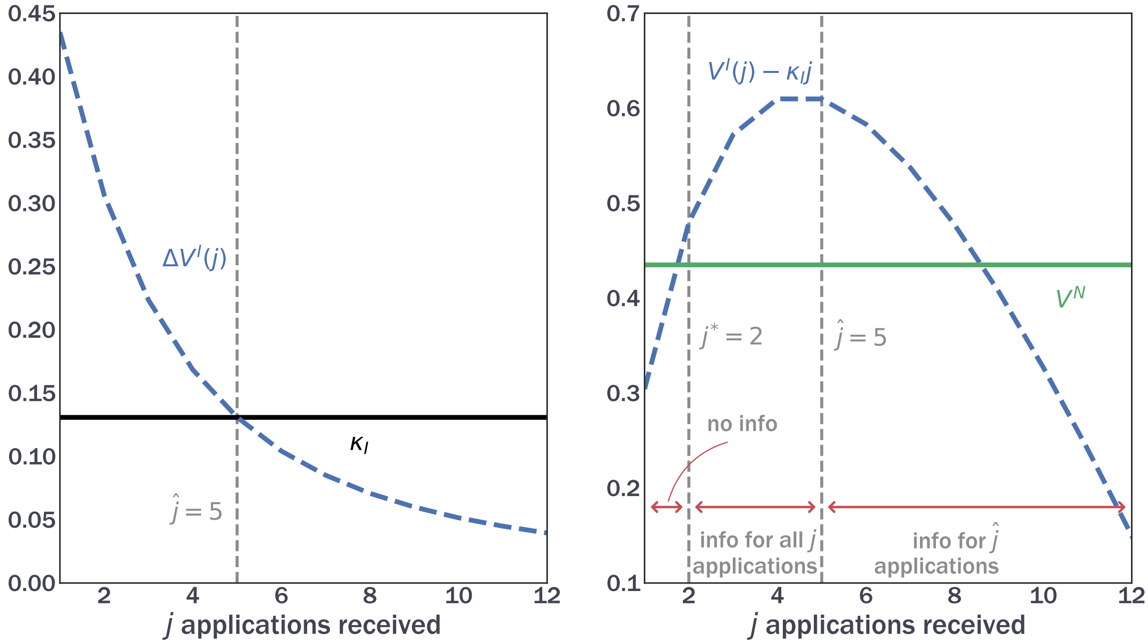
Note: This table summarizes the model-predicted inflow and outflow rates when ξ increases from 2.7 to 7 and compares these results to the results from our baseline model. Baseline refers to our baseline model, while Constant refers to the version of the model where the fixed cost is constant over time, i.e., $\kappa_2^I = 0$.

C.4 Constant fixed cost of information

Here, we provide results for the version of our baseline model where the cost of information is independent of the expected number of applications, which was presented in Section 6.1.1. In particular, we assume that $\kappa_2^I = 0$. Since we drop one parameter in the model, we calibrate over a smaller set of moments. That is, we no longer target the growth in the vacancy rate. Table A11 shows our calibrated parameters under this version.

Our results are largely unchanged moving from our baseline model to the version where the fixed cost of information is independent of ξ. Table A12 shows that under this version of the model, the inflow rate still falls by 15 percent, while the outflow rate remains largely unchanged. This is largely because the same forces present in our baseline model continue to operate in an environment where the fixed cost of information is constant.

Figure A6: Upper bound on benefits of information rises with j with marginal cost of information



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

C.5 Marginal cost of information

We now elaborate on our discussion for the model with a marginal cost of information acquisition in Section 6.1.2. Suppose that κ_I is instead a marginal cost the firm pays for each applicant it acquires information on. Formally, the firm's information problem takes the form of

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

where

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

and

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

We assume that the firm decides to acquire information on n applicants. 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:

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

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

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

and

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

The left panel of Figure A6 shows a numerical example where beyond $\widehat{j}$ applicants the marginal cost of information, κ_I, exceeds the marginal benefit of information, $\Delta V^I(j)$. Since the marginal cost of information exceeds the marginal benefit, the firm acquires information on only a random subset $\widehat{j} < j$ of its applicants. We assume that any applicant for which the firm does not acquire information is automatically rejected. A similar assumption is also made in Wolthoff (2018).

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

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

The right panel of Figure A6 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 acquires information on only a subset $\widehat{j} < j$ applicants for any applicant pool size j such that $j^* \leq \widehat{j} < j$. The two thresholds $(j^*, \widehat{j})$, in turn imply the following probability of receiving an offer of quality x from a firm with j applicants:

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

Table A13: Internally calibrated parameters: Marginal cost model

Parameter	Description	Value	Target	Model	Data
κ_V	Vacancy posting cost	0.84	Outflow rate	0.42	0.41
κ_I	Cost of information	0.023	Recruiting cost/mean wage	1.16	0.93
δ	Exog. separation rate	0.029	Inflow rate	0.040	0.041
λ	Persistence of x	7.71	Variance of income growth	0.06	0.08
A	Beta distribution	1.40	Fraction with no offers	0.46	0.38
B	Beta distribution	1.34	Average acceptance rate	0.30	0.37
b	Home production	0.16	Reservation wage/median wage	0.83	0.62

Note: This table provides a list of internally calibrated parameters for the model with a marginal cost of information. The moments relating to unemployment flows are obtained from the CPS and are presented as averages for 1976-1985. The fraction of workers with no offers and the average acceptance rate are obtained from the EOPP for 1979-1980. The ratio of recruiting costs to average wages in the data is reported by Gavazza, Mongey, and Violante (2018). The variance of annual income growth in the data is calculated by Blundell, Pistaferri, and Preston (2008). Finally, the reservation to median wage ratio represents the ratio of median hourly reservation wage of the unemployed in the EOPP to the median hourly wage of the employed in the CPS.

Table A14: Impact on labor market flows: Marginal cost model

	Baseline		Marginal cost		Percent change	
	$\xi = 2.7$	$\xi = 7$	$\xi = 2.7$	$\xi = 5.7$	Baseline	Marginal cost
Inflow rate	0.042	0.035	0.040	0.035	-15	-11
Outflow rate	0.454	0.450	0.420	0.418	-0.9	-0.5
direct effect					67.5	76.4
indirect effect					-68.4	-76.9

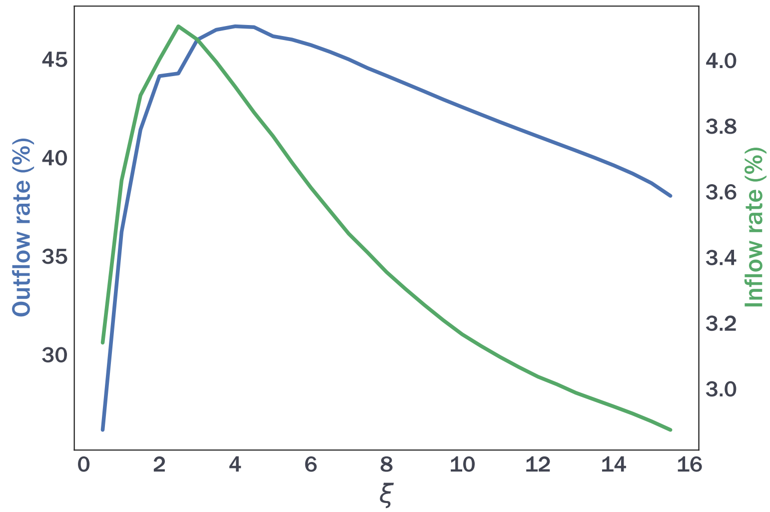
Note: This table reports the model-predicted flow outcomes from our baseline model with a time-varying fixed cost $\kappa_I = \kappa_1^I + \kappa_2^I \xi$ of acquiring information and from a model with a marginal cost of acquiring information.

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

Numerical results While Figure A6 illustrates the outcomes from a demonstration model, to quantitatively assess the effects of a rise in applications on unemployment flows, we re-calibrate the marginal cost model. Since only one parameter governs information costs in this model, we again do not target the growth in the vacancy rate. Table A13 shows our calibrated parameters for this version of the model.

Relative to our baseline model, Table A14 shows that in the re-calibrated marginal cost environment, the inflow rate still falls substantially in response to a rise in applications, but to a lesser extent. Since the benefits of information are limited when firms choose to acquire information on only a subset of applicants for applicant pool size $j > \widehat{j}$, the effects from improved firm selection are weaker. Consequently, the inflow rate declines by less relative to the baseline model. On the other hand, the outflow rate does not change when applications increase. Thus,

Figure A7: Inflow and outflow rates, varying number of applications



Note: This figure compares outflow rates (left axis) and inflow rates (right axis) obtained under different levels of ξ. All other parameters are held fixed to those obtained under the baseline calibration.

we conclude that a version of our model with a marginal cost of information acquisition is still capable of predicting the differential behavior of the inflow and outflow rates over time: a large decline in the inflow rate and a negligible change in the outflow rate as applications increase.

C.6 Inflow and outflow rates across different levels of applications

In Section 6.2, we discuss how changes in the number of applications lead to a non-monotonic profile of inflow and outflow rates. Here, we provide results for this exercise in Figure A7. In particular, we vary ξ between 1 and 16 and present inflow and outflow rates under each value of ξ. Figure A7 shows that the inflow rate initially rises at low levels of ξ as the effects from increased worker selectivity dominate the effects from improved firm selection. The inflow rate peaks at around $\xi = 2.5$ and then declines since the effects from improved firm selection become the dominating force as ξ grows sufficiently large. The outflow rate also exhibits a non-monotonic response to changes in ξ. This is because the magnitudes of the direct and indirect effects on the outflow rate vary in response to changes in ξ. While the direct effect dominates at lower values of ξ, the indirect effects (which stem from changes in offer and acceptance probabilities) dominate at higher values of ξ. Thus, the outflow rate initially rises and then declines in ξ.

C.7 On-the-job search

In this section, we provide details on the model with on-the-job-search discussed in Section 6.3. 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 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.[57]

3. Wage bargaining takes place only 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. The firm cannot observe the employed worker's match quality at their incumbent job.

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

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

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

where the worker's current match quality is x and she draws a new match quality z in the next period, before the search and matching stage. As such, the probability that the worker quits to a new job depends on the new match quality z that she draws in her current match x, which is given by $\int_z^{\overline{x}} \sum_{a=1}^{\infty} p^e(a) a \phi^e(y,z,a)\, \pi(y)\, dy$. 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 $\Gamma^e(y,z,a)$ 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 y. Clearly if $y < z$, then $\Gamma^e(y,z,a) = 0$. For all $y \geq z$, 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 any offer. Thus, for a given $y \geq z$, we have:

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

Denote $\Gamma^e(y,z) = \sum_{a=1}^{\infty} p^e(a)\Gamma^e(y,z,a)$. 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

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

at the firm's vacancy:

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

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:

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

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:

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

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

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

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

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

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

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

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

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

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

Notice the additional term stems from the worker's gain as they can do an 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 $(\theta_u,\theta_e,\widetilde{x},j_e^*,j_u^*)$.

In steady state, the measure of unemployed is:

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

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

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

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