Endogenous Job Offer Rate, Search Effort & Educational Attainment

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Abstract

This paper studies how job search effort shapes the arrival rate of job offers. I develop a search-and-matching model in which the arrival rate of job offers depends endogenously on workers' search effort. Using data from the Survey of Consumer Expenditures, I document a steep increase in job contact rates with search effort. Across education groups, the median contact rate of job offers increases tenfold under endogenous search compared to a baseline model with exogenous arrival rates. The estimates reveal significant heterogeneity in search behavior by skill group. Workers with only a high school diploma devote more time to job search relative to workers with some college or a college degree, despite similar returns to additional search hours. For workers who do not search, the estimates for job arrival rates closely match the exogenous contact rate in classical labor search models. These results highlight the importance of incorporating endogenous search effort when evaluating unemployment dynamics and designing policies to support job seekers.

1. Introduction

The arrival rate of job offers is a key parameter in canonical labor search models. Traditionally, standard job search models treat this arrival rate as exogenous, as seen in foundational works such as Mortensen (1977) and Burdett-Mortensen (1998). However, job search is inherently interactive — workers shape their job prospects through their own effort. This paper reframes the arrival rate by making it dependent on individual search intensity, with the goal of obtaining a structural estimate for the arrival rate of job offers, λ, with endogenous search intensity.

This paper asks: how does endogenous search effort affect the rate of receiving job offers? Using data from the Survey of Consumer Expenditures, I find that job offer arrival rates increase substantially with active search. Across all education levels, endogenous search increases the median contact rate of job offers tenfold compared to baseline models with exogenous arrival rates. This approach reveals distinct search patterns across skill levels: individuals with only a high school education tend to spend more time searching than their college-educated counterparts, even when the returns to search are similar. For those who do not engage in active search, the model yields estimates consistent with contact rates found in standard models with exogenous arrival rates.

This paper contributes new empirical insights into the relationship between job search intensity and offer rates, highlighting how search patterns and labor market dynamics differ by skill level. My empirical estimates complement the theoretical literature on search models and provide insights by skill level, proxied by educational attainment. Additionally, I develop an extended model that incorporates measurement error in the log-likelihood function, which is applicable to a wide-range of empirical settings. The findings offer both theoretical and practical value, underscoring the role of search intensity in shaping labor outcomes across diverse skill groups.

1.1. Contribution to Literature

The theoretical literature on job search begins from Mortensen (1977) and Burdett-Mortensen (1998), who model the contact rate of job offers, λ, as exogenous. More recent papers incorporate the choice of search effort in the model, which endogenously determines the arrival rate. Notably, Pissarides (2000) and Christensen, Lentz, Mortensen and Werwatz (2005) both describe theoretical models with endogenous search effort, which have inspired empirical research of job search behavior.

There are many papers that study the empirics of job search behavior. Christensen et. al. (2005) find a negative relationship between wage and search effort supported by Danish labor market data. Aguiar, Hurst, and Karabourbanis (2013) study the life-cycle properties of job search, and Mukoyama, Patterson, and Sahin (2018) look at job search behavior over the business cycle. A growing literature has begun investigating job search behavior from online job search applications (for example: Hershbein and Kahn, 2018; Faberman and Kudlyak, 2019). I contribute to this literature by adding empirical estimates of job search behavior from new, high quality job search data.

Empirical Literature

The lack of reliable and high-quality data has been an important challenge for the empirical estimation of the job-offer rate, λ.

Early papers estimating endogenous search use CPS (Current Population Survey) data. While the CPS has a large sample of employed and non-employed individuals, it lacks reliable data on search intensity. Shimer (2004) attempts to overcome this limitation by proxying search intensity with the number of different job search methods used by unemployed workers. Table 18 in the appendix lists active and passive job search methods as defined by the BLS for the CPS. Doing so, Shimer finds that job search intensity is acyclical over the business cycle.

However, Shimer's results have an important limitation: it is difficult to believe that more search methods necessarily imply a more intensive job search. An unemployed worker may only be using a couple of job search methods, but focusing a lot of their time on searching with them. For instance, Shimer's method would classify an unemployed worker who has only been sending resumes and having job interviews (two active job search methods) as searching less intensely than a worker who asks family and friends for job openings, sends resumes, and uses a private employment agency, a public employment agency and a university employment center (five active job search methods). This classification would hold true even if the first unemployed worker was sending out 40 resumes a week and had 5 job interviews, and the second unemployed worker had sent out 1 resume, asked two friends for job openings and contacted one employment agency or job board of each type. Thus the number of job search methods is not necessarily a strong indicator of job search intensity and more accurate measures of job search intensity are needed.

The beginning of the American Time Use Survey (ATUS) in 2004 introduced more accurate data on job search intensity for economic research. In the ATUS, respondents complete a 24-hour time diary detailing their activities from the day before and note how much time they spent doing each activity. The ATUS sample draws from households that have completed their 8th and final month in the CPS survey, and interviews one person per household 2 to 5 months after the final CPS interview.

Krueger and Mueller (2010) use job search activities reported in the ATUS time-diary data to study job search intensity. Job search activities include time spent contacting a potential employer, calling or visiting an employment agency, reading and replying to job advertisements, job interviewing, etc. They use both the participation as well as the duration of job search activities in the ATUS time diary to determine how Unemployment Insurance (UI) benefits affect the job search of unemployed workers. They find that job search is inversely related to UI benefit levels for unemployed searchers and search intensity increases before UI benefit exhaustion. For searchers who are ineligible for UI benefits, job search activity remains fairly constant over unemployment duration. DeLoach and Kurt (2013) is another paper that makes use of ATUS time-diary data to endogenize job search. The authors focus on discouraged workers, and find that their job search is procyclical but offset by increased search from wealth effects.

Nonetheless, despite the improved quality of search data collected in the ATUS, its survey design poorly captures job search behavior. In particular, the single day 24-hour diary is ill-suited to capture intermittent search behavior. Job search does not tend to be a routine occurrence which is done for the same amount of time each day. Therefore, the day of the ATUS diary can have a strong influence on the data collection, such as whether it is a weekend or a day where less job search than average took place. Furthermore, the ATUS only collects data on primary activities, and as the time diary is self-reported, many reported times are rounded. Strikingly, for unemployed workers – who are by definition actively looking for work – ATUS data from 2013-2017 estimates that only 16.5% of unemployed workers looked for work the previous day. Hence, using job search data from the ATUS greatly underestimates search time.

More recently, Faberman, Mueller, Sahin and Topa (2021) collect highly detailed data on job search behavior for employed and non-employed workers in a supplement to the Survey of Consumer Expectations (SCE), which they use to estimate a macro-labor model of job search. They find that non-employed individuals search more than employed individuals, but unsolicited job offers allow the employed to receive more job offers per unit of search.

I use this new and highly-detailed SCE dataset made public by Faberman et. al. (2021) to explore the effect of job search activity on the job arrival rate λ with much greater accuracy than was previously possible. This data allows me to contribute to the existing literature on job search, drawing on the theoretical modeling framework and finding new estimates for the job arrival rate.

This paper proceeds as follows: In section 2, I set up the model with exogenous and endogenous arrival rates of job offers. In section 3, I describe the new, detailed data set used in this paper as well as key descriptive statistics and identification, followed by the methodology in section 4. In section 5, I present the results of the model with exogenous and endogenous job offer arrival rates, including results by worker education level. I propose an extension considering measurement errors to the estimated model in section 6, and conclude in section 7.

2. Model

This paper departs from the canonical labor search model a la Burdett-Mortensen (1998), focusing on a model with no on-the-job-search. The model endogenizes the contact rate of job offers based on workers' endogenous job search effort.

2.1. Standard model - Exogenous Contact Rate λ

In this section, I describe the canonical job search model which serves as a starting point for my analysis. Employed and unemployed individuals face the value functions $W(w)$ and U respectively that satisfy the standard Bellman equations below. The notation uses wage w, wage distribution $F(w)$, discount rate ρ, flow value of unemployment b, reservation wage R, exogenous job separation rate η and exogenous job arrival rate λ.

Bellman of Employed:

$$W(w) = V_e(w) = \frac{w + \eta \cdot U}{\rho + \eta}$$

Bellman of Unemployed:

$$\begin{aligned}\rho \cdot U =& b + \lambda \int_R^{\overline{w}} [W(y) - U]\, dF(y) \\ =& b + \frac{\lambda}{\rho + \eta} \int_R^{\overline{w}} [w - \rho U]\, dF(w)\end{aligned}$$

At the reservation wage, $R = \rho U \implies$

$$R = b + \frac{\lambda}{\rho + \eta} \int_R^{\overline{w}} [w - \rho U]\, dF(w)$$

2.2. Endogenous Contact Rate λ

The model departs from a job search model as in Burdett-Mortensen with no on-the-job search. The novel element of the model is that job offers arrive endogenously. The arrival rate of job offers now depends on the level of search effort s, and unemployed workers can potentially increase their job finding rate by applying greater job search effort.

The arrival rate of job offers depends on the level of search s with the following functional form:

$$\lambda(s) = \gamma + \beta s \tag{1}$$

where

- γ is a constant representing the arrival rate of unsolicited job offers (offers received without search effort)
- β is a constant representing the rate of receiving an offer per unit of search effort: *search efficiency*
- and s is the intensity of search for job seekers

Without on-the-job search, the contact rate λ is determined by the job search behavior of the unemployed only. This generalized specification of $\lambda(s)$ is also used in Faberman et. al. (2017), and applies to a wide range of labor search models including Mortensen (1977) and detailed in Pissarides (2000).

I further categorize individuals into three groups i by education level: high school, some college and college. Within each education group, workers are assumed to be homogeneous. Therefore for each education group i, the arrival rate of job offers becomes:

$$\lambda_i(s) = \gamma_i + \beta_i s \tag{2}$$

Search Costs

Individuals can exert search effort s to potentially increase their job offer arrival rate $\lambda(s)$. However, search effort is costly. The search cost function $c(s)$ describes this relationship, and is increasing and convex in s with the following properties:

- $c' \geq 0$
- $c" \geq 0$
- $c(0) = 0$
- $c'(0) = 0$

A simple example for a search cost function that satisfies the above properties is $c(s) = \frac{1}{2}cs^2$.

2.2.1. Bellman Equations

With no on-the-job-search, the Bellman equations are very similar to those specified in the standard model with exogenous λ. Unlike before, now the Bellman faced by unemployed individuals depends on their level of search effort s.

Bellman of Employed:

$$W(w) = V_e(w) = \frac{w + \eta \cdot U}{\rho + \eta} \tag{2.1}$$

Bellman of Unemployed:

$$\rho \cdot U = \max_{\overline{s} \geq s \geq 0, R} \left\{ b - c(s) + \lambda(s) \int_R^{\overline{w}} [W(y) - U] \, dF(y) \right\} \tag{2.2}$$

$$= \max_{\overline{s} \geq s \geq 0, R} \left\{ b - c(s) + \frac{\lambda(s)}{\rho + \eta} \int_R^{\overline{w}} [w - \rho U] \, dF(w) \right\} \tag{2.3}$$

By definition of the reservation wage R, an individual must be indifferent between working at the reservation wage $w = R$ and the value of being unemployed. i.e. $U = W(R)$

Rearranging this into the Bellman of the employed gives:

$$\begin{aligned} W(R) &= \frac{R + \eta \cdot U}{\rho + \eta} \\ U &= \frac{R + \eta \cdot U}{\rho + \eta} \\ \big(\rho + \eta\big)U &= R + \eta U \\ \rho U &= R \end{aligned}$$

Therefore $\rho U = R$. Plugging this into the expression for the Bellman of the unemployed:

Bellman of Unemployed:

$$R = \max_{\bar{s} \geq s \geq 0} \left\{ b - c(s) + \frac{\lambda(s)}{\rho + \eta} \int_{R}^{\overline{w}} [w - \rho U] \, dF(w) \right\} \tag{2.4}$$

3. Data

3.1. Data Description

The dataset I use is a job search supplement to the Survey of Consumer Expectations (SCE), collected from 2013 to 2017 by the Federal Reserve Bank of New York. The microdata can be accessed publicly under SCE Job Search Survey at `https://www.newyorkfed.org/microeconomics/databank.html` .

The SCE is a nationally representative survey in the US conducted from 2013 onwards. The survey focuses on expectations about the economy for the labor market, inflation and household finance, and tracks demographic variables such as age, income, education, geographic region and employment history. The survey is conducted online, with a rotating panel of approximately 1300 heads of households. Respondents participate in the panel for one to twelve months. Each month, an approximately equal number of households rotate in and out of the sample. For more details, see the NY Fed website at `https://www.newyorkfed.org/microeconomics/sce#/` .

The SCE Job Search Survey supplements the SCE, and asks a multitude of questions on employment status, job search behavior, and job search outcomes. The sample includes approximately 1300 individuals who previously participated in the SCE and are paid to complete the survey online. Similarly to the SCE, respondents are nationally representative and in the sample from one to twelve months, with a roughly equal share of respondents rotating in and out each month. The survey defines labor force status analogously to the CPS. In particular, the unemployed are defined as per the Bureau of Labor Statistics definition: someone who "does not have a job, has actively looked for work in the prior four weeks, and is currently available for work", as well as those on temporary layoff.

3.2. Data Processing

As mentioned in the section above, I use data from the SCE and SCE Job Search Supplement from 2013-2017 in my analysis.

To begin, I merge the unique user IDs interviewed in the Job Search Supplement with the larger SCE data set in order to have data on job search behavior and demographic information. The larger SCE dataset includes the data from 2013-2019 and 104 125 observations, with 14 830 unique user IDs. A unique user has a new observation every month in which they are interviewed, explaining the multiple observations per user. The SCE Job Search Supplement has 5917 unique observations from 2013 to 2017.

I am able to match almost all (99.9%) of the interviewed individuals in the Job Search supplement to their demographic characteristics. In merging, it is implicitly assumed that the demographic characteristics remain the same for the up to twelve months individuals are interviewed. This is true in nearly all cases. There are only a minority of individuals who move during the course of the survey. From this minority, many of the moves are relatively small, between commuting zones while staying in the same state and geographic region. For individuals who move, I assign their location as that reported in their initial interview. In my preferred specification, I run the analysis on non-movers only, who are the majority of the dataset, to ensure there is no potential confounding effect between job search behavior and moving. Since the majority of moves are at the commuting zone level, it is unlikely that job search behavior would be vastly different than their counterparts who do not move. Moving across the country during the survey is very rare, and the reason for the move, such as family or personal reasons, could potentially affect job search behavior. In any case, I find that the results are very similar for both the subset of non-movers and for the dataset with all matched individuals. The remainder of this paper will focus on the results of my preferred no mover specification.

I retain only employed and unemployed individuals in the dataset, removing individuals who are not in the labor force. Following the CPS definition of unemployment, an unemployed individual is one who is not working, but on layoff awaiting recall, or who is not working but actively looking for a job (in the last 4 weeks) and available to work. Similarly, the CPS defines an individual as employed if they are currently working, or not working because of a temporary absence from their job (i.e vacation, illness, etc.).

Three key variables I focus on are unemployment duration in months (L8), as well as reported wages (JH9) and reservation wages. One key benefit of the SCE Job Search survey data is that individuals' reservation wage is asked directly and for all labor force statuses. The reservation wage is elicited by the question: "Suppose someone offered you a job today. What is the lowest wage or salary you would accept (before taxes and deductions) for the type of work you are looking for?" as well as follow up questions including how many hours of work would be preferred at that reservation wage. The reservation wage being asked directly and to employed and non-employed individuals is preferable to estimating the reservation wage as the minimum accepted (windsorized) wage by employed workers, and ensures the wage preferences of unemployed individuals are considered.

I windsorize the dataset to remove extreme values of unemployment durations and wages. I find there is little difference between windsorizing 1% and 2.5% for unemployment durations and wages, and therefore windsorize at the 1% level. For reservation wages at the bottom end of the wage distribution, I windsorize below $7.25 per hour, which is in line with windsorizing the bottom 1% of reservation wages and is consistent with the federal minimum wage from 2013 onwards.

The wage information in dataset is reported as either an hourly wage, weekly wage, or annual wage. I impute the missing wage information from the reported wage and the usual hours worked per week. If weekly wages are reported in the data, but there is no annual wage information, I assume that individuals work 48 weeks per year, which is the average number of work weeks per year for a US worker. If weekly wages are reported in the data but there is no hourly wage information, then I divide the weekly wage by the usual hours worked per week (L10). I check that there are no dividing by zero errors in this process.

3.3. Descriptive Statistics

After cleaning the data, I have a sample size of 3264 unique individuals. The table below reports the sample size of my dataset by educational attainment. The majority of individuals in my sample have some college education or have completed college. There is a minority of individuals who have only a high school diploma.

Table 1: Sample Size by Education Level

	High School	Some College	College	All Education Levels
Number of Observations (N)	299	1001	1964	3264

Table 2 below also shows the number of observations of unemployed and employed workers by education group, which are used for the maximum likelihood estimation. I classify individual observations as unemployed if they have positive unemployment duration (L8), and individuals as employed if they have positive observations for wages. Similarly to the total number of observations, college educated individuals make up the largest proportion of the sample, about 50% of unemployed and 65% of the employed samples respectively. Individuals with some college are fairly well represented in both the unemployed and employed samples, though less prevalent than those who completed college. High-school educated individuals again find themselves as the smallest proportion of the unemployed and employed samples with less than 15% in each category[1]. Overall, the large majority of individuals sampled are presently employed.

Table 2: Number of Observations by Education Category

	High School	Some College	College	All Education
Number of Unemployed (N_u)	19	65	92	176
Number of Employed (N_e)	156	632	$1,488$	$2,276$
Number of Observations (N)	175	697	$1,580$	$2,452$

Descriptive statistics for the key variables in the overall sample with all education groups are shown in table 3. I report the summary statistics by education group in the appendix (tables 20, 21, and 22).

The measure of job search intensity used in this paper is number of hours actively searching for a job in the past seven days, captured in the dataset by the JS7 variable. Ongoing unemployment durations in months are denoted by the variable L8. I also summarize the hourly reservation wage, as well as the hourly wages for currently employed individuals.

Most individuals search little for jobs. The median search time for all individuals is 3 hours per week, with 25% searching one hour or less per week. Individuals who only have a high school education have a higher median search time than other education groups at 3.5 hours a week,

[1]There are some discrepancies between tables 1 and 2 because some employed individuals do not have a reported wage and/or are missing hours worked. I present both table 1 which is used for summary statistic observations and table 2 which is the sample used for maximum likelihood estimation.

compared to the median of 3 hours of job search for those with some college education and only 2 hours a week of job search for college graduates. The standard deviations of search effort are also the highest for high school graduates and lowest for college graduates. Though many unemployed workers search little, the mean search time is driven up by few individuals who search intensively, at more than seven hours per week.

Table 3: Summary Statistics - All Education Levels

	Min	1st Q	Median	Mean	3rd Q	Max	SD	N
Hours of Job Search, Last 7 Days JS7	0	1	3	5.727	6	80	8.50	774
Hourly Reservation Wage	7.250	12.019	18.229	24.220	28.646	538.462	21.20	2,938
Hourly Wage JH9	7.292	13	18.939	25.041	30	179.167	19.38	2,276
Unemployment Duration in months L8	0	2	10.500	17.409	24	96	20.65	176

The data shows that more educated individuals earn higher mean and median wages. The highest average earners are college graduates who make nearly \$30 per hour (with a median hourly wage of \$22.50). Workers who attended some college make \$18 per hour on average, while workers with only a high school diploma earn slightly less at \$15 per hour. Not only is education level correlated with wages, but the variance of wages is also higher for workers with more formal education. In annual terms, the standard deviation of wages for high school and some college workers is approximately \$21,000 and \$25,000, whilst college graduates have a much larger standard deviation close to \$45,000 per year. Since the sample is largely composed of individuals who have attended some college or who have completed college, the median and mean wages for all education groups lie in between, at \$19 and \$25 per hour respectively.

Reservation wages are slightly lower than accepted hourly wages across the distribution, which is consistent with the theoretical model. The minimum reservation wage in the sample is \$7.25 per hour and the median is \$18.23. As expected, individuals who are more educated demand a higher reservation wage throughout the distribution. The median reservation wage of a high school graduate is $12.89 per hour, whilst individuals with some college have a median reservation wage of $15 per hour. The median reservation wage jumps to $21.50 for college educated individuals, implying the wage distribution for college graduates is higher.

Separated by education level, I find the minimum hourly reservation wages are weakly increasing in education level (see table below). This is in line with the economic intuition that workers with higher human capital are better compensated. I round the reservation wage for high school workers up to the 2013 federal minimum wage of $7.25 per hour.

Table 4: Hourly Reservation Wages by Education Level

	High School	Some College	College	All Education Levels
Reservation Wage	7.25	7.50	7.50	7.25

Finally, unemployment spells are fairly persistent in the dataset, and last nearly a year (10.5 months) for the median unemployed worker. There is a long right tail of ongoing unemployment durations, with the 75th percentile of unemployed workers remaining without work for two years and more. High school educated individuals have the highest median unemployment duration of one year and college graduates have the shortest at 9 months. This suggests that many college workers find new jobs more quickly than their counterparts with less education. However, college workers who do not quickly join a new job find themselves unemployed for much longer than their high school educated peers. Additionally, more educated workers face higher variance in unemployment lengths, which implies they may have more difficulty finding a suitable match for their skillset.

3.4. Identification

For this paper, I focus on explaining the differences in search and job arrival rates between education groups.

Concentrating on differences between education groups is useful because of the nature of the data. The cross-sectional SCE data tracks ongoing unemployment spells, but does not follow individuals from unemployment into employment. Therefore similarly to CPS data, the ongoing unemployment spells are truncated, and the full duration of unemployment and employment spells, as well as the future wages of currently unemployed individuals, are unknown and do not allow me to identify the differences in job search within education group. If job arrivals do not take place according to an exponential distribution as in the standard labor search models, including if the coefficient beta of search intensity is non-zero, the distribution of unemployment spells would not be the same as the population distribution. Furthermore, since the wage data comes from currently employed individuals, I cannot fully identify the wage distribution conditional on search effort. Different levels of search effort within an education group correspond to different reservation wages $w^*(s)$. The procedure of taking the minimum wage as the reservation wage w^* is therefore problematic, because I can only consistently estimate the reservation wage w^* of the lowest search group, and cannot estimate it for groups which exert higher search effort. For these reasons, I assume that within an educational group search effort is the same, and I concentrate on the differences of job arrival rates across different educational groups.

The focus on search time differences between educational groups is justified in the data. I decompose the variance of job search times between education groups using an ANOVA model. I run the analysis of variance model to determine whether job search time in the last seven days (JS7) is significantly different by education category. The ANOVA results are presented in table 5. I find that the search time is significantly different between education levels at the 5% level of significance, with a p-value of 0.0182. Therefore, different education attainment is important to explain differences in search effort by job seekers.

Table 5: Analysis of Variance Table (ANOVA), Response: JS7

Response: Number of Hours Searching for Job in Last 7 days, JS7 by Education Category

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Education Category	2	578.25	289.12	4.03	0.0182 **
Residuals	771	55319.23	71.75		
Significance Codes			*** 0.01	** 0.05	* 0.10

I also run a Kruskal-Wallis rank sum test of search times by education category, which is a non-parametric one-way analysis of variance test for more than two groups. This is a good way to corroborate the ANOVA results above as the Kruskal-Wallis test does not assume a normal distribution for the data. The results of test find a p-value of 0.02279. Therefore, I can reject the null hypothesis and confirm that there are significant differences in search times between education groups. Additionally, I conduct the Kruskal-Wallis rank sum test across education group conditional on positive search time (JS7 $>$ 0). The resulting p-value is even smaller (0.00957), and I can reject the null hypothesis that the mean ranks of search time by education group are the same at the 1% significance level. Hence, I conclude that the job search time is significantly different by education level.

Moreover, I verify that the analysis of variance results aren't due to outlier search values. To do so, I group the number of hours spent searching for a job in the past seven days into several categories. The table below shows an example of such a grouping into no search (0 hours), low search (1 to 5 hours), and high search (6 or more hours) in the past seven days. I use Pearson's Chi-squared test to determine whether educational attainment and job search effort groups are independent. An ANOVA approach is not appropriate in this case because there are now two categorical variables. For the grouping below, I obtain a p-value equal to 0.0165, and can conclude at the 2% confidence level that education and search effort groups are not independent. Therefore educational attainment and job search effort are significantly related.

Table 6: Grouping of Job Search Intensity (Hours in the Last 7 Days, JS7) by Education Level

JS7_group	High School	Some College	College	All Educ
0	4	27	52	83
1-5	39	125	313	477
6+	21	80	113	214

I try many other reasonable groupings of search time, including low and high search levels (0-5 hours, and 6 plus hours in the last seven days); low, medium and high search times (for ex: 0-1 hours, 2-6 hours, 7 + hours); and zero, low, medium and high search times. The majority of these specifications find search time and education level are dependent at the 5% significance level, and virtually all reject independence at the 10% significance level. These results support significant differences in search time by education group.

Therefore there are significant differences in search time between education groups.

4. Empirical Methodology

To take the model to data, I translate the theoretical model to a standard log likelihood function, as seen with CPS style data with ongoing unemployment spells in months for individual i, $\tilde{t_u}(i)$ and wages $w(i)$ for employed individuals. In the equations below, h_u denotes the hazard rate out of unemployment, f_u is the population density of unemployment spells, $F(w)$ and $f(w)$ the cdf and pdf of the wage distribution, and S_u, S_e the sample size of unemployed and employed individuals respectively.

Log Likelihood

The standard likelihood function for CPS data is with reservation wage $R = w^*$ is:

$$L = \prod_{i \in S_u} \left[f_u(\tilde{t}_u(i)) \times P(U) \right] \times \prod_{i \in S_e} \left[\frac{f(w(i))}{1 - F(w*)} \times P(E) \right]$$

where

$$P(U) = \frac{\eta}{h_u + \eta} \quad \text{and} \quad P(E) = \frac{h_u}{h_u + \eta}$$

Then the log likelihood function with reservation wage $R = w^*$, N_u unemployed individuals and N_e employed individuals ($N = N_u + N_e$) can be clearly written as:

$$\log L = N \log \lambda + N_u \log \tilde{F}(w^*) - \lambda \tilde{F}(w^*) \sum_{i=1}^{N_u} \tilde{t}_u(i) + N_u \log \eta + \sum_{i=1}^{N_e} \log f(w(i)) - N \log \left(\lambda \tilde{F}(w^*) + \eta \right) \tag{4.2}$$

The log likelihood equation above will be used to structurally estimate the model via maximum likelihood (MLE) for the exogenous and endogenous λ specifications. I assume a lognormal wage distribution $F(w)$ with parameters μ and σ_w.

5. Results

I run the structural estimation of the model using maximum likelihood (MLE). The results are presented below. I first present my findings under a model with an exogenous lambda parameter, and then compare those to my findings in a model where lambda is endogenous and depends on job search effort.

5.1. Estimates with Exogenous λ

To begin, I solve the model under the canonical assumption that job offers arrive exogenously. My parameter results are summarized in table 7.

Table 7: Parameters with Exogenous Job Offers

	Lambda	Eta	Mu	σ_w
High School	0.135	0.008	1.986	0.755
Some College	0.075	0.006	2.425	0.706
College	0.062	0.004	3.092	0.673
All Education Levels	0.065	0.004	2.851	0.733

High school educated individuals receive job offers at the highest rate $\lambda = 0.135$ in table 7, noticeably higher than their more educated counterparts. Individuals with some college and college education have lower contact rates of job offers, approximately 0.075 and 0.062 respectively. As I use monthly data, the λ estimates for some college and college education imply a job offer arrival of slightly less than once a year ($\lambda = 1/12 = 0.0833$). For high school educated individuals, the estimate corresponds to a job offer arrival rate slightly less than 1/7, i.e. once every seven months. Looking at the total sample with all education levels, the rate of arrivals for job offers is in between the estimates for college and some college, due to the data composition being heavily skewed with mostly some-college and college graduates.

At the same time, I find individuals with only high school education also have the highest rate of exogenous job separation, η, and are therefore the most likely of any education group to move from employment to unemployment. Individuals with some college are less likely to lose their job than those with only a high school education. The least likely to be separated from their job are individuals who have completed college, with an $\eta = 0.004$. The overall sample, with no division by education groups, has a separation rate close to that of college educated individuals, with η approximately equal to 0.004. The difference in magnitudes of η between education groups is much smaller than the differences in the job offer rate parameter λ.

The estimates for the mean μ and the standard deviation σ_w parameters of the lognormal wage distribution for all education groups are approximately the average of the estimates by education group. For high school educated individuals, the wage distribution has the lowest parameter μ, with a value slightly below 2, and the highest σ_w. The mean parameter μ in the wage distribution increases with education level, and the standard deviation parameter σ_w decreases with education level, which corresponds to the higher average wages for higher education levels. The mean and median wages for college educated individuals are significantly higher than their peers with only some college or high school education.

The higher arrival rate of job offers λ for individuals with a high school education is counter-balanced by a higher separation rate η, as well as a worse wage distribution with a lower mean and higher variance. The model thus implies that the least educated workers have more transitions in and out of employment as well as lower earnings, likely because their labor is more substitutable.

5.1.1. Standard errors and significance

I calculate the standard errors using the delta method, and report them in brackets in table 8 below. I find that all the parameters are statistically significant with a 99th percentile confidence interval, each with a p-value less than 0.01.

Table 8: Parameters and Standard Errors with Exogenous Search

	Lambda	Eta	Mu	Sigma_w
High School	0.135	0.008	1.986	0.755
	(0.051)	(0.003)	(0.283)	(0.121)
Some College	0.075	0.006	2.425	0.706
	(0.010)	(0.001)	(0.074)	(0.042)
College	0.062	0.004	3.092	0.673
	(0.006)	(0.0005)	(0.022)	(0.017)
All Education Levels	0.065	0.004	2.851	0.733
	(0.005)	(0.0005)	(0.024)	(0.018)

5.1.2. Flow Value of Unemployment, b

I can back out an estimate for the flow value of unemployment b by rearranging the reservation wage equation 3. I use the estimates from table 7 for $\hat{\lambda}, \hat{\eta}$, as well as $\hat{\mu}$ and $\hat{\sigma_w}$ of the lognormal wage distribution $F(w|\hat{\theta})$ and $\hat{w^*}$. I assume the discount rate $\rho = 0.005$.

$$\hat{b} = \hat{w^*} - \frac{\hat{\lambda}}{\rho + \hat{\eta}} \int_{w^*}^{\overline{w}} (w - w^*) dF(w|\hat{\theta}) \tag{3}$$

The estimates for b, the flow value of unemployment, with the exogenous search model are summarized in table 9. The table shows that the flow value of unemployment is negative for all groups, and is increasingly negative as individuals are more educated. College-educated individuals have the most negative flow value of unemployment, followed by the unsegregated sample with all education levels.

Table 9: Flow value of unemployment - Exogenous Search

	b
High School	−31.022
Some College	−46.586
College	−136.100
All Education Levels	−99.497

5.1.3. Likelihood Ratio Test

Finally, I conduct a likelihood ratio test to determine whether the labor markets are different across education levels with respect to the parameters $\lambda, \eta, w^*, \mu, \sigma_w$. The null hypothesis of my test is that the parameters from different educational levels are not significantly different, and I can therefore pool all education levels together.

The likelihood ratio test statistic follows a χ^2 distribution with 10 degrees of freedom and relies on the likelihood function from each educational specification. The test statistic takes the form:

$$LR = 2 \cdot (LL_{hs} + LL_{some.college} + LL_{college} - LL_{all.educ}) \tag{4}$$

I find the p-value of the likelihood ratio test to be less than 0.01. Therefore, I reject the null hypothesis and can conclude that the estimates by educational attainment are significantly different and should not be pooled together.

5.2. Estimates with Exogenous λ and Same η

In this section, I extend the model with exogenous job offers under the restriction that all education groups have the same exogenous job separation parameter η. I set η equal to the separation rate estimated for all education levels above (table 7). That is, every education group is now restricted to the same separation rate of $\eta \approx 0.004$. Table 10 below summarizes the MLE results.

Table 10: Parameters with Exogenous Search and Same Eta

	Lambda	Mu	Sigma_w
High School	0.100	1.988	0.754
Some College	0.067	2.426	0.705
College	0.068	3.092	0.673
All Education Levels	0.065	2.852	0.733

Comparing the parameter estimates in Table 7 and Table 10, the contact rate of job offers, λ, is lower when η is constant across education groups. This is necessary in the model with constant η to account for more frequent transitions between employment and unemployment. The difference in λ estimates is most notable in high school educated workers, who have a contact rate of job offers of 0.10 in the constant η specification versus 0.135 in the model where η is not restricted. The contact rate for individuals who have completed some college is also slightly lower when η is held constant across education group (0.0673 vs 0.0747). There is barely any difference for the contact rate of college educated individuals (0.0683 vs 0.0618).

The parameter estimates for μ and σ_w of the lognormal wage distribution when η is constant are nearly identical to those estimated the unrestricted exogenous search model in table 7 for all education levels. Again, high school educated workers have the lowest mean parameter and highest variance in wages, while college educated workers draw from a better wage distribution with a higher mean and lower variance.

5.2.1. Standard errors and significance

I calculate the standard errors of the parameter estimates using the delta method as before, and report them in parentheses in table 11 below. For the contact rate λ, the standard errors are slightly smaller for all education groups than in the specification where η can vary by education group. The standard errors for μ and σ_w are virtually the same as before. Similarly to the exogenous search specification with no restriction on η, I find that all the parameters are statistically significant with a 99th percentile confidence interval, each with a p-value less than 0.01.

Table 11: Parameters and Standard Errors with Exogenous Search and Same Eta

	Lambda	Mu	Sigma_w
High School	0.100	1.988	0.754
	(0.036)	(0.282)	(0.121)
Some College	0.067	2.426	0.705
	(0.008)	(0.074)	(0.042)
College	0.068	3.092	0.673
	(0.005)	(0.022)	(0.017)
All Education Levels	0.065	2.852	0.733
	(0.004)	(0.024)	(0.018)

5.2.2. Flow Value of Unemployment

As before, I back out an estimate for the flow value of unemployment b by rearranging the reservation wage equation 3 and make the assumption that the discount rate $\rho = 0.005$. The estimates for b in the model with exogenous search and constant η are summarized in table 12. The flow value of unemployment is negative for all groups, and is increasingly negative with more education.

Table 12: Flow vaue of unemployment - Exogenous Search with Same Eta

	b
High School	-32.765
Some College	-46.849
College	-137.131
All Education Levels	-99.493

College-educated individuals have the greatest negative flow value of unemployment, and high school educated individuals have the least negative flow value of unemployment. The estimates for b are extremely similar to the exogenous search flow value of unemployment estimates in table 9 from before, when η could differ by education group.

5.2.3. Likelihood Ratio Test

Lastly, I run a likelihood ratio test to determine whether the labor markets are different across education levels with respect to the parameters $\lambda, w^*, \mu, \sigma_w$ when η is held constant across education levels. The null hypothesis of my test is that the parameters from different educational levels are not significantly different, and therefore all education levels can be pooled together. Here, the likelihood ratio test statistic follows a χ^2 distribution with 8 degrees of freedom, and the test statistic takes the same form as described in equation 4 before.

As in the model with exogenous search, I find the p-value of the likelihood ratio test is less than 0.01. Thus, I reject the null hypothesis and conclude that the estimates by education level with exogenous search and constant separation rate η are significantly different and should not be pooled together.

5.3. Estimates with Endogenous λ

In this section, I present the estimation results from the model with endogenous job offer arrivals that depend on search effort. Table 13 summarizes the parameter estimates. The endogenous search parameters are fairly sensitive to the initial values for optimization, in contrast to the exogenous job arrivals case. My preferred specification therefore targets initial values close to the exogenous estimates of η, μ and σ_w. Additional estimates with other initial values are shown in the appendix (see tables 23, 24).

Table 13: Parameters with Endogenous Search using Monthly JS7 Hours of Job Search

	Eta	Mu	Sigma_w	Gamma	Beta
High School	0.008	1.986	0.755	0.135	1.000
Some College	0.006	2.426	0.705	0.075	1.000
College	0.004	3.091	0.672	0.061	1.004
All Education Levels	0.004	2.856	0.734	0.064	1.059

The parameter estimates with endogenous search effort in the table above are almost exactly the same as the estimates for η, μ, and σ_w in the exogenous job arrivals case in table 7. The separation rate η and the standard deviation parameter of the lognormal wage distribution σ_w are decreasing in education level, with the lowest estimates found for college educated individuals. As before, the μ parameter of the wage distribution is increasing in education level.

In the endogenous job arrival rate model, λ is decomposed into the γ and β parameters. The γ estimates in table 13 line up almost exactly to those in the exogenous job arrivals case in table 7. This result makes sense as γ represents the rate of arrival of unsolicited job offers. Without exerting any search effort, this is akin to an exogenous contact rate of job offers as seen before. When individuals *do* search, the arrival rate of job offers increases quickly, as indicated by the β of approximately 1 for all education groups. In the data, I find that many individuals do not exert search effort, and those that do often search little.

Using the definition of $\lambda(s)$ as described in equation 1 in the model $\lambda(s) = \gamma + \beta s$, I compute the following job contact rates conditional on search quantiles in table 14. A more comprehensive table is included in the appendix (table 25). With no search, i.e. for the 0% quantile of search time, $\lambda(s)$ equals γ. Accordingly, the estimates of $\lambda(s)$ with no search effort in table 14 match the estimates of γ shown in table 13.

Table 14: $\lambda(s)$ for Quantiles of Search s by Educational Attainment

	0%	25%	Median	Mean	75%
High School	0.135	0.597	0.942	1.677	1.982
Some College	0.075	0.306	0.767	1.659	2.210
College	0.062	0.292	0.523	1.227	1.215
All Education Levels	0.061	0.295	0.765	1.405	1.468

For the first quartile of search effort, $\lambda(s)$ increases substantially for every education level. In the pooled education data, searching less than 1 hour per week as the bottom 25% of workers, corresponds to a contact rate of job offers $\lambda(s)$ of 0.295. This rate implies that job arrivals increase from slightly less than once a year ($\lambda = \frac{1}{12} = 0.0833$) to a job offer approximately every 4 months ($\lambda = 0.25$). For high school educated individuals, the contact rate is even more frequent with $\lambda = 0.597$ corresponding to a job offer more than once every two months. This comes from the higher search effort for high school educated individuals (and therefore a higher s at the first quartile of search), as well as more frequent job arrivals under no search, γ. Individuals in every education group have β virtually equal to 1, which indicates that the return of search effort is rewarded evenly for every education level.

The median search time for all education levels is 3 hours per week. This search effort corresponds to a much higher job arrivals rate $\lambda(s)$ compared to the contact rate with no search effort or the first quartile of search. The contact rate of $\lambda(s) = 0.765$ implies the arrival of 3 job offers in 4 months, which is more than double the contact rate of the first quartile. Individuals with a high school diploma search more than the pooled sample, with a median search time of 3.5 hours per week, and also receive more unsolicited job offers γ without searching. As a result, $\lambda(s)$ for high school graduates is equal to almost one job offer per month for their median search time. Individuals who have completed some college receive approximately 3 offers every 4 months for the median search time of their group, while college graduates secure a job offer approximately once every two months corresponding to their median search level.

As in the exogenous contact rate case in section 5.1, individuals with higher education levels have more transitions into and out of employment. This is seen through the higher job separation rates η as well as the higher endogenous job offers arrival rates $\lambda(s)$ for workers with high school diplomas compared to their peers who attended college. Workers with less formal education also receive lower compensation on average, and their earnings are more volatile than their more educated counterparts. This implies that workers with less education do not command a wage premium and are more easily substitutable in the labor market.

5.3.1. Standard errors and significance

The standard errors of the parameter estimates are calculated using the delta method and presented in parentheses in table 15. Similar to the exogenous contact rate specification, I find that all parameters are statistically significant at the 99th percent confidence interval, each with a p-value less than 0.01.

Table 15: Parameters and Standard Errors with Endogenous Search, using JS7, Hours of Job Search in Last 7 Days

	Eta	Mu	Sigma_w	Gamma	Beta
High School	0.008	1.986	0.755	0.135	1.000
	(0.0003)	(0.035)	(0.015)	(0.007)	(0.009)
Some College	0.006	2.426	0.705	0.075	1.000
	(0.0001)	(0.005)	(0.003)	(0.001)	(0.003)
College	0.004	3.091	0.672	0.061	1.004
	(0.000)	(0.004)	(0.003)	(0.0002)	(0.002)
All Education Levels	0.004	2.856	0.734	0.064	1.059
	(0.000)	(0.001)	(0.001)	(0.0002)	(0.001)

5.3.2. Flow Value of Unemployment

In the sections with exogenous search, I could back out an estimate for the flow value of unemployment b by rearranging the reservation wage equation 3. Similarly, by rearranging the model with endogenous search, I can isolate the flow value of unemployment net of the cost of search $b - c(s)$ for a given level of search s. The right hand side is like in equation 3. I use the $\lambda(s)$ estimated in table 14 and I assume the discount rate $\rho = 0.005$. The estimates for b in the model with endogenous are summarized in table 16 below for a given quantile of search.

Table 16: Flow Value of Unemployment Net of Search Cost $b - c(s)$ by Search Effort

	No Search (0%)	Median Search	Mean Search
High School	-31.457	-262.726	-473.564
Some College	-45.682	-537.756	$-1,171.230$
College	-135.813	$-1,209.124$	$-2,844.914$
All Education Levels	-93.885	$-1,263.475$	$-2,326.784$

The flow value of unemployment is negative for all groups, and is increasingly negative with more education. When individuals do not search for a job (i.e. search effort $s = 0$), the cost of search $c(s) = 0$ as defined by the model. Therefore, the "no search" column of table 16 is able to pin down the flow value of unemployment b by education level. The estimates of b are remarkably similar to the estimates of the flow value of utility in the exogenous search framework in table 9. This is consistent with the above analysis, as with no search effort $s = 0$, the arrival rate of job offers $\lambda(s) = \gamma$, and the estimates for γ are nearly identical to the estimates of λ in the exogenous job arrivals rate benchmark in table 7.

When individuals devote effort to job search, the flow value of unemployment net of the search cost is substantially more negative. Thus, search costs greatly reduce the flow utility of unemployment. Taking b from the no search effort case, I can isolate the cost of search $c(s)$ for a given search level s. I present the cost of search for the median search level and mean search level by education group in table 17 below. For an individual who searches at the median or mean level of search, the search cost makes up the majority of their negative flow utility of unemployment $b - c(s)$. The cost of search can be determined for every level of search s following this procedure.

Table 17: Median and Mean Search Cost c(s) by Education

	Median Search Cost	Mean Search Cost
High School	-231.268	-442.106
Some College	-492.074	-1,125.549
College	-1,073.312	-2,709.101
All Education Levels	-1,169.590	-2,232.899

5.3.3. Likelihood Ratio

Finally, I run a likelihood ratio test to determine whether the labor markets are different across education levels with respect to the parameters $\eta, w^*, \mu, \sigma_w, \gamma$ and β when the contact rate is determined endogenously through search effort. The null hypothesis of my test is that the parameters from different educational levels are not significantly different, and therefore all education levels can be pooled together. Here, the likelihood ratio test statistic follows a χ^2 distribution with 12 degrees of freedom, and the test statistic takes the same form as described in equation 4 before.

As in the model with exogenous search, I find the p-value of the likelihood ratio test is less than 0.01. Thus, I reject the null hypothesis and conclude that the estimates by education level with endogenous job arrivals $\lambda(s)$ are significantly different and should not be pooled together.

6. Extension of Log Likelihood with Measurement Error

I derive the likelihood function with measurement error. The likelihood can be used for my data and CPS style data, with ongoing unemployment spells $\tilde{t}_u$ and an observed wage distribution cdf $F(w)$. The wage distribution $F(w)$ is truncated from below at the reservation wage w^*, because individuals only accept wages greater than or equal to their reservation wage.

There are multiple reasons why measurement error is useful to include in the model. As Flinn, Todd and Zhang (2019) discuss in their paper, rounding and reporting errors are commonplace in survey data. In the SCE dataset, wages are often rounded and job search times are reported to the nearest hour. When wages are rounded at the annual level, seemingly small misreporting of wages or hours worked can generate important differences between the actual and reported hourly wage. Furthermore, incorporating measurement error allows for an individual's wage to potentially change without changing jobs. This is useful to account for promotions or bonuses, where the individual's compensation changes without job separation and unemployment spells.

Finally, incorporating measurement error into the likelihood function is an important step towards estimating a model with on-the-job search. With on-the-job search, measurement error can help explain cases where individuals transition job to job with wage decreases. Accepting a new job with a lower wage cannot be rationalized by the search model, and with maximum likelihood estimation, it would cause a degenerate likelihood function. Although I do not include on-the-job-search in this paper, there is the opportunity to extend the model in future work.

As before, the probabilities of unemployment and employment are:

$$P(U) = \frac{\eta}{h_u + \eta} \quad \text{and} \quad P(E) = \frac{h_u}{h_u + \eta}$$

I allow for the possibility of measurement error in the data with the modifications below. I follow the assumption that the measurement error ϵ in wages is distributed i.i.d. log-normal, as in Wolpin (1987), Flinn (2002), etc.

The density of the measurement error ϵ is

$$m(\epsilon) = m(\frac{\tilde{w}}{w}) = \frac{\phi(\frac{\log(\epsilon)-\mu_\epsilon}{\sigma_\epsilon})}{\epsilon\sigma_\epsilon} \tag{5}$$

where ϕ is the normal pdf, μ_ϵ is the mean of the normal distribution and σ_ϵ the standard error of the normal.

Following Flinn, Todd and Zhang (2019), I restrict the correlation $Corr(\mu_\epsilon, \sigma_\epsilon) = -\frac{1}{2}\sigma_\epsilon^2$ to ensure that $E(\epsilon|w) = 1$. Therefore the expected observed wages $\tilde{w}$ are the same as the expected true wages w: $E(\tilde{w}) = E(\epsilon|w)E(w) = E(w)$

The likelihood function takes the form

$$L = \prod_{i\in S_u} \left[f_u(\tilde{t}_u(i)) \times P(U)\right] \times \prod_{i\in S_e} \left[\int_{w^*} \left(\frac{f(w(i))}{1-F(w_s^*)} \times m\left(\frac{\tilde{w}(i)}{w(i)}\right) \times \frac{1}{w(i)}\right) dw(i) \times P(E)\right] \tag{6}$$

where

- $m(\cdot)$ is the log normal distribution of the error $\epsilon = \frac{\tilde{w}}{w}$ as defined in Flinn, Todd & Zhang (2019).

- $m(\frac{\tilde{w}}{w})\frac{1}{w}$ is the density function of the observed wage $\tilde{w}$ with measurement error.

- $\frac{1}{w}$ is the Jacobian of the transformation of $m(\epsilon)$.

The probabilities of unemployment and employment are thus

$$P(U) = \frac{\eta}{h_u + \eta} = \frac{\eta}{\lambda\tilde{F}(w^*) + \eta} \quad \text{and} \quad P(E) = \frac{h_u}{h_u + \eta} = \frac{\lambda\tilde{F}(w^*)}{\lambda\tilde{F}(w^*) + \eta}$$

where

$$h_u = \lambda \tilde{F}(w^*|\theta) \qquad \tilde{F}(w^*) = 1 - F(w^*) \qquad f_u(\tilde{t}_u) = h_u \exp(-h_u \tilde{t}_u)$$

I also assume a parametric pdf of the wage distribution, $f(w)$, which follows a lognormal distribution.

Log likelihood

The log likelihood with measurement error takes the form:

$$\log L = N_u \log \eta + N \log(h_u) - N \log(h_u + \eta) - h_u \sum_{i=1}^{N_u} \tilde{t}_u(i) + \sum_{i=1}^{N_e} \log \int_{w^*} \frac{f(w(i))}{1 - F(w_s^*)} \times m\left(\frac{\tilde{w}(i)}{w(i)}\right) \times \frac{1}{w(i)} dw_i \tag{7}$$

which can also be written as

$$\begin{aligned} \log L = & N_u \log \eta + N \log \lambda + N \log \tilde{F}(w_s^*) - N \log(\lambda \tilde{F}(w^*) + \eta) - \lambda \tilde{F}(w^*) \sum_{i=1}^{N_u} \tilde{t}_u(i) \\ & + \sum_{i=1}^{N_e} \log \int_{w^*} \frac{f(w(i))}{1 - F(w_s^*)} \times m\left(\frac{\tilde{w}(i)}{w(i)}\right) \times \frac{1}{w(i)} dw_i \end{aligned} \tag{8}$$

The log likelihood with measurement error is similar to the log likelihood for the CPS data with*out* measurement error.

$$\log L = N \log \lambda + N_u \log \tilde{F}(w^*) - \lambda \tilde{F}(w^*) \sum_{i=1}^{N_u} \tilde{t}_u(i) + N_u \log \eta + \sum_{i=1}^{N_e} \log f(w(i)) - N \log \left(\lambda \tilde{F}(w^*) + \eta\right) \tag{9}$$

For the unemployed, the terms are similar to the CPS log likelihood. For the employed, the differences are highlighted in red.

The derivation of the employed term in the loglikelihood is:

$$\log\left(\prod_{i\in S_e}\left[\int_{w^*}\Big(\frac{f(w(i))}{1-F(w_s^*)}\times m\big(\frac{\tilde{w}(i)}{w(i)}\big)\times\frac{1}{w(i)}\Big)dw(i)\times P(E)\right]\right)$$
$$=\log\prod_{i\in S_e}\left[\int_{w^*}\Big(\frac{f(w(i))}{1-F(w_s^*)}\times m\big(\frac{\tilde{w}(i)}{w(i)}\big)\times\frac{1}{w(i)}\Big)dw(i)\right]+\log\big(P(E)^{N_e}\big)$$
$$=\log\prod_{i\in S_e}\left[\int_{w^*}\Big(\frac{f(w(i))}{1-F(w_s^*)}\times m\big(\frac{\tilde{w}(i)}{w(i)}\big)\times\frac{1}{w(i)}\Big)dw(i)\right]+N_e\log\big(\frac{h_u}{h_u+\eta}\big)$$
$$=\log\prod_{i\in S_e}\left[\int_{w^*}\Big(\frac{f(w(i))}{1-F(w_s^*)}\times m\big(\frac{\tilde{w}(i)}{w(i)}\big)\times\frac{1}{w(i)}\Big)dw(i)\right]+N_e\log\big(\frac{\lambda\tilde{F}(w^*)}{\lambda\tilde{F}(w^*)+\eta}\big)$$
$$=\sum_{i=1}^{N_e}\log\left[\int_{w^*}\Big(\frac{f(w(i))}{1-F(w_s^*)}\times m\big(\frac{\tilde{w}(i)}{w(i)}\big)\times\frac{1}{w(i)}\Big)dw(i)\right]+N_e\log\lambda+N_e\log\big(\tilde{F}(w^*)\big)-\log\big(\lambda\tilde{F}(w^*)+\eta\big)$$

7. Conclusion

In this paper, I extend the canonical labor search model to include an endogenous arrival rate of job offers, $\lambda(s)$, which depends on workers' search effort, s. My research question asks: how does endogenous search effort affect the rate of receiving job offers?

I present a model of labor search with endogenous search effort among different educational groups - high school, some college, college, all education levels - and no on-the-job-search. I find there is a statistically significant relationship between educational attainment and search effort, measured in my data as the number of hours spent actively searching for a job in the past seven days. I therefore focus my paper on search differences between education groups.

Using survey data from the Survey of Consumer Expenditures, I estimate the structural parameters via Maximum Likelihood Estimation (MLE). To begin, I estimate a baseline model with exogenous job offer arrivals. I find high school educated individuals receive job offers and separate from jobs at the fastest rates, followed by individuals with some college education, and lastly college graduates. Moreover, the wage distribution is more favorable for individuals with higher educational attainment. High school diploma holders face the lowest mean wages as well as the most wage volatility, whereas college graduates enjoy the highest and most stable wage distribution. These results are likely driven by the substitutability of labor, with the least educated workers corresponding to the least specialized and most substitutable. The parameter estimates between education groups are significantly different at the one percent level, and therefore indicate that different education groups should not be pooled.

Additionally, I estimate a specification with exogenous job arrivals where the job separation is pooled. With constant job separation across education groups, I find very similar results to the baseline estimation. The job arrivals rate is attenuated slightly compared to the unrestricted specification, to account for more frequent transitions from employment to unemployment. The remaining parameters including those from the lognormal wage distribution are nearly identical to the baseline specification. My results demonstrate that there are significant differences between education groups and thus they should be analyzed separately.

In the model with endogenous search effort, I can decompose the effect of search effort on the contact rate of job offers. In the data, many individuals do not search or search little, because search effort is costly. When individuals do not search, I find the estimated arrival rate is as in the exogenous baseline. This is consistent with individuals receiving unsolicited job offers at an exogenous rate. When individuals do search, I find the contact rate of job offers increases rapidly with search effort and the net flow utility of unemployment decreases due to search cost. For all education levels, the median contact rate of job offers increases ten-fold compared to the exogenous baseline, with approximately three job offers every four months. My results also show the exogenous separation rate, as well as the parameters of the lognormal wage distribution, remain very similar to the baseline exogenous λ specification. I continue to find important differences in the parameters between education groups, and conclude that the data should not be pooled.

Finally, I derive a log likelihood formulation of my model with measurement error. This is valuable in the context of labor search estimation because rounding and reporting errors are commonplace in survey data, and also presents the foundations for further empirical study, including models with on-the-job search.

This paper finds there are important differences in search behavior and outcomes across educational groups. More research can continue to explore endogenous search effort, including dimensions such as the number of job applications sent, and the importance of active versus passive search methods. Heterogeneity in search behavior can also be expanded upon in terms of gender and region. The framework of this paper is useful for studying counterfactuals such as increases in unemployment insurance, and presents the opportunity to extend the model to include on-the-job search.

8. References

Bibliography

Aguiar, M., E. Hurst, and L. Karabarbounis (2013). The life-cycle profile of time spent on job search. *American Economic Review 103*(3), 111–16.

Ahn, H. J. and L. Shao (2017). Precautionary on-the-job search over the business cycle. Finance and Economics Discussion Series 2017-025, Board of Governors of the Federal Reserve System U.S.

Burdett, K. and D. T. Mortensen (1998). Wage differentials, employer size, and unemployment. *International Economic Review*, 257–273.

Christensen, B. J., R. Lentz, D. T. Mortensen, G. R. Neumann, and A. Werwatz (2005). On-the-job search and the wage distribution. *Journal of Labor Economics 23*(1), 31–58.

DeLoach, S. B. and M. Kurt (2013). Discouraging workers: Estimating the impacts of macroeconomic shocks on the search intensity of the unemployed. *Journal of Labor research 34*(4), 433–454.

Faberman, R. J. and M. Kudlyak (2019). The intensity of job search and search duration. *American Economic Journal: Macroeconomics 11*(3), 327–57.

Faberman, R. J., A. I. Mueller, A. Şahin, and G. Topa (2017). Job search behavior among the employed and non-employed. Technical report, National Bureau of Economic Research.

Flinn, C. J. (2002). Labour market structure and inequality: A comparison of italy and the us. *The Review of Economic Studies 69*(3), 611–645.

Flinn, C. J., P. E. Todd, and W. Zhang (2018). Personality traits, intra-household allocation and the gender wage gap. *European Economic Review 109*, 191–220.

Hershbein, B. and L. B. Kahn (2018). Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review 108*(7), 1737–72.

Krueger, A. B. and A. Mueller (2010). Job search and unemployment insurance: New evidence from time use data. *Journal of Public Economics 94*(3-4), 298–307.

Mortensen, D. T. (1977). Unemployment insurance and job search decisions. *ILR Review 30*(4), 505–517.

Mukoyama, T., C. Patterson, and A. Şahin (2018). Job search behavior over the business cycle. *American Economic Journal: Macroeconomics 10*(1), 190–215.

Pissarides, C. A. (2000). *Equilibrium unemployment theory*. MIT press.

Shimer, R. (2004). Search intensity. Technical report, University of Chicago.

Wolpin, K. I. (1987). Estimating a structural search model: The transition from school to work. *Econometrica: Journal of the Econometric Society*, 801–817.

A. Appendix A

Table 18: Active and Passive Job Search Methods as Defined by the CPS

Active Job Search Methods

- Contacting an employer directly about a job
- Having a job interview
- Submitting a resume or application to an employer or to a job website
- Using a public employment agency, job service
- Using a private employment agency, job service, placement firm
- Using a university employment center
- Contacting a job recruiter or head hunter
- Seeking assistance from friends, relatives, or via social networks
- Placing or answering a job advertisement
- Checking union or professional registers

Passive Job Search Methods

- Looked at ads (ex: only browsed job postings but did not respond to any)
- Attended job training programs/courses
- Other passive (ex: studied for a real estate license or received email alerts about available jobs)

B. Appendix B

B.1. Additional Summary Statistics

This section reports the summary statistics of key variables by education group. I also present summary statistics for the whole sample with annual wages for informational purposes[2]. Hours of search in the past seven days is captured in the dataset by JS7 and is my measure of search effort. Unemployment durations in months are reported by L8. I also summarize the hourly reservation wage as well as the hourly and annual wages of currently employed individuals.

Table 19: Summary Statistics for All Education Levels

	Min	1st Quartile	Median	Mean	3rd Quartile	Max	NA's	SD	N
Hours of Search JS7	0	1	3	5.727	6	80	2,490	8.50	774
Unemp Duration L8	0	2	10.500	17.409	24	96	3,088	20.65	176
Hourly Res Wage	7.250	12.019	18.229	24.220	28.646	538.462	326	21.20	2,938
Hourly Wage JH9	7.292	13	18.939	25.041	30	179.167	988	19.38	2,276
Annual Wage JH9	250	20,736	34,530	45,301	55,000	600,000	562	41,308	2,702

[2]Note that since I focus on hourly wages throughout my analysis, I do not formally windsorize extreme values for the annual wages. Nonetheless, the quartiles, mean and median provide useful benchmarks to describe the data and I include them in the presentation of the paper.

Table 20: High School Education Only Summary Statistics

	Min	1st Quartile	Median	Mean	3rd Quartile	Max	NA's	SD	N
Hours of Search JS7	0	2	3.500	6.688	8	70	235	10.406	64
Unemp Duration L8	0	7	12	14.737	17.5	50	280	12.914	19
Hourly Res Wage	7.250	10	12.889	16.423	19	150	39	12.913	260
Hourly Wage JH9	7.292	9.928	11.952	15.082	16.167	67.708	143	9.976	156
Annual Wage JH9	1,440	16,128	21,120	26,021	30,351	221,538	88	20,901	211

Table 21: Some College Only Summary Statistics

	Min	1st Quartile	Median	Mean	3rd Quartile	Max	NA's	SD	N
Hours of Search JS7	0	1	3	6.862	9.250	80	769	9.716	232
Unemp Duration L8	0	2	10	18.585	30	96	936	21.521	65
Hourly Res Wage	7.500	10	15	18.204	20.192	130.208	136	13.119	865
Hourly Wage JH9	7.500	10.417	14.583	18.303	20.875	130.208	369	13.271	632
Annual Wage JH9	624	17,712	25,000	31,361	38,400	288,000	198	24,827	803

Table 22: College Only Summary Statistics

	Min	1st Quartile	Median	Mean	3rd Quartile	Max	NA's	SD	N
Hours of Search JS7	0	1	2	5.048	5	60	1,486	7.480	478
Unemp Duration L8	0	2	9	17.130	21.250	84	1,872	21.411	92
Hourly Res Wage	7.500	15	21.500	28.209	34.615	538.462	151	24.093	1,813
Hourly Wage JH9	7.500	15	22.561	28.947	35.417	179.167	476	21.084	1,488
Annual Wage JH9	250	26,400	42,000	54,348	67,200	600,000	276	46,519	1,688

B.2. Additional Results with Endogenous Contact Rate λ

The below tables are parameter estimates for the model with endogenous search. I try several different initial values to test the sensitivity of my estimates. The parameter estimates are quite sensitive to initial values, unlike those from the exogenous search model. My preferred specification therefore targets initial values close to the exogenous estimates of η, μ and σ_w.

Table 23: Parameters with Endogenous Search, using JS7, Hours of Job Search in Last 7 Days
Initial Values: c(1,1,1,1,1)

	Eta	Mu	Sigma_w	Gamma	Beta
High School	5.070	1.244	3.843	2.639	0.740
Some College	5.070	1.244	3.843	2.639	0.740
College	4.202	1.183	3.493	2.719	1.068
All Education Levels	5.070	1.244	3.843	2.639	0.740

Table 24: Parameters with Endogenous Search, using JS7, Hours of Job Search in Last 7 Days
Initial Values: c(0,0,0,0,0)

	Eta	Mu	Sigma_w	Gamma	Beta
High School	0.008	1.992	0.753	0.134	1.000
Some College	0.006	−1.734	1.968	2.182	1.004
College	0.004	3.093	0.672	0.062	1
All Education Levels	0.007	2.868	0.716	0.137	1.004

The table below shows more comprehensive quantiles of the endogenous contact rate of job offers, depending on the quantile of search effort s exerted.

Table 25: $\lambda(s)$ for Quantiles of Search s by Education Level (Comprehensive)

	0%	10%	25%	33%	50%	67%	75%	90%	100%
High School	0.135	0.366	0.597	0.597	0.943	1.338	1.982	3.367	16.295
Some College	0.075	0.075	0.306	0.537	0.767	1.460	2.210	4.692	18.542
College	0.062	0.062	0.292	0.292	0.523	0.985	1.215	2.831	13.907
All Education Levels	0.061	0.061	0.295	0.530	0.765	1.234	1.468	3.580	18.829

The table below summarizes the median and mean search times and search costs by education group.

Table 26: Median and Mean Search Time s and Search Cost c(s) by Education Level

	Median Time s	Median Search Cost	Mean Time s	Mean Search Cost
High School	3.5	-231.268	6.688	-442.106
Some College	3	-492.074	6.862	$-1,125.549$
College	2	$-1,073.312$	5.048	$-2,709.101$
All Education Levels	3	$-1,169.590$	5.727	$-2,232.899$