The views expressed are those of the individual authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors.

Federal Reserve Bank of St. Louis Working Papers are preliminary materials circulated to stimulate discussion and critical comment. References in publications to Federal Reserve Bank of St. Louis Working Papers (other than an acknowledgment that the writer has had access to unpublished material) should be cleared with the author or authors.
Job Applications and Labor Market Flows*

Serdar Birinci
St. Louis Fed

Kurt See
Bank of Canada

Shu Lin Wee
Bank of Canada

July 2020

Abstract

Unemployment inflows have declined sharply since the 1980s while unemployment outflows have remained mostly steady despite a rise in workers’ applications over time. Using a random search model of multiple applications with costly information, we show how rising applications incentivize more firms to acquire information, improving the realized distribution of match qualities. Higher concentrations of high productivity matches reduce the incidence of endogenous separations, causing unemployment inflow rates to fall. Quantitatively, our model replicates the relative change in inflow and outflow rates as well as the decline in acceptance rates, job offers and the rise in reservation wages.

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

*Birinci: serdar.birinci@stls.frb.org, See: seek@bankofcanada.ca, Wee: shulinwee.econ@gmail.com. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Bank of Canada.
1 Introduction

Since the 1980s, the U.S. has observed a steady decline in the unemployment inflow (job separation) rate. Conversely, unemployment outflow (job finding) rates have not exhibited any long-run trend. At the same time, the advent of online search has led to an improvement in search technologies, enabling each job-seeker to sample and contact more vacancies. Notably, the number of applications submitted by an unemployed job-seeker per month has roughly doubled since the 1980s. Given these trends, we ask how the increase in the number of worker applications can give rise to the differential behavior in unemployment inflow and outflow rates.

In addressing this question, we make two contributions. On the empirical side, we use data from the Current Population Survey (CPS) and document how the fall in unemployment inflow rates has largely been driven by the stark decline in inflows amongst individuals without a college degree, whom we define as “non-college”. In contrast, the unemployment inflow rates of individuals with a college degree - whom we term as “college” - observe little to no change. Both college and non-college also exhibit no significant long-run trend in their outflow rates. In addition, we utilize information from the Employment Opportunity Pilot Project (EOPP) and the Survey of Consumer Expectations (SCE) and provide new stylized facts on how the application behavior of unemployed job-seekers has evolved over time. Specifically, we show that the rise in worker applications has been accompanied by a decline in acceptance rates and number of offers received, and a rise in workers’ reservation wages. We also document substantial heterogeneity in job application outcomes: changes in average job offer rates are more prominent for non-college workers. On the theoretical side, we build a tractable equilibrium labor search model to explain how a rise in worker applications can generate a decline in unemployment inflow rates without precipitating a simultaneous trend in unemployment outflow rates. Our model departs from the standard labor search model in two ways. First, to address the rise in applications, workers can send multiple applications. Second, we also allow for information frictions in the form of costly information acquisition by firms. Quantitatively, our model can rationalize why the differences in the trend inflow and outflow rates are most pronounced for non-college individuals, while that of college has remained mostly unchanged. To our knowledge, this is the first paper to link the changing application behavior of workers to the observed long-run trends in labor market flows across different education groups.

In our model, workers submit multiple applications to separate vacancies and costlessly observe the match quality drawn in each of their applications. Match quality evolves over time but is persistent, with future draws correlated with current values. High productivity matches are also less susceptible to match quality shocks. Firms can receive more than one application. Unlike workers, firms can only observe the match qualities of all their applicants if they pay a fixed cost of information. Firms’ incentives to acquire information are, in turn, increasing in the
number of worker applications. While a rise in applications increases the probability that a firm receives at least one high quality application, firms can only exploit this benefit if they acquire information and are thus able to rank applicants. Further, firms reduce their probability of being rejected when they can identify and offer a job to their highest quality applicant since wages are rising in match productivity. Crucially, the share of informed firms affects the extent to which a rise in applications can have any significant effect on workers’ job dissolutions. More informed firms cause the distribution of realized match qualities among the employed to improve, resulting in fewer endogenous separations arising from negative match quality shocks.

While rising applications from workers can lead to declines in unemployment inflow rates, the effect on outflow rates is less clear. On one hand, an increase in worker applications directly raises the worker’s probability of finding a job by virtue of more vacancies contacted. On the other hand, the increase in applications exerts indirect effects on a single application’s probability of receiving an offer and on the worker’s acceptance probability. The former declines due to increased competition amongst workers while the latter falls when workers can sample more vacancies. In our model, the change in unemployment outflow rates depends on the extent to which the direct effect of sending more applications outweighs the latter two indirect effects. Critically, information acquisition is pivotal in determining the effect of multiple applications on job flows. When few firms acquire information, the ability of workers to reject low quality jobs is limited as a large share of firms make offers at random.

Having developed our model, we apply our framework to the data. To consider the differences between non-college and college individuals, we assume that workers are ex-ante heterogeneous in education and each education group applies for jobs in separate segmented markets. We calibrate our model to match labor market moments and application outcomes both in the aggregate and across education groups for the period 1976-1985. Using our calibrated model, we ask how unemployment inflows and outflows would change if we were to only increase the number of applications workers can send. We compare our results to data on labor market flows and application outcomes for the period 2013-2017 as this is the period covered in the SCE.

The model is able to capture the differential trends in unemployment inflow rates rates between college and non-college workers: a significant decline in inflow rates of non-college workers from 4.5% to 2.1% (4.9% to 2.9% in the data) and in contrast, a more modest change for college workers from 1.8% to 2.0% (1.4% to 1.1% in the data). The rise in applications sent and consequent increased higher share of informed firms lead to an improvement in the distribution of realized match qualities, which, in turn, causes the sharp decline in unemployment inflow

1In models of multiple applications - see Albrecht et al. (2006), Wolthoff (2018), Galenianos and Kircher (2009), and Kircher (2009) for example - the rejection probability of the worker is endogenous and depends on the number of applications.

2We use this time period as the EOPP is a cross-sectional dataset that provides information for the year 1980. Since we are interested in long-run comparisons, we treat the 10 year period around 1980 as our steady state period.
rates for non-college. Conditional on receiving a match quality shock, high quality matches are less likely to re-draw low match qualities below the reservation match quality threshold and be endogenously destroyed. Conversely, college individuals already draw on-average higher match qualities. As such, the improvement in the distribution of realized match qualities has a more minute impact on their inflow rates.

For outflow rates, our model predicts much smaller changes in unemployment outflow rates for both college and non-college individuals similar to the data. A rise in applications causes a modest decline for non-college individuals from 49% to 44% (53% to 42% in the data) as both expected offers and acceptance probabilities fall, and a modest increase for college individuals from 61% to 67% (vs. a decline from 46% to 36% in the data) as the increase in expected offers outweighs the decline in acceptance probabilities. Importantly, the model not only correctly predicts a decline in acceptance rates for both education groups but also captures the large fall in the average and median number of offers for non-college individuals relative to college workers.

The decline in acceptance rates in our model for non-college does not stem from a sharp increase in their reservation wage. Rather, when workers submit more applications, their probability of rejecting a job of any particular match quality increases. This occurs as the likelihood of drawing and receiving an offer for a high quality match in at least one of her other applications increases. The probability of receiving an offer for a high match quality draw in turn depends on the firm’s information acquisition decision. Thus, our model, by focusing on workers’ application behavior and firms’ information investment decisions, provides a rationale for why acceptance rates have declined. Because we have only changed the number of worker applications in our quantitative exercises, our results underscore how the changing application behavior of workers goes a long way in explaining the long run trends in labor market flows.

Finally, we argue that a model which internalizes the interaction between the firms’ information problem and the workers’ application behavior is necessary to explain the trends in labor market flows. We consider two thought experiments, a case where firms pay zero cost to reveal their applicants’ match qualities, and a case where firms face infinite cost. We show that neither of these models is capable of generating the decline in unemployment inflow rates for non-college individuals. Intuitively, in the zero cost environment, all firms always make offers to the highest quality applicant in their pool. Conversely, in the infinite cost environment, all firms make offers at random and are unable to take advantage of the increased probability that at least one of their applicant possesses high match quality. As such, in both the zero cost and infinite cost environment, the improvement in the distribution of realized match quality amongst the employed from an increase in workers’ applications is either very small or non-existent. In contrast, our baseline model features a changing share of firms acquiring information in response

---

3Because 2013-2017 captures the recovery period after the Great Recession, recorded average outflow rates are lower for that time period.
to the changing number of workers’ applications. A greater share of informed firms in our model has a non-trivial effect on the concentration of matches with high match quality, and this in turn affects the unemployment inflow rates in our model. We thus see our model as instructive on elucidating how information frictions interact with the workers’ application behavior to affect long-run trends.

Related Literature Our paper contributes directly to the growing literature on multiple applications. Earlier papers in the literature by Albrecht et al. (2006), Kircher (2009), and Galenianos and Kircher (2009) focused on the efficiency properties of such models in a directed search environment. Gautier and Wolthoff (2009) consider a model where workers can send at most two applications, and focus on ex-ante heterogeneity on the firm’s side. These papers assume that workers are homogeneous in productivity and thus negate the role on information acquisition in firms’ hiring decisions.

Bradley (2020) features a similar set-up where workers draw match quality and firms pay a cost to reveal information about their workers. While Bradley (2020) allows firms to receive multiple applications and pay a screening cost per application received, workers can only send one application. The restriction of one application per worker implies that such a framework cannot be used to address our question of how an increase in the number of worker applications can affect firms’ incentives to acquire information and in turn affect unemployment inflows and outflows.

Most closely related to our work is the seminal paper by Wolthoff (2018) who examines the business-cycle properties of firms’ recruiting decisions through the lens of a directed search model with multiple applications. He finds that the number of applicants interviewed by firms are procyclical when applicants vary by match quality, and firms can choose how many applicants to be interviewed given a cost per interview. While not the focus of his paper, our paper addresses how the changing number of applications strengthens the firm’s incentive to acquire information. In our model, firms who are visited by only one applicant have no incentive to acquire information as the benefit of information in this case is equivalent to the benefit of no information and acquiring information is costly. An increase in the number of applications sent by workers reduces the likelihood of firms receiving only one applicant and changes the share of informed firms in our environment. Thus our question of interest and analysis differs from Wolthoff (2018). Critically, in our model, the share of informed firms interacts with the number of multiple applications to affect labor market flows. To our knowledge, ours is the first paper to link the rise in applications to long run trends in labor market flows in and out of unemployment.

Our work also contributes to the literature on the recruiting behavior of firms. Recent papers by Davis et al. (2012), Acharya and Wee (2020) and Gavazza et al. (2018) highlight the extent to which firms actively try to fill their positions - an activity defined as “recruiting intensity”
- can affect labor market flows over the business cycle. Acharya and Wee (2020) show that with rationally inattentive firms, recruiting intensity declines in a recession precisely because firms reject more often when firms are unable to acquire accurate information about the worker, raising the potential of large losses from the hiring of an unsuitable worker. Gavazza et al. (2018) argue that the decline in recruiting intensity in a recession is due to general equilibrium effects where increased slack in the labor market allows firms to exert less effort to fill a position. While we do not focus on the business cycle, our paper provides insights on the extent to which firms can actively fill a position. Firms, by acquiring information, can reduce their probability of being rejected by making offers to their highest quality applicant. A lower rejection probability naturally raises the firm’s ability to fill its position. Thus, our model, by studying the firm’s information problem with respect to applications received, can microfound firms’ recruiting intensity.

Finally, in terms of the empirical literature, among many others, Elsby et al. (2009), Elsby et al. (2010), and Shimer (2012) document the changes in unemployment inflow and outflow rates over time using CPS. Recently, Crump et al. (2019) analyze differential changes of these trends (especially inflow rate) across various age groups and gender. Similarly, we study the changes in these trends both in aggregate and also by education-groups. We find that the decline in unemployment inflow rate over time is largely driven by non-college workers, while the unemployment outflow rate does not exhibit a long-run trend both in aggregate and across these education-groups. An important contribution we make is to relate these findings on unemployment inflow and outflow rates with data on number of job applications, job offers, job acceptance rates, and reservation wages of the unemployed for both education-groups at two different points in time by using both EOPP and SCE surveys. We provide novel empirical findings on i) the substantial rise in the number of job applications sent by the unemployed, ii) the decline in the job acceptance rates especially for the non-college unemployed, and iii) the decline in the number of offers and rise in reservation wages. We use these empirical findings in a structural model to relate the changes in unemployment inflow and outflow rates to changes in the job search behavior and outcomes of the unemployed over time.

The rest of the paper is organized as follows. In Section 2, we present our empirical findings on the time trends of unemployment inflow and outflow rates as well as number of job applications, offers, acceptance rates, and reservation wages both in aggregate and across education-groups. Section 3 discusses our model and Section 4 provides the calibration strategy. In Section 5, we present our results. Section 6 concludes. Additional details on the model, data, and the results are given in the Appendix.
2 Empirical Findings

In this section, we discuss our empirical findings that motivate the model and quantitative exercises. In Section 2.1, we first show that unemployment inflow rates declined dramatically while unemployment outflow rates have remained roughly constant over the last four decades. Importantly, we document that the decline in the inflow rate is largely driven by workers without a college degree. Next, in Section 2.2, we document new findings on the changes in the number of job applications, job offers, job acceptance rates, and reservation wages of the unemployed over time. Specifically, we find that while the unemployed now send more applications than they used to, they now ask for higher wages, receive lower number of offers, and reject these offers more often than before. The results of this section motivates our modelling choices and our quantitative exercise.

2.1 Labor market flow rates

Using monthly data from the Current Population Survey (CPS) on the number employed, unemployed, and unemployed with at most five weeks of unemployment duration (i.e. “short-term unemployed”). We calculate the unemployment inflow rate (employment separations) and the unemployment outflow rate (job findings) over time using standard procedures found in the literature (see Elsby et al. (2009), Shimer (2012), and Crump et al. (2019) among many others). Appendix B provides details on our data and methodology.

Figure 1 plots quarterly averages of monthly inflow and outflow rates for the 1976:Q1 - 2019:Q4. Our findings align well with the findings of Crump et al. (2019), who follow the same methodology using the same dataset between 1976:Q1 - 2018:Q4. Figure 1 shows that there are differential long-run trends in inflow and outflow rates, confirming the findings of the earlier literature. The inflow rate exhibits roughly a 50 percent decline (from 4 percent to 2 percent) since early 1980s. On the other hand, while the outflow rate is more cyclical, its long-run trend is mostly flat.

Next, we analyze the cross-sectional variation in flow rates over time. Specifically, we measure how these flow rates change over time separately for individuals with and without a four year college degree. For brevity, we will refer to these groups as college and non-college. Figure 2 presents two important results. First, the unemployment inflow rate of college workers has been flat over the last four decades, which is in contrast to the significant decline for the non-college group. This implies that the decline in unemployment inflow rates documented in the literature and shown in the left panel of Figure 1 is primarily driven by the non-college individuals. Second, the unemployment outflow rates of both education groups are almost the same and do not exhibit any long-run trend.

As a final step in this section, we investigate whether the decline in inflow rates is simply a
Figure 1: 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 B. We compare our time series (blue solid lines, labeled as BSW) to these calculated by Crump et al. (2019) (gray dashed lines, labeled as CEGS), who follow the same methodology using the same dataset between 1976:Q1 - 2018:Q4. Gray shaded areas indicate NBER recession periods.

Figure 2: Unemployment inflow and outflow rates across education groups

Note: This figure shows the unemployment inflow rate (left panel) and outflow rate (right panel) between 1976:Q1 - 2019:Q4 for individuals without a four year college (bachelor’s) degree (blue solid lines) and individuals with at least a four year college degree (green dashed lines) separately. Quarterly time series are averages of monthly inflow and outflow rates, which are calculated using CPS data as described in Appendix B. Gray shaded areas describe NBER recession periods.
byproduct of a rise in the share of college-educated workers or reflects a more fundamental change in each group’s labor market experience. To do so, we implement a shift-share decomposition exercise on the unemployment inflow rate. Let $s^j_t$ be the inflow rate of education group $k \in \{NC, C\}$ at time period $t$, where $NC$ represents the non-college group and $C$ represents the college group. Let $\omega^i_t$ be the average share (weight) of group $i$ at time $t$. Finally, let $\bar{s}_t$ be the economy-wide average inflow rate at time $t$, i.e., $\bar{s}_t = \sum_i \omega^i_t s^i_t$. Then, change in the average inflow rate over two time periods $t_1$ and $t_2$ is given by

$$\Delta \bar{s} = \bar{s}_{t_2} - \bar{s}_{t_1} = \sum_i \omega^i_{t_2} s^i_{t_2} - \sum_i \omega^i_{t_1} s^i_{t_1} = \sum_i (\omega^i_{t_2} - \omega^i_{t_1}) s^i_{t_2} + \sum_i \omega^i_{t_1} (s^i_{t_2} - s^i_{t_1})$$

where the between-group measure holds the inflow rates within each group constant and asks how much of the total change in the average inflow rate is due to the change in weights, i.e. compositional changes, while the within-group measure holds the weights constant and asks how much of the total change in the average inflow rate can be attributed to a change in group-specific inflow rates. To be consistent with our analysis in Section 4, if we define $t_1$ as the period spanning 1976-1985 and $t_2$ as 2013-2017, we find that the within-group measure accounts for 86 percent of the total change in the average inflow rate, while the remaining 14 percent is due to between-group changes. Hence, we conclude that group-specific declines in inflow rates (especially for that of non-college) explain most of the decline of the average inflow rate over time.

To summarize, we find that unemployment inflow rates have declined substantially over time, a trend largely driven by non-college workers. In contrast, unemployment outflow rates have remained roughly constant for both education groups. Finally, the decline in inflow rates can be attributed to within-group changes as opposed to between group changes.

### 2.2 Job applications, job offers, and job acceptance rates

In this section, we use two different survey data that provides information on the job search activities, decisions, and outcomes in two different time periods.

The first dataset we use is the Employment Opportunity Pilot Project (EOPP) household baseline database. EOPP was implemented to analyze the impacts of an intensive job search program together with a work and training program. The household survey took place between

---

$4$In this case, we find $s^C_{t_2} = 0.011$, $s^{NC}_{t_2} = 0.029$, $s^C_{t_1} = 0.014$, $s^{NC}_{t_1} = 0.049$, and $\omega^C_{t_2} = 0.29$, $\omega^{NC}_{t_2} = 0.71$, $\omega^C_{t_1} = 0.15$, $\omega^{NC}_{t_1} = 0.85$. 
Table 1: Changes in job search process over time

<table>
<thead>
<tr>
<th></th>
<th>All College</th>
<th>Non-college</th>
<th>All College</th>
<th>Non-college</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Job Applications/month</td>
<td>2.70</td>
<td>2.46</td>
<td>2.82</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>[6.82]</td>
<td>[4.98]</td>
<td>[7.36]</td>
<td>[1.13]</td>
</tr>
<tr>
<td>1980</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Job Offers/month</td>
<td>0.28</td>
<td>0.50</td>
<td>0.20</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>[1.13]</td>
<td>[1.45]</td>
<td>[1.03]</td>
<td></td>
</tr>
<tr>
<td>2013-2017</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>[10.79]</td>
<td>[11.48]</td>
<td>[10.48]</td>
<td>[0.58]</td>
</tr>
<tr>
<td>Offer Acceptance Rate</td>
<td>2013-2017</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5.06</td>
</tr>
<tr>
<td></td>
<td>[0.15]</td>
<td>[0.22]</td>
<td>[0.12]</td>
<td>[6.98]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[9.85]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[5.67]</td>
</tr>
<tr>
<td>Real Hourly Reservation Wage</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2013-2017</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5.06</td>
</tr>
<tr>
<td></td>
<td>[0.15]</td>
<td>[0.22]</td>
<td>[0.12]</td>
<td>[6.98]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[9.85]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[5.67]</td>
</tr>
</tbody>
</table>

Note: This table shows the median number of job applications per month, the median number of job offers received per month, the median offer acceptance rate (defined as the ratio of an indicator variable denoting whether or not the individual accepted any of the job offers to the number of job offer received, conditional on having at least one offer), and the median real hourly reservation wage (adjusted by CPI) for 1980 and 2013-2017. The bracketed values present the mean of each moment. 1980 values are calculated from EOPP and 2013-2017 values are calculated from SCE datasets. In both datasets, we use a sample of unemployed individuals of ages 25-65 with at least one job application during the unemployment spell. We calculate these moments separately for all unemployed individuals, unemployed individuals without a four year college degree (non-college), and unemployed individuals with at least a four year college degree (college).

February and December 1980, with around 80 percent of interviews occurring between May and September, and a total of 29,620 families interviewed. The second dataset we use is the Survey of Consumer Expectations (SCE) Labor Market Survey, which was developed by the Federal Reserve Bank of New York. The SCE annual survey typically has more than 1000 respondents complete the survey. We use this data for each year between 2013-2017. Both of these datasets provide individual level information on demographics (age, race, education, gender, and marital status), employment, wages, and regular hours of work. A unique feature of both datasets is that they offer insights into job search behavior and unlike other household surveys, provide information on application behavior such as the number of job applications sent, the number of offers received, and the acceptance decision of a worker. In addition, these datasets offer information on workers’ reservation wages. Appendix B gives more details on these datasets, provides a list of variables we use, and explains how we calculate moments using these variables.

---

Footnotes:

5In this section, we use the individual level dataset. However, as part of the EOPP, employers were also surveyed both in 1980 and 1982. See Faberman and Menzio (2018) for the details of the employer level survey of the EOPP.
In both of these datasets, we focus on unemployed individuals age 25-65 with at least one job application during their unemployment spell. In both of these samples, we calculate the number of job applications per month, the number of job offers received per month, the offer acceptance rate, and real hourly reservation wages. We calculate these data moments for 1980 using the EOPP sample and for 2013-2017 using a pooled SCE sample. Finally, we calculate these moments for college and non-college separately. Table 1 summarizes the results.

We emphasize several results in Table 1. First, the median number of monthly job applications more than doubled between 1980 and 2013-2017 for all unemployed and for two education groups. Second, the median number of monthly job offers received decreased over time for all unemployed, especially so for college-education individuals. Third, among the unemployed who received at least one offer during their unemployment spell, job acceptance rates decreased over time, especially so for the unemployed without a college degree. Finally, median real hourly reservation wages increased by around 20 percent for all individuals, but the magnitude of this change in reservation wages of the two education groups are quite different. Reservation wages increased by around 34 percent for the unemployed with a college degree, but by only 4 percent for the unemployed without a college degree.

When these findings are considered jointly, we conclude that while the unemployed are now sending more applications than before, they also ask for higher wages, receive lower number of offers, and reject these offers more often than before.

Given the trends we observe in the inflow and outflow rates documented in Section 2.1 and the differences in application behavior across time documented in Section 2.2, we now develop a framework to see changes in application behavior.

---

6Offer acceptance rates are defined as the ratio of an indicator variable denoting whether or not the individual accepted any of the job offers to the number of job offer received, conditional on having at least one offer. This definition is reasonable under the assumption that individuals primarily work at one main job.

7We refer to median values of relevant moments due to the small sample size of the SCE. Mean values are reported in brackets.

8The EOPP survey collects information on the number of job applications and job offers received during the unemployment spell, while the SCE survey asks for the number of job applications and job offers received for the last 4 weeks of the unemployment spell. However, the EOPP survey also provides individual level information on the length of each unemployment spell. To make a comparison between these two datasets, we calculate the monthly number of job applications and job offers received in the EOPP dataset by dividing the total number of job applications and job offers received during an unemployment spell by the length of the unemployment spell in months. For this reason, in Table 1, the monthly number of job applications and job offers are integers for 2013-2017 as calculated from the SCE dataset, while they are not for 1980 as calculated from the EOPP dataset.


3 Model

3.1 Environment

Time is discrete. The economy comprises of a unit mass of infinitely-lived workers who are ex-ante identical. All workers are risk neutral and have discount factor \( \beta \). Workers can either be employed or unemployed. Unemployed workers receive unemployment benefit payments \( b \). On the other side of the market are firms that can employ one worker at any period. A firm-worker pair with match quality \( x \) produces \( x \) units of output at each period. The match quality \( x \in [\underline{x}, \bar{x}) \) is drawn from a time invariant distribution \( \Pi(x) \) at the time the firm and worker meet. The match quality of an existing matched firm-worker pair can evolve over time. In particular, with probability \( \rho(x) \), workers re-draw new match quality \( y \) from a conditional distribution \( \Psi(y \mid x) \) where \( d\Psi(y \mid x)/dx > 0 \), implying that new draws of match quality \( y \) are positively correlated with their previous values \( x \). We assume that \( \rho(x) \) takes values in the interval \([0, 1]\) and is decreasing in \( x \). This implies that matches of higher match quality are also less volatile, that is, matches with high match quality are less likely to receive a match quality shock. Finally, job destruction can occur both exogenously at rate \( \delta \) and endogenously, when the new draw of match quality falls below a threshold such that the match is no longer sustainable.

Search is random. Only unemployed workers search for jobs. An unemployed worker can costlessly send \( a \) applications in total each period. A worker sends each of her \( a \) applications to a separate vacancy. For each application sent, she observes her match quality draw \( x \) for that particular application.

Firms can receive more than one application, where the number of applications received is a random variable. Unlike workers, firms do not observe the match quality realized for each application they receive. A firm can choose to pay information acquisition cost \( \kappa_I \) to reveal information about all its applicants' match qualities at its vacancy. Thus, \( \kappa_I \) is a fixed information cost rather than the marginal cost of acquiring information for each applicant. While paying \( \kappa_I \) enables the firm to acquire information about the match qualities of its applicants, it does not provide the firm with information about the number of offers an applicant has nor does it provide information about the applicant’s match qualities at other jobs. As such, information is asymmetric in the sense that the worker knows all her match qualities across all applications and the number of offers received, while a firm that acquires information only knows the worker’s match quality for the match it is associated with. We restrict our attention to symmetric equilibria in pure strategies. In other words, we assume that all firms with \( j \) number of applicants employ the same information acquisition and hiring strategy. In addition to information costs, each vacancy costs \( \kappa_V \) to post.

The timing of the model is as follows. At the beginning of each period, firms post vacancies. Next, individuals in existing matches observe both separation and match quality shocks. We
assume that newly separated workers cannot immediately apply for jobs and must wait one period before they are able to send applications. Following this, unemployed workers send out applications and observe their match quality at each application. Firms receive applications and choose whether or not to acquire information. Firms then make offers to their chosen applicants and workers can decide whether to accept or reject offers. Once an offer has been accepted, workers and firms then bargain over wages. At the end of the period, production occurs.

**Matching** Denote $u$ as the measure of unemployed and $v$ the measure of vacancies. Let $j$ be the number of applications a firm receives. We will denote $q(j)$ as the probability that a firm receives $j$ applications. Since workers can send $a$ applications, the probability that an unemployed worker has applied to any one particular vacancy is $a/v$. Correspondingly, the number of applications, $j$, that a firm receives is given by $j \sim \text{bin}(u, a/v)$. The probability that a firm receives $j$ number of applications can thus be expressed as:

$$q(j) = \binom{u}{j} \left(\frac{a}{v}\right)^j \left(1 - \frac{a}{v}\right)^{u-j}$$

In the limit when $u \to \infty, v \to \infty$, the probability the firm receives $j$ applications collapses to:

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

(1)

where $\theta = v/u$ is the ratio of vacancies to unemployed job-seekers. Because firms can receive multiple applications, the rate at which firms receive applications is not the same as its job-filling probability. The probability that a firm fills its vacancy also depends on the acceptance probability of workers. The acceptance probability of workers in turn depends on the likelihood of receiving an offer, an object that is affected by the firm’s information acquisition problem. In what follows we define the worker’s and firm’s problem. All value functions are expressed as end of period value functions, i.e. after search and matching has occurred. We begin with the firm’s problem.

### 3.2 Firm’s Problem

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

$$V^F(x) = x - w(x) + \beta (1 - \delta) \left[(1 - \rho(x))V^F(x) + \rho(x) \int_x^x V^F(y) \psi(y \mid x) dy\right]$$

where $x - w(x)$ represents the firm’s period profits. With probability $\delta$, the job is exogenously destroyed, and the firm shuts down. If a job is not exogenously destroyed, it is subject to a match quality shock with probability $\rho(x)$ where a new match quality $y$ is re-drawn from conditional
distribution $\Psi(y \mid x)$ with $\psi(y \mid x)$ being the associated density. Let $\bar{x}$ be the reservation match quality – an endogenously-determined object to be formally defined below. As long as new match quality $y \geq \bar{x}$, the match is preserved with continuation value $V^F(y)$. With probability $1 - \rho(x)$, no match quality shock occurs and the firm observes continuation value $V^F(x)$.

**3.3 Firm’s information acquisition problem**

**No information acquisition** Consider a firm who has received $j$ applications. If a firm chose not to acquire any information, it is unable to rank any of its applicants in terms of match quality and randomly selects one applicant out of his pool of $j$ applicants. The expected value of the match, $V^{NI}(j)$, to such a firm is then given by

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

where $\pi(x)$ is the probability density that the applicant chosen draws match quality $x$ and $\Gamma(x)$ is the acceptance probability of the worker conditional of receiving an offer. Because firms do not know what match quality the worker will draw, the expectation is taken over $x \in [\bar{x}, \bar{x}]$ as workers reject any job that has match quality below reservation match quality $\bar{x}$. Before we elucidate the derivation of $\Gamma(x)$, it is useful to first consider what the firm would receive if it chose to acquire information.\(^9\)

**With information acquisition** Consider a firm who received $j$ applicants and has chosen to pay cost $\kappa_I$ to learn the match qualities of all its $j$ applicants. At this point, the firm can rank all its applicants’ match quality. Then, provided that the expected value of the job is increasing in match quality $x$, the firm always has an incentive to make an offer to the best candidate he has identified.

**Lemma 1** (Firm’s hiring choice). *As long as the surplus of a match is increasing in match quality $x$, then the firm always makes an offer to the applicant with the highest match quality.*

*Proof.* See Appendix A.1.

The intuition for this result is simple. By making an offer to the applicant with the highest match quality, the firm maximizes its expected value from hiring since a higher match quality applicant raises the value of an operating firm, $V^F(x)$ - which itself is a function of surplus - and also simultaneously lowers the probability that the firm’s offer would be rejected. As will become clear in Section 3.7, wages and thus employment values are increasing in $x$, as such all

\(^9\)In Section 3.6, we outline what the worker’s acceptance probability looks like.
workers always accept the highest match quality offer they have.\textsuperscript{10} Further, match quality is persistent. Conditional on a match of quality \( x \) experiencing a match quality shock, future draws of match quality \( y \) are likely to be high when \( x \) itself is high. Thus, by making an offer to his highest quality applicant, the firm - if successful in hiring - also ensures that he has on average a longer-lived match.

Conditional on receiving \( j \) applications, the firm’s expected benefit from acquiring information is:

\[
V^I(j) = \int_{\tilde{x}}^{x} V^F(x) \Gamma(x) j |\Pi(x)| j^{-1} \pi(x) dx
\]

where \( j |\Pi(x)| j^{-1} \pi(x) = d[\Pi(x)]^j/dx \) is the density of the maximum order statistic.\textsuperscript{11}

Given the firm’s expected benefit when it acquires and when it does not acquire information, we can now characterize the information acquisition problem for a firm with \( j \) applicants as:

\[
\Xi(j) = \max \left\{ \int_{\tilde{x}}^{x} V^F(x) \Gamma(x) j |\Pi(x)| j^{-1} \pi(x) dx - \kappa_I, \int_{\tilde{x}}^{x} V^F(x) \Gamma(x) \pi(x) dx \right\}
\]

\textbf{Proposition 1} (Firm’s information acquisition threshold). \textit{For finite \( \kappa_I \), there exists a threshold \( j^* > 1 \) above which the firm always chooses to acquire information.}

\textit{Proof.} See Appendix A.2.

Note that as the number of applications received \( j \) increases, so does the likelihood that one of the applicants has drawn a high match quality. This implies that the expected benefit of information acquisition is strictly increasing in \( j \) because it allows the firm to detect which applicant possessed the highest match quality. In contrast, firms that do not acquire information randomly select a candidate from the applicant pool. Given that each applicant’s match quality is independently drawn from the unconditional distribution \( \Pi(x) \), the value of not acquiring information is invariant to the number of applications received. Although the probability that at least one applicant has high match quality is higher when the applicant pool is larger, the firm with no information cannot take advantage of this when he makes offers randomly.\textsuperscript{12}

\textsuperscript{10}The highest match quality offer is not necessarily the same as the highest match quality out of a applications. A worker could have drawn match quality \( y > x \) in her other \( a - 1 \) applications but would still accept a match of quality \( x \) if the applications with match quality \( y > x \) did not yield any offers.

\textsuperscript{11}In other words, \( |\Pi(x)|^j \) is the probability that the largest match quality in the pool with \( j \) applicants is less than or equal to \( x \).

\textsuperscript{12}To see this, consider the simple example where there are two types of match quality \( x \in \{x_L, x_H\} \) where \( x_L < x_H \). Suppose with probability \( \alpha \), a job-seeker has quality \( x_L \), and with probability \( 1 - \alpha \), the applicant has quality \( x_H \). With one applicant, the firm’s expected value conditional on being successfully able to hire is given by: \( \alpha x_L + (1 - \alpha) x_H \). With two applicants, the firm’s expected value is given by \( \alpha^2 x_L + (1/2) 2\alpha(1 - \alpha) x_L + (1/2) 2\alpha(1 - \alpha) x_H + (1 - \alpha) (1 - \alpha) = \alpha x_L + (1 - \alpha) x_H \). With probability 1, the firm gets \( x_L \) if both workers have \( x_L \) match quality and the firm makes an offer to either one of them. This case occurs with probability \( \alpha^2 \). Conditional on one worker being \( x_H \) while the other is \( x_L \) - where this case occurs with probability \( 2\alpha(1 - \alpha) \) - the firm randomly makes one of them an offer and with probability \( 1/2 \) offers it to an \( x_L \) (\( x_H \)) worker. Finally
Since the value of not acquiring information is a constant, the net value from acquiring information \( V'(j) - \kappa_I \), which is strictly increasing in \( j \), crosses \( V^{NI} \) once from below. As such, there exists \( j^* \) applications such that \( V'(j) - \kappa_I \geq V^{NI} \) for all \( j \geq j^* \). Here, a pure strategy equilibrium exists: for any applications \( j \geq j^* \) received, the firm always chooses to acquire information.

Finally, it is clear that \( j^* > 1 \). Observe that when firms only have 1 applicant, the net value of acquiring information is strictly less than the value of not acquiring information:

\[
V'(1) - \kappa_I = \int_{\tilde{x}}^{\tau} V^F(x) \Gamma(x) \pi(x) dx - \kappa_I < \int_{\tilde{x}}^{\tau} V^F(x) \Gamma(x) \pi(x) dx = V^{NI}
\]

Thus, firms do not acquire information when they only have 1 applicant. Intuitively, when firms have only one applicant, the benefit of acquiring information, \( V'(1) \), is exactly equal to the value of not acquiring information, \( V^{NI} \). Learning the match quality of the single applicant does not provide firms with additional value since all workers reject jobs with match quality \( x < \tilde{x} \), bounding the benefit of making an offer to their one applicant below by zero. Further, a firm would never reject the single applicant if she brings the firm positive surplus and if there is free entry of vacancies.\(^{13}\) Since the benefits are the same but acquiring information is costly, firms strictly prefer not to acquire information when they only have a single applicant.

### 3.4 Free Entry

Finally, under free entry, the value of a vacancy is driven to zero. As such, free entry is characterized by:

\[
\kappa_V = \sum_{j=1}^{\infty} q(j) \Xi(j)
\]

### 3.5 Employed Workers

The value of an employed worker with match quality \( x \) at the end of the period can be characterized as:

\[
V^W(x) = w(x) + \beta (1 - \delta) (1 - \rho(x)) V^W(x) + \beta [\delta + (1 - \delta) \rho(x)] U + \beta (1 - \delta) \rho(x) \int_{\tilde{x}}^{\tau} V^W(y) \psi(y | x) dy
\]

conditional on both workers being \( x_H \) - this case occurs with probability \( (1 - \alpha)^2 \) - the firm has probability 1 of making an offer to a \( x_H \) worker.

\(^{13}\)Under free entry, the value of rejecting the current applicant and waiting until next period to create another vacancy is zero.
where $w(x)$ is the worker’s current wage. With probability $\delta$, the employment relationship is exogenously destroyed and the worker becomes unemployed. Jobs that are not exogenously destroyed are subject to a match quality shock with probability $\rho(x)$. If the new match quality drawn is above the reservation match productivity, i.e. $y \geq \bar{x}$, the worker remains employed with continuation value $V^W(y)$. Otherwise, the worker endogenously exits into unemployment. With probability $(1 - \rho(x))$, the job is not subject to a match quality shock and the worker continues to observe continuation value $V^W(x)$.

### 3.6 Unemployed Workers

Before characterizing the unemployed worker’s problem it is useful to first characterize what the acceptance decision of a job-seeker is conditional on receiving an offer. So long as employment values, $V^W(x)$, are increasing in match quality, the worker would prefer to accept a job for which she has the highest match quality and so long as that match quality is above the reservation match productivity $\bar{x}$.\(^{14}\) Consider a worker who has drawn match quality $x$ in one of his $a$ applications and has received an offer for this match quality draw of $x$. The worker will choose to accept the offer of match quality $x$ if 1) it is the best match quality she has drawn out of her $a$ applications. This occurs with probability $[\Pi(x)]^{a-1}$. The second term corresponds to the cases where the unemployed worker has drawn some match quality greater than $x$ in her $i$ other applications for $i \in \{1, 2, \ldots, a - 1\}$ while the remaining $(a - 1 - i)$ drew match quality

\[ \Gamma(x) = [\Pi(x)]^{a-1} + \sum_{i=1}^{a-1} (a - i) [1 - \Pi(x)]^i [\Pi(x)]^{a-1-i} [Pr(\text{no offer} | y > x)]^i \]  

\[ Pr(\text{no offer} | y > x) = \int_x^\infty \sum_{\ell=1}^\infty q(\ell) \left\{ I[\ell \geq j^*] \left( 1 - [\Pi(y)]^{\ell-1} \right) \frac{\pi(y)}{[1 - \Pi(x)]} dy \right. \]  

\[ + \int_x^\infty \sum_{\ell=1}^\infty q(\ell) \left( 1 - I[\ell \geq j^*] \right) \left( 1 - \frac{1}{\ell} \right) \frac{\pi(y)}{[1 - \Pi(x)]} dy \]  

The first term on the right-hand-side of Equation (5) corresponds to the case where the worker accepts an offer of match quality $x$ because it is the best match quality she has drawn out of her $a$ applications. This occurs with probability $[\Pi(x)]^{a-1}$. The second term corresponds to the cases where the unemployed worker has drawn some match quality greater than $x$ in her $i$ other applications for $i \in \{1, 2, \ldots, a - 1\}$ while the remaining $(a - 1 - i)$ drew match quality

\(^{14}\)It is trivial to show that a worker strictly prefers accepting the job with the highest match quality she has drawn when employment values are increasing in $x$.  

16
less than $x$. This occurs with probability $(a - i)[1 - \Pi(x)]^i[\Pi(x)]^{a-1-i}$. All the $i$ applications that drew match quality greater than $x$, however, failed to yield an offer, and so she accepts her next best outcome which is $x$. Equation (6) represent the probability that a worker receives no offer conditional on her drawing match quality $y > x$ for that application. The first term on the right-hand-side of Equation (6) depicts the case where the worker meets firms who have $\ell \geq j^*$ applicants and who have thus acquired information. Since these firms can observe their applicants’ match quality, they always make offers to the best applicant they have. Thus, with probability $1 - [\Pi(y)]^{\ell-1}$ the worker receives no offer at the application where she drew match quality $y$, and at least one of the $\ell - 1$ applicants at this firm has higher match quality than $y$. The second term on the right-hand-side of Equation (6) depicts the case where the worker meets firms who have $\ell < j^*$. In this case, firms do not acquire information and randomly select one candidate out of their applicant pool. Thus, the worker receives no offer in this case with probability $1 - 1/\ell$.

Given this conditional acceptance probability, $\Gamma(x)$, we can further define the probability that a worker accepts and is hired into a job with match quality $x$ then is given by:

$$
\phi(x) = \frac{\Gamma(x)}{Pr(\text{accept|offer, } x)} \sum_{j=1}^{\infty} q(j) \left( I[j \geq j^*] [\Pi(x)]^{j-1} + (1 - I[j \geq j^*]) \frac{1}{j} \right)
$$

(7)

To understand the worker’s probability of being hired for a job with quality $x$, observe that under a symmetric equilibrium, firms who have $j \geq j^*$ applicants acquire information and only make an offer to an applicant with match quality $x$ if all $j - 1$ applicants have lower match quality. This occurs with probability $[\Pi(x)]^{j-1}$. All firms who have $j < j^*$ applicants do not acquire any information and randomly select one of their applicants. Thus, the worker gets a job offer with probability $1/j$. Because the worker does not know how many applications the firm might receive, the offer probabilities are a weighted sum over the $j$ possible applications the firm could receive, with the weights given by $q(j) -$ the probability that the firm receives $j$ applications. The probability that a worker is hired with given match quality $x$ is the product of the expected offer probability and the conditional acceptance probability, $\Gamma(x)$.

Given this acceptance probability, the unemployed worker’s value at the end of the period is given by:

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

(8)

In the next period, the probability density of drawing match quality $x$ for a single application is given by $\pi(x)$. The worker is hired into this job with probability $\phi(x)$ and gets continuation value $V^W(x)$. Any of the $a$ applications that the worker sent out could have yielded this outcome. Thus, the unemployed worker’s overall probability of finding a job is given by $\int_{\tilde{x}}^{\pi} a\phi(x)\pi(x)dx$. 

17
With probability \(1 - \int_x^\pi a\phi(x)\pi(x)dx\), the worker is unable to find a job next period and continues in unemployment.

Focusing on the worker’s job-finding probability, \(\int_x^\pi a\phi(x)\pi(x)dx\), it is useful to note that a rise in the number of applications has a direct positive effect on the job-finding rate. Intuitively, holding all else constant, the more vacancies a worker can contact, the higher her chance of at least one application yielding an offer. Equation (7) and Equation (5), however, reveal that the number of applications a worker can send, \(a\), also has an indirect effect on the worker’s conditional acceptance probability, \(\Gamma(x)\), and the probability of getting an offer. In Section 3.10, we highlight how an increase in the number of applications sent by the worker can have the opposite impact on a worker’s offer probability as well as her conditional acceptance probability. Intuitively, an increase in the number of applications sent by each worker shifts the distribution of applications received by the firm rightward, lowering the probability that the worker is the sole applicant for a job and thus, the probability that she receives an offer as she now faces more competitors for the same job. At the same time, an increase in the number of applications sent by a worker implies that each worker has more job opportunities to choose from and thus her probability of accepting any job of match quality \(x\) conditional on receiving an offer is weakly lower.\(^{15}\) We highlight these results both analytically and quantitatively in Sections 3.10 and 5.1.

### 3.7 Surplus and Wage Determination

Finally, we assume that wages are determined through Nash Bargaining after the worker has chosen which offer to accept. Upon accepting an offer, the worker discards all other offers, implying that at the bargaining stage, the outside options of the firm and worker are equal to their values from remaining unmatched. Wage is re-bargained every period, implying that match quality shocks can lead to a change in wage.

Under Nash-bargaining, the wage for a job of match quality \(x\) is given by:

\[
w(x) = \arg \max_w \left[ V^F(x) \right]^{1-\eta} \left[ V^W(x) - U \right]^{\eta}
\]  

(9)

where \(\eta \in [0, 1]\) is the worker’s bargaining weight. Under the Nash-bargained wage, the surplus from a match of quality \(x\), \(S(x)\), is split such that:

\[
V^F(x) = (1-\eta)S(x) \quad \text{and} \quad V^W(x) - U = \eta S(x)
\]

\(^{15}\)The conditional acceptance probability is weakly declining in \(a\) as for \(x = \pi\), the worker can have no better option than to accept that job offer with probability 1.
where surplus can be expressed as:

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

(10)

with

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

The discounted surplus of a match of quality $x$ is given by the output $x$ plus the expected value stemming from a match quality shock less what the worker gains if she continues to search in unemployment. Given that output is given by $x$ and there is persistence in match quality, $d\Psi(y \mid x)/dx > 0$, surplus $S(x)$ is strictly increasing in $x$. Since the firm’s value is a share of surplus and wages are increasing in $x$, both the firm and employed worker’s values are also increasing in $x$. Thus, workers always accept offers for which they have the highest match quality and firms always make offers to applicants with the highest match quality.

### 3.8 Labor Market Flows

Having described each agent’s problem, we now turn to labor market flows.

**Unemployed** Let $G(x)$ be the steady state distribution of employed workers across match quality $x$, with associated density $g(x)$. In steady state, the unemployment rate is implicitly given by:

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

(11)

the left-hand-side of Equation (11) represents the outflows from unemployment from finding a job. The right-hand-side represents the inflows into unemployment stemming all the employed who were i) exogenously separated from their jobs with probability $\delta$ and ii) endogenously separated from their jobs because they suffered a match quality shock and their new match quality was below the reservation match productivity value, $y < \bar{x}$.

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

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

(12)
the left-hand-side of Equation (12) describes the outflows from the measure of employed with match quality $x$ from exogenous separations and from suffering a match quality shock. The first term on the right-hand-side describes the inflows from employed individuals who experienced a match quality shock and drew $x$ as their new match quality. The second term on the right-hand-side represents inflows from unemployment. Integrating over density $g(x)$, we can derive the distribution of match qualities, $G(x)$. The distribution, $G(x)$, is suggestive of how frequently endogenous separations may occur. Because $\rho(x)$ is assumed to be declining in $x$, an economy where the distribution of employed is skewed toward lower values of $x$ is more likely to observe a higher incidence of match quality shocks and is thus more likely to observe endogenous separations than a distribution of employed concentrated at higher values of $x$.

3.9 Equilibrium

Closing the model, we show that all equilibrium objects depend critically on $\{\tilde{x}, \theta, j^*\}$. The following lemma summarizes the key equations that pin down equilibrium in our model:

Lemma 2 (Key Equilibrium Conditions). In steady state, equilibrium $\{\tilde{x}, \theta, j^*\}$ are implicitly determined by the free entry condition given by Equation (3), as well as by the following conditions:

$$\tilde{x} = b + \beta \eta \int_{\tilde{x}}^{\bar{x}} a \phi(y) S(y) \pi(y) dy - \beta (1 - \delta) \rho(\tilde{x}) \int_{\tilde{x}}^{\bar{x}} S(y) \psi(y | \tilde{x}) dy \quad (13)$$

and $j^*$ is the smallest $j$ for which the net value of information is greater than or equal to the value of no information:

$$\begin{cases} V^I(j) - \kappa_I < V^{NI}, & \text{for } j < j^* \\ V^I(j) - \kappa_I \geq V^{NI}, & \text{for } j \geq j^* \end{cases} \quad (14)$$

where $V^I(j) = (1 - \eta) \int_{\tilde{x}}^{\bar{x}} j [\Pi(x)]^j \Gamma(x) S(x) \pi(x) dx - k_I$, and $V^{NI} = (1 - \eta) \int_{\tilde{x}}^{\bar{x}} \Gamma(x) S(x) \pi(x) dx$.

Equation (13) is derived by evaluating $S(x)$ at the reservation match quality, $\tilde{x}$ and represents the lowest match quality where workers are indifferent between remaining in unemployment or being employed. Because the number of applications a firm receives is a discrete random variable, Equation (14) implies that $j^*$ is the smallest number of applications for which the net value of acquiring information is greater than the value of no information. Finally, the free entry condition, Equation (3) provides information on $\theta$.\textsuperscript{16}

\textsuperscript{16}Technically, we also require a consistency condition to be satisfied, that is the number of applications sent by workers must be equal to the number of applications received by firms. In our model, this is trivially satisfied as in the limit when $u \to \infty, v \to \infty$, the Binomial distribution collapses to a Poisson, making the expected number of applicants per firm equal to $au/v = a/\theta$. Thus, the total number of applications received by firms is $va/\theta$. Given that the number of applications sent by workers is $au$, it is straightforward to show that consistency is satisfied since $au = va/\theta$. 

20
3.10 Forces at Play

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

Outflow from Unemployment  Recall that the unconditional outflow rate is given by

$$\text{outflow rate} = a \int_{\tilde{x}}^{\bar{x}} \phi(x) \pi(x)$$

where $\phi(x)$ is the probability that a worker accepts an offer for an application that yielded with match quality $x$. Since $\phi(x) = \Gamma(x) \times Pr(\text{offer} | x)$ and $\Gamma(x) = Pr(\text{accept} | \text{offer}, x)$,

$$\text{outflow rate} = \int_{\tilde{x}}^{\bar{x}} \left[ a \times Pr(\text{offer} | x) \right] \times \frac{Pr(\text{accept} | \text{offer}, x)}{\pi(x)} \, \pi(x) \tag{15}$$

This job-finding probability is a function of two components labeled: 1) the number of offers the worker can expect to receive as well as 2) her conditional acceptance probability.

The first component in Equation (15), the number of offers a worker can expect to receive, in turn, depends on the number of applications the worker can send, $a$, and the probability a worker receives an offer for a single application $Pr(\text{offer} | x)$. Clearly, the increase in applications sent $a$ directly impacts the worker’s expected number of offers. Holding all else constant, the more applications sent, the higher the likelihood that at least one application comes back with an offer. The more applications sent, however, also affects the probability that a single application yields an offer, which is reproduced below:

$$Pr(\text{offer} | x) = \sum_{j=1}^{\infty} q(j) \left( \mathbb{I}[j \geq j^*] \mathbb{I} \{ \pi(x) \}^{j-1} + (1 - \mathbb{I}[j \geq j^*]) \frac{1}{j} \right)$$

To see this, we first look at how the distribution of job applications received by firms, i.e. the distribution of $q(j)$, responds to increases in $a$. Since $q(j)$ controls the number of competitors a worker is likely to face, it influences the probability of securing an offer.

Since the number of applications received by the firm follows a Poisson distribution, the mean number of applications received by a firm is given by $a/\theta$. For expositional purposes, assume for
the moment that $a$ is a continuous variable. Differentiating $q(j)$ with respect to $a$, we get:

$$q_a(j) = \left[ \frac{j - a/\theta}{a/\theta} \right] \frac{1}{\theta^j j!} \left( \frac{a}{\theta} \right)^j \exp \left(-\frac{a}{\theta}\right)$$

The above derivative shows that for any $j$ applications that are less than the mean $a/\theta$, the derivative $q_a(j)$ is negative, while for any $j$ applications above the mean of $a/\theta$, the derivative is positive. This implies that as workers send more applications, i.e. $a$ increases, the distribution of $q(j)$ shifts rightward away from zero applications, with greater concentration at higher $j$ values and lower probability on low $j$ numbers of application. More generally, one can show that the firm’s probability of zero applications $q(0) = \exp(-a/\theta)$ is strictly declining in $a$ holding all else constant. Figure 3 shows how the distribution of $q(j)$ shifts rightward as $a$ increases.

Thus, a rise in applications overall raises the likelihood that the firm has more than 1 applicant. The higher likelihood that a firm has more than one applicant in turn negatively affects the probability that a worker’s application yields an offer. To see this, consider a worker whose application drew match quality $x > \bar{x}$. The conditional probability a worker gets an offer for an application which yielded match quality $x$ when the firm has $j$ applicants is given by:

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

(16)
and the probability that a worker with match quality \( x \) gets an offer is given by:

\[
Pr(\text{offer} \mid x) = \sum_{j=1}^{\infty} q(j) \left( \mathbb{I}[j \geq j^*] [\Pi(x)]^{j-1} + (1 - \mathbb{I}[j \geq j^*]) \frac{1}{j} \right)
\]

From Equation (16), one can observe that for a particular \( x \), \([\Pi(x)]^{j-1}\) is weakly declining in \( j \) and \( 1/j \) is strictly declining in \( j \). Thus as the distribution of applications received by firms \( q(j) \) shifts rightward as \( a \) increases, each worker’s application is more likely to compete against more applicants and the probability that an application with any given match quality \( x \) yields an offer declines.

In summary, the number of applications \( a \) has a direct effect of increasing a worker’s offers by sheer force of numbers but at the same time, indirectly decreases the probability that each application yields an offer through increased competition. Hence, an increase in applications sent \( a \) only raises expected offers if the former direct effect dominates.

Next, we focus on the second component in the job-finding probability in Equation (15), the conditional acceptance probability \( \Gamma(x) \). Conditional on having match quality \( x \) and the worker receiving an offer, it is straightforward to show that going from \( a = 1 \) to \( a = 2 \), the conditional acceptance probability for any \( x \geq \tilde{x} \) is strictly lower:

\[
\Gamma(x \mid a = 2) - \Gamma(x \mid a = 1) = -[1 - \Pi(x)] (1 - Pr(\text{no offer} \mid y > x, a = 2)) < 0
\]

Numerically, we can also show that holding all else constant, \( \Gamma(x) \) is weakly decreasing in \( a \) as depicted in Figure 4. Intuitively, as workers are able to send out more applications, they are able to sample more opportunities and thus have the potential to draw more match qualities greater than a particular \( x \). Thus, the conditional acceptance probability for a particular \( x \), i.e. \( \Gamma(x) \), is declining in \( a \).

Combining these elements together, the extent to which outflows from unemployment changes with respect to increases in \( a \) depends on how much conditional acceptance probabilities fall relative to the expected number of offers.

**Inflows into Unemployment** Turning to inflows into unemployment, the right-hand-side of Equation (11) shows that the inflow rate depends on

\[
\text{inflow rate} = \delta + (1 - \delta) \int_{\tilde{x}}^{\pi} \rho(x) \Psi(\tilde{x} \mid x) g(x) \, dx
\]

The first term refers to exogenous separations while the second term refers to endogenous separations. The only margin in the inflow rate that can respond to changes in \( a \) are endogenous

\(^{17}[\Pi(x)]^{j-1}\) is weakly declining as for \( x = \pi \), \( \Pi(x) = 1 \) and hence an increase in \( j \) does not reduce \([\Pi(x)]^{j-1}\).
separations. Holding $\theta, \bar{x}$ and $j^*$ constant, an increase in $a$ raises the share of firms receiving $j \geq j^*$ applications. From Proposition 1 a greater share of firms with $j \geq j^*$ implies that more firms on average acquire information. Following from Lemma 1, when more firms acquire

information, they identify and hire their highest match quality applicant, causing the realized distribution of match qualities, $G(x)$, to improve. When the distribution of realized match qualities, $G(x)$, has greater concentration at higher $x$ values, match separation risk declines as 1) the arrival rate of match quality shocks are declining in $x$, and 2) the persistence in match qualities draws makes it less likely that an individual with high $x$ draws a low $x$ conditional on a shock. Thus, holding all else constant, inflows into unemployment decline when an increase in $a$ leads to a larger share of firms acquiring information and an improvement in the realized distribution of match qualities.

Thus far, we have limited our analysis to a partial equilibrium setting to highlight how the different components in the job-finding rate and endogenous destruction rate respond to changes in $a$. In general equilibrium, however, $\bar{x}, \theta$ and $j^*$ can vary in response to changes in $a$. Changes in these key equilibrium objects in turn affect the distribution of applications received, the expected value of a match and the value of information, the acceptance rates of workers, the expected number of offers and the rate at which jobs are endogenously destroyed. As such, we now turn to our calibrated model to understand the general equilibrium impact of an increase in $a$ on the inflow and outflow rates of unemployment.
4 Calibration

In the following section, we discuss details of the model’s calibration. In Section 4.1, we discuss how we segment the economy into two labor markets: non-college and college. We then detail how we combine both markets to calculate aggregate moments. Finally, Section 4.2 outlines the relationship between calibrated parameters and targeted moments. A summary of internally calibrated parameters can be found in Table 2.

4.1 Segmented Labor Markets

As is apparent in Figure 2, college- and non-college-educated workers faced substantially different unemployment inflow rates during later half of the 1970’s. Furthermore, the narrowing of this gap over time has been driven by a declining inflow rate among non-college workers, in contrast to the roughly constant profile among those with college degrees. In order to account for the different initial levels and dynamics of job flows between these two groups, we segment the economy two labor markets: non-college and college. Each submarket’s structure follows the same model in Section 3. What distinguishes each market is the invariant distribution of match quality that a firm-worker pair draws from upon meeting $\Pi_k (x), k \in \{nc, c\}$. Importantly, we assume that both submarkets operate independently of each other.

Let $\gamma$ be the share of college-educated workers in the population. We can then combine both markets in order to calculate aggregate moments. For example, aggregate unemployment rate is simply the population-weighted unemployment rate in both markets: $u = \gamma u_c + (1 - \gamma) u_{nc}$. The same logic allows us to construct a wide-range of other moments related to job flow, wages, inequality, and job search outcomes.

4.2 Calibration Strategy

Our model period is a month. We calibrate the initial steady state to the period of 1976 to 1985.\footnote{The U.S. economy experienced two recessions in early 1980s. Given that our framework is a stationary model, we choose to calibrate the model to the period of 1976-1985 in order to mitigate the effects of these recessions on our calibration targets.} Unless otherwise stated, all target moments are calculated from the CPS.

We set several parameters outside of our model. We set the discount factor $\beta = 0.99$ and the worker’s bargaining power $\eta = 0.5$. The median number of job applications in a month is 2.46 for college-educated workers and 2.82 for non-college-educated workers according to EOPP in 1980. In our model, the number of job applications $a$ in our model takes integer values. For this reason, we set $a = 3$ for both non-college- and college-educated workers. Finally, using the CPS, we find that the average share of population with at least a four year college degree between 1976-1985 is 15 percent. Hence, we set $\gamma = 0.15$.\footnote{The U.S. economy experienced two recessions in early 1980s. Given that our framework is a stationary model, we choose to calibrate the model to the period of 1976-1985 in order to mitigate the effects of these recessions on our calibration targets.}
Below, we discuss our calibration strategy for the remaining set of model parameters.

**Evolution of match quality** The invariant distribution of initial match quality $\Pi_k(x)$ for submarket $k \in \{nc, c\}$ is assumed to be log normal with parameters $(\mu_k, \sigma_k)$. We normalize $\mu_{nc} = 0$ and set $\mu_c = 0.43$ to match a college premium of 0.45.\(^{19}\) We then use the standard deviation of initial match quality draws $\sigma_{nc}$ and $\sigma_c$ to target the median value of job offer acceptance rates of 1 and 0.5 among non-college- and college-educated workers respectively, according to the EOPP data in 1980.

A worker is subject to a match quality shock with probability $\rho(x) = \min\{1, \exp(-(x - x_{\text{ref}}))\}$ in each period, where $x_{\text{ref}} = \gamma \exp(\mu_c + 0.5\sigma_c^2) + (1 - \gamma) \exp(\mu_{nc} + 0.5\sigma_{nc}^2)$ is set to be the weighted average of the unconditional mean of the initial match quality distribution. The joint distribution of match quality shocks $\Psi(x, x')$ is derived from Frank’s copula which takes the form

$$\Psi(x, x') = -\frac{1}{\lambda} \log \left\{ 1 + \frac{[\exp(-\lambda \Pi(x)) - 1] [\exp(-\lambda \Pi(x')) - 1]}{\exp(-\lambda) - 1} \right\}$$

which implies a conditional distribution of match quality re-draws $\psi(x' \mid x)$. Note that $\lambda$ controls the degree to which draws of $x'$ are positively correlated with current match quality $x$.

The functional forms of the probability of a match quality shock $\rho(x)$ and the conditional distribution of match quality re-draws $\psi(x' \mid x)$ imply that employment relationships with higher match quality are less prone to endogenous dissolution because of i) less frequent match quality shocks and ii) conditional on a match quality shock, higher draws of new match quality $x'$. This implies that as $\lambda$ increases, the higher average match quality among college workers translates to better match quality re-draws $x'$. Hence, we use $\lambda$ to match college workers’ unemployment inflow rate of 0.014, as given by the average inflow rate of college workers between 1976-1985 in CPS.

**Labor market** We choose the cost of posting a vacancy $\kappa_V = 0.67$ to match the average unemployment rate between 1976-1985 of 7.6%. The fixed cost of information acquisition $\kappa_I$ determines the degree to which firms can benefit from receiving multiple applications with varying match quality. This is especially relevant in the college submarket where firm-worker pairs are more likely to draw high levels of match quality $x$ upon meeting, and thus access to information becomes more vital. For this reason, we choose $\kappa_I = 0.49$ to match the unemployment rate of college-educated workers of 3% for the same time period.

\(^{19}\)Borjas and Ramey (1994) estimate an average log wage differential between college graduates and high-school graduates (high-school dropouts) between 1975-1985 as 0.4 (0.65) using CPS. Goldin and Katz (2007) estimate the log wage differential between college and high school graduates as 0.45 in 1970 and 0.4 in 1980 using U.S. Census data. Finally, Autor et al. (2008) estimate an average log wage differential between college graduates and high-school graduates as between 0.4 and 0.45 using CPS. We target a log mean wage difference between college and non-college markets of 0.45, which is consistent with these empirical estimates.
Table 2: Internally calibrated parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Explanation</th>
<th>Value</th>
<th>Target</th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa_I$</td>
<td>Cost of information</td>
<td>0.49</td>
<td>Unemployment rate, aggregate</td>
<td>0.076</td>
<td>0.076</td>
</tr>
<tr>
<td>$\kappa_V$</td>
<td>Vacancy posting cost</td>
<td>0.67</td>
<td>Unemployment rate, college</td>
<td>0.028</td>
<td>0.030</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Exog. separation rate</td>
<td>0.002</td>
<td>Inflow rate, aggregate</td>
<td>0.041</td>
<td>0.044</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Persistence of $x$</td>
<td>16.36</td>
<td>Inflow rate, college</td>
<td>0.018</td>
<td>0.014</td>
</tr>
<tr>
<td>$b$</td>
<td>UI benefits</td>
<td>0.49</td>
<td>UI replacement rate</td>
<td>0.40</td>
<td>0.40</td>
</tr>
<tr>
<td>$\mu_c$</td>
<td>Mean $x$, college</td>
<td>0.43</td>
<td>College premium</td>
<td>0.43</td>
<td>0.45</td>
</tr>
<tr>
<td>$\sigma_c$</td>
<td>Std. dev. $x$, college</td>
<td>0.15</td>
<td>Median acceptance rate, college</td>
<td>0.48</td>
<td>0.50</td>
</tr>
<tr>
<td>$\sigma_{nc}$</td>
<td>Std. dev. $x$, non-college</td>
<td>0.17</td>
<td>Median acceptance rate, non-college</td>
<td>0.67</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: This table provides a list of model parameters that are calibrated using our model. Moments relating to unemployment levels and flows are obtained from the CPS as averages between 1976 and 1985. Acceptance rates are obtained from EOPP 1980. Please refer to main text for a detailed discussion.

Recall that employment relationships can dissolve either endogenously, if match quality falls below reservation $\tilde{x}$, or exogenously at rate $\delta$. We choose $\delta = 0.002$ to match the aggregate unemployment inflow rate of 0.044, as the average inflow rate between 1976-1985. Finally, the level of unemployment benefits $b$ received by workers who experience job loss is calibrated to match an average replacement rate of 40%.

5 Quantitative Implications

In this section, we analyze the effects of the increase in the total number of job applications $a$ sent by the unemployed workers every period on i) the equilibrium objects, ii) the unemployment inflow and outflow rates, and iii) the number of job offers received, job acceptance rates, and reservation wages of both college and non-college unemployed workers. We then analyze how the presence of the information acquisition problem of firms affects our the results.

5.1 Equilibrium Response to an Increase in $a$

Table 1 shows that the median number of applications doubled from 3 to 6 between 1980s to 2013-2017. This forms the basis of our main quantitative exercise which involves doubling the number of applications sent from 3 to 6 in the calibrated model, holding all other parameters fixed. Table 3 summarizes our results.

To begin our analysis, we first look at how key equilibrium variables in our model change in response to a doubling in applications sent by workers. Notably, the increase in the amount

---

20In the model, $a$ can only take integer values. Thus, in this quantitative exercise, we take $a = 3$ in 1980 instead of 2.70, 2.46, and 2.82 values for the average monthly number of job applications sent by all workers, college workers, and non-college workers, respectively.
of applications sent results in a modest increase in the reservation match quality of workers. Intuitively, when workers are able to send out more applications, they are able to sample more job opportunities and have a higher probability of at least one application yielding a high match quality value. This raises the worker’s outside option, leading to a rise in $\bar{x}$ for both college and non-college individuals.

<table>
<thead>
<tr>
<th>Table 3: Impact on flow rates from increase in $a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Equilibrium objects</td>
</tr>
<tr>
<td>$\bar{x}$</td>
</tr>
<tr>
<td>------------------------------------</td>
</tr>
<tr>
<td>$\theta$</td>
</tr>
<tr>
<td>$j^*$</td>
</tr>
<tr>
<td>Percent of firms acquire info</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B. Flow rates and job search outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a = 3$</td>
</tr>
<tr>
<td>--------------------------------------</td>
</tr>
<tr>
<td>Unemployment inflow rate</td>
</tr>
<tr>
<td>Unemployment outflow rate</td>
</tr>
<tr>
<td>Average acceptance rate</td>
</tr>
<tr>
<td>Median acceptance rate</td>
</tr>
<tr>
<td>Average number of offers</td>
</tr>
<tr>
<td>Median number of offers</td>
</tr>
<tr>
<td>Reservation wage</td>
</tr>
<tr>
<td>Average match quality</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C. Aggregate outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a = 3$</td>
</tr>
<tr>
<td>-----------------------</td>
</tr>
<tr>
<td>Hiring rate</td>
</tr>
<tr>
<td>Vacancies</td>
</tr>
<tr>
<td>Unemployment rate</td>
</tr>
<tr>
<td>Unemployment inflow rate</td>
</tr>
<tr>
<td>Unemployment outflow rate</td>
</tr>
<tr>
<td>Implied matching efficiency</td>
</tr>
</tbody>
</table>

Note: This table summarizes the results of the model when the total number of applications sent by unemployed workers increases from $a = 3$ to $a = 6$, as in the data. Specifically, it shows the changes in i) the equilibrium objects, ii) unemployment inflow and outflow rates as well as the number of job offers received and reservation wages for both college and non-college workers, and iii) aggregate labor market outcomes.

On the other hand, labor market tightness, $\theta$, declines for both college and non-college workers despite the rise in applications received by firms. Figure 5 shows that the distribution of applications received shifts rightward with the increase in $a$. While an increase in the contact rate for firms - measured as the probability of receiving at least one application - rises as workers send more applications, the acceptance rate of workers conditional on receiving an offer declines substantially when $a$ increases, as shown by Table 3. This latter effect raises the rejection
probability for a firm and partially mitigates the benefits of an increased contact rate for the firm.

In addition, the rise in average applications received by firms as depicted by Figure 5 implies that a larger share of firms acquire information. Panel A of Table 3 shows $j^*$ increases marginally while the share of firms acquiring information unambiguously increases in our model as $a$ doubles.\(^{21}\) Intuitively, when workers are able to send more applications, the firm has a larger probability that at least one of its applicants has drawn a high match quality value. This, together with the increase in workers’ rejection probabilities, reinforces the firm’s incentive to acquire information about its applicants as identifying and offering the highest match quality applicant a job not only brings the firm the largest possible surplus but also lowers the likelihood that the firm’s offer is rejected. This increase in the share of firms acquiring information, however, raises the cost of job creation as more firms expect to pay for information. Thus, the emergence of higher expected job creation costs and higher rejection rates counteract the benefits from a higher contact rate, causing a decline in incentives to post a vacancy in equilibrium and

\(^{21}\)Because college workers on average draw higher match qualities than non-college individuals and since higher match quality draws are both more persistent and less likely to suffer a match quality shock, the value of information for identifying high quality college individuals relative to non-college individuals is lower.
labor market tightness \( \theta \) to fall. Panel C of Table 3 makes clear that the labor market tightness here does not fall because there is more unemployed, but rather because fewer vacancies are created.

Before moving to our main question of interest - which is to what extent can the trends in inflow and outflow rates of unemployment be explained by a rise in applications sent - we first note how the equilibrium objects in our model would affect these inflows and outflows. First, an increase in reservation match quality \( \tilde{x} \) may have opposing effects on unemployment flows. It can raise inflows as match quality re-draws need to exceed the higher \( \tilde{x} \) in order to preserve the match, but can also depress inflows if it leads to a rise in average match quality. An increase in average match quality lowers inflows by lowering the frequency of match quality shocks \( \rho(x) \) and by raising the chances of re-drawing higher match quality from \( \Psi(y \mid x) \). In addition, a rise in \( \tilde{x} \) may also lead to lower outflow rates as workers become more selective with the jobs they accept. Second, a decline in the number of vacancies posted by the firms has a tendency to increase competition amongst workers and thus may negatively affect outflows from unemployment. Finally, an increase in the share of firms acquiring information implies that conditional on hiring, realized matches are on average of higher quality. This improvement in expected match quality acts towards tempering both the increase inflow rates and decline in outflow rates.

### 5.2 The Response of Inflow and Outflow Rates

We now examine how inflow and outflow rates of non-college and college workers are affected in our model by a rise in \( a \). In order to isolate the effect of a rise in applications, we hold all other parameters fixed. The results of this exercise are detailed in Table 3. A key finding is that an increase in the number of applications allows the model to capture trends highlighted in Section 2.1: a significant decline in inflow rates of non-college workers (4.5% to 2.1% in the model vs. 4.9% to 2.9% in the data) and in contrast, only a modest change for college workers (1.8% to 2.0% in the model vs. 1.4% to 1.1% in the data).

What explains this difference? In our model, workers with high initial draws of match quality are less likely to suffer match quality shocks and undergo a change in match quality. Moreover, because match quality is persistent, conditional on receiving a shock, individuals with initially high match quality are more likely to re-draw high match quality values. In the baseline model with \( a = 3 \) applications, we see that the distribution of realized match qualities for employed college individuals FOSD that of non-college individuals as depicted in Figure 6 by the blue solid lines. Moreover, the arrival rate of match quality shocks as depicted by the dotted-red lines \( \rho(x) \) was higher for non-college individuals than for college individuals. The increase in applications sent by workers to \( a = 6 \) and consequent rise in the fraction of firms acquiring information caused both distributions of realized match quality to shift rightward as

30
Figure 6: Realized match quality distribution improves as $a$ increases

Note: The top panels show how the distribution of employed across match quality $x$ in the non-college labor market, i.e., $g(x)$, changes with a doubling in $a$. The bottom panel shows the equivalent for the college labor market. The dotted red line represents arrival rates of match quality shocks, while 'triangle' and 'circle' markers represent the probability of the job being destroyed conditional on a match quality shock, i.e., $\Psi(\tilde{x} | x)$, for non-college and college markets respectively.

...evidenced by the green dashed lines. While the shifts in both distributions are comparable, the improvement in realized match qualities has a much larger effect for non-college workers. First, a smaller share of non-college workers now observe probability 1 of receiving a match quality shock. The red dashed line in Figure 6 shows that the probability that a worker at a particular $x$ receives a match quality shock, $\rho(x)$ is declining in $x$. Given that those with initially low match qualities were more likely to redraw new values of match qualities below $\tilde{x}$, this decline in the share of non-college individuals receiving match quality shocks reduces the incidence of endogenous separations despite reservation match quality $\tilde{x}$ being higher. Figure 6 also displays the probability that an individual with match quality $x$ has her job destroyed conditional on receiving a shock, i.e., $\Psi(\tilde{x} | x)$. The green circle markers outline $\Psi(\tilde{x} | x)$ for $a = 6$ applications while the blue triangle markers show the counterpart for $a = 3$ applications. Notably, the shift towards higher $x$ values for non-college individuals meant that a significantly smaller proportion of individuals observe a large non-zero probability of drawing a new match...
quality below the reservation match quality (shaded green region smaller relative to shaded blue region). As such, the improvement in realized match qualities play a large role in causing the decline in unemployment inflow rates for non-college individuals, causing the inflow rate to more than halve.

Conversely, while most college individuals have a lower probability of receiving match quality shocks, the green circle markers in the bottom-right panel of Figure 6 shows that conditional on receiving such a shock, a larger fraction of employed college individuals were likely to separate into unemployment as the reservation match quality value is more elastic with respect to the rise in applications. Thus, the unemployment inflow rate for college individuals climbs a negligible 0.2 percentage points.

Moving onto unemployment outflow rates, a rise in applications causes a modest decline for non-college individuals (49% to 44% in the model vs. 53% to 42% in the data) and a modest increase for college individuals (61% to 67% in the model as opposed a decline from 46% to 36% in the data). The differences in the can be understood by examining how the expected number of offers and average acceptance rate change in response to the increase in applications sent. Panel B of Table 3 shows that the average acceptance rate (conditional on receiving an offer) is declining for all workers regardless of education status (50% to 30% for non-college, 35% to 23% for college). As foreshadowed in Section 3.10, this occurs because an increase in applications sent raises the likelihood that the worker has at least one other application and offer with higher match quality, raising the likelihood that she rejects a job of a particular match quality. These findings reflects patterns in the data where the average acceptance rates for non-college and college individuals declined from 64% to 12% and from 57% to 22% respectively.

In contrast, the expected number of offers declines for non-college workers in our model (from 0.70 to 0.57 offers per month) but is roughly constant for college workers (from 1.54 to 1.60). In the data, offers per month of non-college workers decline from 1.03 to 1.39 while college workers experienced a less drastic decline from 1.45 to 1.02. While the model is unable to capture the decline for the college group, it captures the differential response between both groups. In order to see why, note that the offer probability, \( Pr(offer) \), for a single application for both non-college and college individuals is declining in our model as discussed in Section 3.10. However, because the unconditional offer probability falls to a lesser extent for college individuals, the direct impact from an increase in \( a \) offsets this and raises slightly the expected offers for college individuals.\(^{22}\) This overall increase in expected offers for college individuals offsets the effect from a decline in conditional acceptance probabilities and is the key factor behind the roughly constant unemployment outflows for college individuals in the model. Conversely, both expected number of offers and the conditional acceptance probability for non-college individuals fell, causing non-college individuals’ unemployment outflow rates to be lower. Nonetheless, we view our model’s

\(^{22}\)Offer probabilities fall by 60% for non-college individuals and by about 48% for college individuals.
predicted percentage changes in outflow rates out of unemployment to be small relative to the percentage changes in inflow rates. Overall, our model can largely capture the trends observed in data.

Turning to aggregate moments, Panel C of Table 3 shows that the model is able to replicate certain key aggregate moments in the data. In particular, our model predicts that the steady state aggregate unemployment rate is lower in the economy with a higher number of applications. Our model implied aggregate unemployment rate is about 4.3%, below the observed 5.6% in the data. At the same time, our model also predicts a decline in the hiring rate defined as the number of hires divided the total employed. This is consistent with the observed decline in the hiring rate in the CPS and also with the decline in the job creation rate observed in the Business Employment Dynamics (BED) database.

Finally, our model provides some insight as to why there has been a distinct decline in the aggregate unemployment inflow rates but no significant trend in aggregate unemployment outflow rates despite the fact that search technology has improved and workers can now send more applications. Using predicted data from our model, one can view our model’s results through a standard Cobb-Douglas matching function where total matches, $M$, are affected by the level of unemployment, the level of vacancies and a matching-efficiency term, $\zeta$.

$$M = \zeta u^\alpha v^{1-\alpha}$$

Assuming as standard in the literature that the elasticity of the matching function with respect to unemployment, $\alpha$, is equal to 0.5, we can back out matching efficiency, $\zeta$, as implied by our model. Panel C of Table 3 shows that matching efficiency declined slightly by about 5% across the two time periods. This lack of a substantial shift in implied matching efficiency despite improving search technology over time allowing workers to sample more job opportunities can be easily explained through the lens of our model. When workers can send out more applications, they are more likely to reject jobs with low match quality values, causing lower conditional acceptance rates to mitigate any rise in job finding stemming from an increase in applications sent. Thus even if $\alpha$ increases, acceptance rates on average decline and this prevents large swings in matching efficiency. It is important to note that in our model the decline in acceptance rates does not stem from a large increase in reservation wages. In our model, the increase in reservation wages are small as in the data. Rather, it is the fact that workers have more options to choose from that lead to acceptance rates declining.

Finally, our model can explain why an improvement in search technology and the number of

---

23It should be noted that unemployment rates were higher in 2013 following the aftermath of the Great Recession.

24The job creation rate as defined in the BED is equal to the gross job gains divided by the total employed. In our model, a job is a single-firm worker pair. Thus, all hires in our model are equal to gross job gains.
applications sent has an impact on the unemployment inflow rates. The rise in applications and higher probability of discovering a high quality applicant raises firms’ incentive to acquire information. Whenever more firms acquire information, there is less randomness in hiring and this causes inflow rates into unemployment to decline as better matches are formed. In what follows, we outline the role of information and its interaction with multiple applications by conducting two extreme thought experiments, 1) where information is free and 2) where information is infinitely costly. We will show that both of these versions of our baseline model would ignore the changes in firms’ investment in information as the number of job applications increase, leading to conclusions on the changes in the unemployment inflow rates for non-college workers as well as unemployment and hiring rates that are inconsistent with the observed empirical patterns over time.

5.3 The Role of Information

Without re-calibrating our model, we now consider two thought experiments to uncover how information acquisition interacts with the multiple application behavior of individuals to affect labor market flows over time. In the first thought experiment, we set $\kappa_I = 0$, and term this the “Full Information” (FI) environment. It should be noted that while we call this “full information”, firms are only allowed to observe the match qualities of all their applicants at the time of receiving applications. They are still unable to observe the their applicants’ match qualities at other jobs nor do they know of the competing offers that their applicant might possess. In our second thought experiment, we consider the other extreme and set $\kappa_I \to \infty$. We term this the “No Information” (NI) environment. In this environment, firms make offers randomly as they cannot observe their applicant’s match quality. Because wage negotiations are only conducted after a worker has accepted an offer, this implies that even in the NI environment, the worst the firm can obtain at the time of hiring is zero profit.\(^{25}\)

Table 4 shows our results. Focusing on our results for non-college workers in Panel A, a few comments are in order. First, both our baseline model with a fixed cost of information and the FI model predict that reservation match quality rises with an increase in $a$ for non-college workers. The NI model, however, predicts that reservation match quality falls with the rise in applications. In our baseline and FI model, firms can take advantage of information if they choose to do so and identify the highest quality applicant. Thus, workers who draw high match quality have a higher chance of receiving offers. Conversely, in the NI model firms are unable to observe applicants’ match quality and are as such unable to take advantage of the fact that the probability of at least one applicant being of high quality is increasing in the number of applications received. As such, NI firms hire randomly and workers do not observe an improvement in their outside

\(^{25}\)This is because the worker’s participation constraint ensures that no worker wants to work at a job with negative surplus.
Table 4: Flows in response to information costs and increases in \( a \)

<table>
<thead>
<tr>
<th>A. Non-college</th>
<th>Baseline ( a = 3 )</th>
<th>Baseline ( a = 6 )</th>
<th>FI ( a = 3 )</th>
<th>FI ( a = 6 )</th>
<th>NI ( a = 3 )</th>
<th>NI ( a = 6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equilibrium objects</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
</tr>
<tr>
<td>( \bar{x} )</td>
<td>0.950</td>
<td>0.964</td>
<td>0.964</td>
<td>0.976</td>
<td>0.907</td>
<td>0.884</td>
</tr>
<tr>
<td>( \theta )</td>
<td>0.556</td>
<td>0.517</td>
<td>0.337</td>
<td>0.356</td>
<td>0.674</td>
<td>0.735</td>
</tr>
<tr>
<td>Percent of firms acquire info</td>
<td>78.94</td>
<td>99.01</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Moments</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
</tr>
<tr>
<td>Unemployment inflow rate</td>
<td>0.045</td>
<td>0.021</td>
<td>0.021</td>
<td>0.028</td>
<td>0.017</td>
<td>0.027</td>
</tr>
<tr>
<td>Unemployment outflow rate</td>
<td>0.492</td>
<td>0.435</td>
<td>0.335</td>
<td>0.320</td>
<td>0.475</td>
<td>0.365</td>
</tr>
<tr>
<td>Average acceptance rate</td>
<td>0.499</td>
<td>0.300</td>
<td>0.444</td>
<td>0.326</td>
<td>0.545</td>
<td>0.424</td>
</tr>
<tr>
<td>Average number of offers</td>
<td>0.705</td>
<td>0.572</td>
<td>0.388</td>
<td>0.380</td>
<td>0.872</td>
<td>0.860</td>
</tr>
<tr>
<td>Reservation wage</td>
<td>1.025</td>
<td>1.039</td>
<td>1.007</td>
<td>1.017</td>
<td>0.990</td>
<td>0.971</td>
</tr>
<tr>
<td>Average match quality</td>
<td>1.178</td>
<td>1.209</td>
<td>1.205</td>
<td>1.216</td>
<td>1.162</td>
<td>1.142</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B. College</th>
<th>Baseline ( a = 3 )</th>
<th>Baseline ( a = 6 )</th>
<th>FI ( a = 3 )</th>
<th>FI ( a = 6 )</th>
<th>NI ( a = 3 )</th>
<th>NI ( a = 6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equilibrium objects</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
</tr>
<tr>
<td>( \bar{x} )</td>
<td>1.495</td>
<td>1.553</td>
<td>1.557</td>
<td>1.598</td>
<td>1.478</td>
<td>1.484</td>
</tr>
<tr>
<td>( \theta )</td>
<td>1.703</td>
<td>1.245</td>
<td>0.680</td>
<td>0.707</td>
<td>1.614</td>
<td>1.381</td>
</tr>
<tr>
<td>Percent of firms acquire info</td>
<td>31.30</td>
<td>71.45</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Moments</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
</tr>
<tr>
<td>Unemployment inflow rate</td>
<td>0.018</td>
<td>0.020</td>
<td>0.023</td>
<td>0.020</td>
<td>0.013</td>
<td>0.014</td>
</tr>
<tr>
<td>Unemployment outflow rate</td>
<td>0.611</td>
<td>0.674</td>
<td>0.540</td>
<td>0.541</td>
<td>0.571</td>
<td>0.549</td>
</tr>
<tr>
<td>Average acceptance rate</td>
<td>0.350</td>
<td>0.232</td>
<td>0.330</td>
<td>0.214</td>
<td>0.375</td>
<td>0.307</td>
</tr>
<tr>
<td>Average number of offers</td>
<td>1.535</td>
<td>1.600</td>
<td>0.880</td>
<td>0.821</td>
<td>1.521</td>
<td>1.787</td>
</tr>
<tr>
<td>Reservation wage</td>
<td>1.599</td>
<td>1.648</td>
<td>1.610</td>
<td>1.647</td>
<td>1.582</td>
<td>1.588</td>
</tr>
<tr>
<td>Average match quality</td>
<td>1.811</td>
<td>1.855</td>
<td>1.851</td>
<td>1.896</td>
<td>1.809</td>
<td>1.812</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C. Aggregate</th>
<th>Baseline</th>
<th>FI</th>
<th>NI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate Moments</td>
<td>( a = 3 )</td>
<td>( a = 6 )</td>
<td>( a = 3 )</td>
</tr>
<tr>
<td>Hiring rate</td>
<td>0.041</td>
<td>0.021</td>
<td>0.022</td>
</tr>
<tr>
<td>Vacancies</td>
<td>0.047</td>
<td>0.025</td>
<td>0.021</td>
</tr>
<tr>
<td>Unemployment</td>
<td>0.076</td>
<td>0.043</td>
<td>0.057</td>
</tr>
<tr>
<td>Unemployment inflow rate</td>
<td>0.041</td>
<td>0.021</td>
<td>0.022</td>
</tr>
<tr>
<td>Unemployment outflow rate</td>
<td>0.509</td>
<td>0.471</td>
<td>0.366</td>
</tr>
<tr>
<td>Implied matching efficiency</td>
<td>0.633</td>
<td>0.598</td>
<td>0.583</td>
</tr>
</tbody>
</table>

Note: This table summarizes the results of the model when the total number of applications sent by unemployed workers increases from \( a = 3 \) to \( a = 6 \) under i) the baseline model with fixed cost of acquiring information (Baseline), ii) a version of the baseline model with full information (FI) where firms can observe the match qualities of their applicants at no cost, and iii) a version of the baseline model with no information (NI) where firms cannot observe the match qualities of their applicants at all.
option as 1) they do not necessarily get an offer even if they draw high match quality and 2) each application sent is now more likely to end up at a firm who has multiple applicants, raising the competition faced by the worker. All this causes the reservation match quality of non-college workers to fall in the NI model. Second, labor market tightness, \( \theta \), falls in the baseline model for non-college workers but rises in the FI and NI model. In both the FI and NI models, the expected effective job creation cost is fixed at \( \kappa_V \) since firms either get information for free or firms never pay for information when \( \kappa_I \to \infty \). Conversely, our baseline model with fixed costs of information allows for the expected effective job creation cost to vary with the average share of firms acquiring information. Because the expected effective job creation cost is higher in our baseline model as applications increase, these higher costs temper the benefit firms receive from a higher contact rate and from - conditional on hiring- on average higher quality matches. Thus, fewer vacancies are created in the baseline model when \( a \) rises while the converse is true in the FI and NI model.

Turning to our moments of interest, a key feature that stands out is that unlike our baseline model, both the FI and NI model would predict a rise in unemployment inflow rates for non-college individuals with a rise in \( a \), although the reasons for this rise are different across the two models. In the NI model, the lack of firms’ ability to identify good matches and the decline in reservation match quality due to increased congestion amongst workers actually causes the average realized match quality amongst the employed to decrease. Because, on average matches are now of lower quality than before, workers are more likely to observe a match quality shock as the arrival rate, \( \rho(x) \), is declining in \( x \). This on average higher incidence of match quality shocks, together with the fact that matches with initially low \( x \) are more likely to re-draw low match qualities below the reservation level, i.e. \( x' < \tilde{x} \) imply a higher endogenous destruction rate of jobs. Thus, unemployment inflows rise in the NI model.

Conversely, in the FI model, average match quality rises but by less than the observed increase in the baseline model. The reason for this is that the share of firms acquiring information in the FI model is unchanged across \( a = 3 \) and \( a = 6 \). As such, firms are always making offers to the highest match quality job-seeker in their applicant pool. Thus, the marginal improvement in the average match quality of employed non-college in the FI model implies that there was a smaller increase in the concentration of matches at high \( x \) values relative to the baseline model. At the same time, reservation match quality increases in the FI model, making it such that conditional on receiving a match quality shock, a larger fraction of low quality matches are more likely to separate into unemployment if they draw below the higher \( \tilde{x} \). Hence, the marginal improvement in the distribution of realized match qualities and overall reservation match quality are the reasons why the FI model display a higher unemployment inflow rate when applications, \( a \), increase.

Across all models, unemployment outflows rates for the non-college decline. This is largely
due to the decline in both average acceptance rates and expected number of offers. The decline in the former occurs precisely because workers have more options to choose from when they can send out more applications while the latter occurs because of more competition amongst workers. It is worth noting that average offers decline the most in the baseline model precisely because there was less entry (lower $\theta$) of vacancies when effective job creation costs are expected to be higher.

Focusing on our results for college workers, Panel B of Table 4 shows that reservation match quality increases in all models, although the increase is very minute - about 0.4% - in the NI model. Again, the random hiring by firms in the NI model limit the extent to which workers’ outside options can improve from their increased ability to send more applications. Labor market tightness, $\theta$, falls in all but the FI model. As aforementioned, the decline in the baseline model stems from increased effective costs of job creation while the cost of job creation remains fixed in the FI model. For the NI model, the increase in reservation match quality together with lower acceptance rates by workers cause vacancy creation to fall. In addition, unemployment is higher in the NI model, causing labor market tightness to be overall lower.

In terms of labor market flows, we see that all three models predict little change in unemployment inflow rates for college individuals. Because college workers in general draw higher match qualities, they are less subject to match quality shocks and are more likely to re-draw high qualities even if they experience such a shock. As such, the unemployment inflow rates do not vary much for this set of workers across these versions of the model. On the other hand, the unemployment outflow rates improve for college workers in the baseline and NI model as the direct effect of sending more applications $a$ outweighs the declines in offer probabilities and acceptance rates. In the FI model, firms always discern the best worker for them and make offers to the highest match quality applicant in their pool, this reduces the chance that a worker gets an offer if she draws middling-to-low match quality. In contrast, there is a non-negative proportion of firms who hire randomly in the baseline and NI model, allowing workers who draw low-to-middling match quality some chance of receiving an offer. Thus, expected offers do not decline in these models relative to the FI model and thus, unemployment outflows improve for college individuals as applications rise.

Finally, Panel C of Table 4 shows the implied aggregate moments from each of the models. Unlike the baseline model and what is observed in the data, both the FI and NI model suggest that hiring rates would increase as applications sent, $a$, increases. Further, both the FI and NI model would suggest an increase in the overall unemployment rate as aggregate inflow rates into unemployment increase when non-college inflow rates increase and aggregate outflow rates decline. In contrast, the baseline model shows a decline in the aggregate unemployment rate as observed in the data precisely because unemployment inflow rates for non-college underwent a stark decline.
Thus far, these experiments suggest that the change in application behavior over time and its impact on the firms’ incentives to acquire information are important for understanding the differential change in unemployment inflow rates. Ignoring changes in firms’ investment in information as in the FI and NI model would not allow our model to explain the stark decline in unemployment inflow rates for non-college individuals observed in the data and would instead predict counterfactual unemployment and hiring rates.

6 Conclusion

Over the past four decades, the unemployment inflow rate in the US has trended downwards, while the unemployment outflow rate has remained largely unchanged. In this paper, we document that the trend in the unemployment inflow rate largely mimics the decline in non-college workers’ unemployment inflow rates. We also document that these patterns in labor market flows coincided with a substantial rise in the number of job applications sent by the unemployed. We develop a model of multiple applications and costly information to reconcile these trends. Taking our model to the data, we find that the doubling in the number of worker applications generates a significant decline in the inflow rates of non-college workers but only a minor change in the inflow rates of college workers, consistent with the observed patterns since 1980s. A key factor behind the stark decline in non-college unemployment inflow rates stems from improvements in the realized distribution of match qualities. Because college workers draw on-average higher match qualities to begin with, the improvement in their realized match qualities was more minute, contributing to the lack of change in inflow rates. The model also correctly predicts the small observed changes on the unemployment outflow rates both for college and non-college workers. Because an increase in the number of job applications has opposing effects on workers’ acceptance probabilities and can also reduce a single application’s offer probability, unemployment outflows in our model observed relatively small changes.

Finally, we show that information acquisition and its interaction with the rise in the number of applications are critical in generating these observed empirical patterns. We considered two alternative environments where firms either had faced zero cost of information or infinite cost of information. Both alternative models fail to generate a decline in inflow rates into unemployment and have counterfactual predictions for the unemployment rate. As a result, we conclude that the endogenous response of firms’ information acquisition decisions to changes in the number of job applications is key to generating the observed long-run patterns in the labor market flows.
References


A Firm’s offer and information acquisition decision

A.1 Proof for Lemma 1
Consider a firm who has acquired information and who has \( j \) applicants. The firm’s value conditional on making an offer to a particular applicant with match quality \( x \) is given by \( V^F(x)\Gamma(x) \). 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 \( V^F(y)\Gamma(y) > V^F(x)\Gamma(x) \).

Without loss of generality, assume that surplus, \( S(x) \), is increasing in match quality, \( x \). Under Nash-bargaining, \( V^F(x) = \eta S(x) \) and \( V^W(x) = (1 - \eta)S(x) + U \). Thus, both \( V^F(x) \) and \( V^W(x) - U \) are also increasing in \( x \). Since the worker’s gain to matching, \( V^W(x) - U \), is increasing in \( x \), the worker is always strictly better off accepting the offer that brings her the highest match quality, implying that \( \frac{d\Gamma(x)}{dx} > 0 \). Since both \( \Gamma(x) \) and \( V^F(x)\Gamma(x) \) are increasing in \( x \), it is straightforward to show that \( V^F(x)\Gamma(x) > V^F(y)\Gamma(y) \) for \( x > y \), and as such the firm would never make an offer to a lower-ranked candidate.

A.2 Proof for Proposition 1
Consider a firm with \( j \) applicants. Suppose the firm chose to acquire information, allowing it to rank its applicants by match quality. The probability that within a sample of \( j \) applicants, the largest match quality observed is less than or equal to \( x \) is given by \( \prod(\Pi(x))^j \), where \( \prod(\Pi(x))^j \) represents the distribution of the maximum order statistic. Denote \( F_j(x) = \prod(\Pi(x))^j \). It is then clear that for a given \( x \), \( \prod(\Pi(x))^j \) is weakly declining as \( j \) increases, implying that:

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

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

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

Thus the benefit of acquiring information is strictly increasing in \( j \).

Finally, given constant fixed cost of acquiring information \( \kappa_I \) and since the benefit of acquiring information when the firm has only one applicant is equal to the value of not acquiring...
information, i.e.

\[ V^I(1) = \int_{x}^{x} \Gamma(x) V^F(x) d\Pi(x) = V^{NI} \]

It is straightforward to then show that given finite \( \kappa^I \) and a \( V^I(j) \) that is increasing in \( j \), 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 chose to acquire information no matter the number of applications received. We want to ask if any single firm then has a profitable deviation to not acquire information. We first note that when all firms acquire information, the probability of no offer for an application that yields match quality \( y > x \) becomes:

\[
Pr(\text{no offer}|y > x) = \int_{x}^{\infty} \sum_{\ell=1}^{\infty} q(\ell) \left( 1 - [\Pi(y)]^{\ell-1} \right) \frac{\pi(y)}{1 - \Pi(x)} dy
\]

and the worker’s probability of accepting conditional on having an offer of match quality \( x \) continues to be characterized by equation 5. Since for a firm with a single applicant, \( V^I(1) = V^{NI} \), a single firm who has received only application always has a profitable deviation to not acquire information when \( \kappa^I > 0 \) and all other firms are acquiring information. Hence, an equilibrium where all firms acquire information cannot exist since firms with \( j = 1 \) applicants are always better off acquiring no information.

Can a pure strategy equilibrium where no firms acquire information exist? Suppose instead that all firms chose not to acquire information. In this case, equation 6 becomes:

\[
Pr(\text{no offer}|y > x) = \sum_{\ell=1}^{\infty} q(\ell) \left( 1 - \frac{1}{\ell} \right)
\]

Since no firms acquire information, all firms randomly make an offer to one of their applicants. Hence with probability \( 1 - 1/\ell \), a worker at a firm with \( \ell \) applicants fails to get an offer. So long as surplus is increasing in \( x \), implying that workers’ gain to matching is increasing in \( x \), the worker’s conditional acceptance probability of accepting an offer of match quality \( x \) continues to be characterized by 5. Since the worker always accepts the best match quality offer she has, a firm who is able to identify and make an offer to his highest match quality applicant lowers his probability of being rejected. As shown earlier, the likelihood of one of the firm’s applicants having high match quality is increasing in applicant pool size \( j \). The fact that the expected benefit of information is strictly increasing in \( j \), together with finite information cost, \( \kappa^I \), implies that a single firm with a 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 finite $\kappa_t$.

B Data

In this data appendix, we provide more details on CPS, EOPP, and SCE and explain our calculations from these datasets.

B.1 CPS

In this section, we first provide details on the measurement of unemployment inflow and outflow rates over time using CPS. In doing so, we follow Elsby et al. (2009), Shimer (2012), and Crump et al. (2019) among many others.

The CPS provides monthly data on the number employed, the number unemployed, and the number unemployed with at most five weeks of unemployment duration (which we use as the “short-term unemployed”).

Let $U_t$, $U^S_t$, 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, the we can define the change in the number of unemployed individuals between time $t$ and $t+1$ as

$$
\frac{dU}{dt} = -f_t U_t + s_t (L_t - U_t).
$$

Moreover, as noted by Shimer (2012), we can write

$$
U_{t+1} = U^S_{t+1} + (1 - F_t) U_t
$$

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

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

Assuming a Poisson process for arrival rate $f_t \equiv -\log (1 - F_t)$, we obtain the unemployment

\footnote{Importantly, the redesign of the CPS in 1994 caused a discontinuity in the time series for the number of short-term unemployed because of a change in the way unemployment duration was recorded, as discussed by Polivka and Miller (1998) and Shimer and Abraham (2002). We correct this by multiplying the standard series for short-term unemployment by a constant of 1.16 in every time period after 1994, as in Elsby et al. (2010). Shimer (2012) finds similar results with alternative ways of correcting the data.}
outflow rate as \( f_t = -\log \left( \frac{U_{t+1} - U_t}{U_t} \right) \).

Next, we can solve the differential equation (17) forward as in Shimer (2012) and obtain

\[
U_{t+1} = \frac{(1 - e^{-(s_t + f_t)}) s_t}{s_t + f_t} L_t + e^{-(s_t + f_t)} U_t.
\]

Finally, we repeat these calculations separately for individuals without a four year college degree and individuals with at least a four year college degree, using individual level educational attainment monthly data from CPS.

B.2 EOPP

The goal of EOPP was to help participants to find a job in the private sector during an intensive job search assistance program. Individuals had to meet income eligibility requirements to be able to participate into this program. Specifically, individuals had to be unemployed and either below a certain household income level. The survey was created to analyze the effects of the program on the labor market outcomes of the participants. As a result, the sample design of the survey incorporated an oversample of low-income families, this did not greatly weakened moments pertaining to the aggregate economy.

The survey incorporates both household level and individual level variables, which can be linked by household and individual identifiers. Individual level dataset, which is the dataset we mostly use, contains main record, training, job, UI, looking for work, disability, and activity spell modules. These modules provide data on demographics of the individual, detailed information on each job held (including earnings and regular hours), data on the individual’s unemployment spell, its duration, job search activities and methods during each unemployment spell, UI receipt, and reservation wages.

In our study, we analyze a sample of unemployed individuals of ages between 25-65 with at least one job application during the unemployment spell. This gives us 5410 unique individual-spell observation.\(^{27}\) For each of these individual-spell observation, we first calculate the monthly unemployment duration.\(^{28}\) Using data on the number of job applications for each of job search type method (e.g., private employment agencies, newspapers, labor unions, friends and relatives etc), we obtain the total number of job applications for each spell. Then, we divide the total number of job application in a spell to the duration of that spell to obtain the monthly number of job application for each spell. Similarly, using information on the number of job offers received through each job search type method, we calculate the total number of job offers received for

\(^{27}\)There are 78 observations in which the recorded beginning date of an unemployment spell happens to appear after the recorded end date of the same unemployment spell. We drop these observations from our sample.

\(^{28}\)To do so, we use variables named STLOOK16, ENDLOOK16, STLOOK26, and ENDLOOK26, which provide beginning and end date (in mm/dd/yy format) of the first and second looking-for-work spell, respectively.
each spell and the monthly number of job offers received for each spell. Next, the data also provides an indicator variable on whether the individual accepted any of the job offers received. Using this variable, we also calculate the offer acceptance rate as the ratio of this indicator variable to the total number of job offer received, conditional on having at least one offer. Last, the survey also asked the lowest hourly wage rate that the individual would accept during the unemployment spell. We use this information to infer the reservation wage of the individual. We then report the mean and the median values of these moments both for all individuals in our sample and also across education-groups.\textsuperscript{29}

\subsection*{B.3 SCE}

The SCE Labor Market Survey was developed by the Federal Reserve Bank of New York.\textsuperscript{30} The survey provides information on on demographics of the respondent, data on the job for employed individuals (earnings, hours, industry, employer size, employer-provided benefits, etc), job search activities, and reservation wages.

We use the annual survey between 2013-2017. Because of the small sample size relative to EOPP data, we pool the observations across these years when analyzing the SCE sample. In this dataset, similar to our sample in EOPP, we study a sample of unemployed individuals of ages between 25-65 with at least one job application during the unemployment spell. Different from the EOPP, SCE survey already provides the total number of job applications and the total number job offers received during the last 4 weeks of job search. We calculate the offer acceptance rate same as in the EOPP dataset. Moreover, the SCE dataset also has a question asking the lowest wage that the individual would accept, which we use to infer the reservation wage of the individual. Finally, we separately report the mean and the median values of these moments for all individuals and across education-groups.\textsuperscript{31}

\begin{itemize}
\item \textsuperscript{29}APLYJOBS and OFERJOBS provide the number of job applications and job offers received through various job search type methods respectively. The indicator variable on offer acceptance is given by variable ACPTJOBS. The variable WAGEACPT provides reservation wage information. Finally, DEGREE and GRADE provide information on the highest degree received and the highest grade of school completed respectively, which we use to classify individuals into education-groups.
\item \textsuperscript{30}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 license terms posted there. FRBNY disclaims any responsibility or legal liability for this analysis and interpretation of Survey of Consumer Expectations data.
\item \textsuperscript{31}Variables JS14 and JS19 give the total number of job applications and the total number of job offers received during the last 4 weeks respectively. The variable JS23 provides an indicator variable on whether the individual accepted or will accept the job offer. The variable RW2h_rc provides the reservation wage information. Finally, variables Q36 and \_EDU\_CAT (categorical) provide information on the highest grade of school completed.
\end{itemize}