

# Labor Market Experience and Worker Flows\*

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## Abstract

This paper presents a model of learning where labor market experience provides information about the quality of future job matches. Previous models focus on the effects of workers' productivity when employed; however, learning is also important to understand workers' search behavior. When past experience provides a signal about prospective job quality, the model can explain the decline in both job finding and separation rates found in the data. Beyond accounting for labor market flows, the model gives predictions that are consistent with observed empirical wage distributions. I examine the lasting consequences for workers who start their careers in a bad economy. The model generates sizable wage losses that last eight to ten years without lasting differences in unemployment. These findings are consistent with empirical studies. Finally, I evaluate the effects of minimum wages on labor outcomes and find that the endogenous decline in job finding rates is essential to understand high unemployment rates for young workers subjected to minimum wages.

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\*This is a copy of my job market paper. Please send comments to [aspen@uchicago.edu](mailto:aspen@uchicago.edu). I thank my advisors Robert Shimer, Fernando Alvarez, Derek Neal, and Nancy Stokey for helpful comments. All mistakes are my own.

# 1 Introduction

During the first ten years of labor market experience workers transition from high job turnover into stable employment and have rapid wage growth. About two-thirds of lifetime job turnover and wage growth occurs during these early years (see [Topel and Ward \(1992\)](#)). Initial high turnover manifests itself in both high job finding and separation rates for young workers. The mechanism where young workers transition from rapid turnover to stable employment is not well understood. Given the importance of early work experience, a theory is needed to explain labor market outcomes of young workers. A full understanding of these labor market transitions must account for the decline in both job finding and separation rates over the life cycle.

I propose a model where labor market experience allows workers to learn about the quality of future matches. Past work experience allows a jobless worker to differentiate between good and bad matches before accepting a new job. This simple mechanism generates the decline in unemployment, job separation and job finding rates with age, the decline in separations with job tenure, the rise in wages with labor market experience, and fat right tails in the wage distribution.

This paper uses a discrete time version of [Jovanovic's \(1979\)](#) search model modified to include accumulated labor market experience. The novel feature of the model is that unemployed workers receive a signal about the quality of a new match. The precision of the signal depends on the worker's experience. Like in [Jovanovic \(1979\)](#) workers are uncertain about the quality of their match and learn about the quality over time by observing realizations of

output.

In this model, workers learn rapidly about the quality of their current job by observing output and this experience is useful in helping them determine the quality of future opportunities when seeking a new job. This result contrasts with classic models of learning that have been used to understand wage growth over workers' careers. These models seek to explain how transferable information learned at a given job is to future employment. On one extreme is the [Jovanovic \(1979\)](#) model where workers only learn about their current job and all human capital investments are firm specific. Here information is lost once the worker decides to change jobs. On the other extreme are models where workers learn about their entire vector of abilities when employed as in [Farber and Gibbons \(1996\)](#) and [Gibbons et al. \(2005\)](#). In these models, workers learn about their ability to perform at all jobs at a constant rate. This paper provides a mechanism that is between the two extremes. Being able to parameterize how transferable the information gained from experience is when searching for new jobs is a useful tool in analyzing labor market outcomes.

My model has implications for both job finding and separation rates as workers gain experience. Job finding rates are determined in the model by two factors. First, workers receive job offers at an exogenous rate. Second, workers can choose to accept or reject job offers that they receive. The model with experience predicts a decline in job finding rates as experience allows individuals to differentiate between good and bad jobs. For inexperienced workers jobs are experience goods; they only learn about the quality of the match by trying it out. However, as workers gain experience jobs become inspection goods. Market experience

influences decisions by unemployed workers about which jobs to accept. This contrasts to the standard Jovanovic (1979) model where workers accept all or a constant fraction of job offers since their information when unemployed does not change with experience.

Moreover, the model with experience is able to account for the full decline in the job separation rate. In Jovanovic's (1979) model, job durations are identically and independently distributed random variables and hence the turnover generated by the model is a renewal process. Each time the worker becomes unemployed she is in an identical position; job finding rates are constant. In the standard Jovanovic (1979) model only statistical sorting generates a decline in job separation rates. In his model, older workers are more likely to have been in their job longer. While this sorting is able to qualitatively match the decrease in separations with age, it does not quantitatively account for the magnitude of the decline found in the data. Adding experience to the model generates a second force that causes separations to decline. Older workers are selective so their new jobs are more likely to be good. This additional feature predicts both a decline in job finding rates and quantitatively captures the full decline in job separation rates.

I consider two experiments with the model to demonstrate the importance of finding and separation rates in understanding the employment experiences of young workers. First, I examine the lasting consequences for a worker who enters the labor force in a bad economy. I assume that for the first two years of labor market experience workers are subject to lower than normal job finding rates. After facing poor job prospects for two years, workers are shown to experience lower wages for 6-8 more years. These lasting declines in wages do not

correspond to greater amounts of future unemployment as workers quickly revert to normal levels of employment after job finding rates return to their standard value. The model's predictions of persistent wage losses with no lasting employment effects is consistent with the empirical literature that has examined the effects of graduating during recessions.

Finally, I consider the effects of minimum wage restrictions on worker outcomes. In the model, minimum wages restrict the jobs that young workers are able to accept. Minimum wage restrictions vary dramatically between the U.S. and Europe. Along with much higher minimum wages, European employment is characterized by having lower levels of job finding and separation rates. I show that high minimum wages drive down job finding and separation rates early in workers' careers leading to the high levels of youth unemployment observed in many European countries. To correctly predict the effect of policies on labor market outcomes a model that can generate changes in both job finding and separation rates is needed.

Related to the literature on learning is an empirical literature that examines the transferability of human capital across jobs. [Altonji and Shakotko \(1987\)](#), [Topel \(1991\)](#), and [Altonji and Williams \(2005\)](#) examine the extent to which wages rise with tenure on a given job rather than general job market experience. While they come to slightly different conclusions, [Altonji and Williams \(2005\)](#) reconcile the methods to find that tenure has a modest effect on wage growth taking into account the effects of labor market experience. Learning in my model has both a firm specific and a general effect. While some experience transfers to allow individuals to better identify the quality of future matches, workers learn about the

quality of their current job at a faster rate. While much of wage growth can be accounted for by career experience, there is still a premium for job tenure. Similarly, [Mincer and Jovanovic \(1982\)](#) and [Bartel and Borjas \(1982\)](#) explore the relationship between turnover and wage growth. They find that much of wage growth is due to general experience while smaller portions can be attributed to firm experience and mobility choices. Job changes early in the career are correlated with positive wage gains where changes later in life have negative effects. These findings are all consistent with model predictions.

[Moscarini \(2003\)](#), [Moscarini \(2005\)](#), and [Papageorgiou \(2007\)](#) present models that are closely related. [Moscarini \(2005\)](#) and [Moscarini \(2003\)](#) embed the [Jovanovic's \(1979\)](#) model into a general equilibrium matching framework. [Moscarini \(2005\)](#) shows that this model can generate a wage distribution of the same shape as the empirical distribution. [Moscarini \(2003\)](#) applies the model to think about the empirical tenure distribution. My paper adapts assumptions in these papers to allow the framework to be embedded into a general equilibrium setting. In both of these models the value of unemployment is static during the worker's career as in the standard [Jovanovic \(1979\)](#) framework, so they are unable to account for changes in the job finding rate.

[Papageorgiou \(2007\)](#) extends [Moscarini \(2005\)](#) by giving workers a vector of abilities on possible jobs that they learn about as they work. This setup is similar to the [Gibbons et al. \(2005\)](#) framework. This paper seeks to explain worker flows across occupations. Since workers direct their search to the job that is best for them in terms of both productivity and learning about their abilities, the model does not account for differences in job finding rates

over the career. Separations and occupational changes decline as workers discover their type over time. While [Papageorgiou \(2007\)](#) focuses on the worker's optimal decision regarding occupation selection, he does not explore how learning in his model effects job finding and separation rates with age.

An empirical literature related to [Papageorgiou \(2007\)](#) exists on career and job specific matches that seeks to explain the decline in turnover over the life cycle. [Neal \(1999\)](#) presents a model where workers search for both a career and job specific match. Once they have a career match they can draw a new job match, but if they decide to get a new career match they must also draw a job match. [Pavan \(2007\)](#) argues that a model of this type is better able to match separation behavior than standard models while [Pavan \(2006\)](#) explores this model's predictions for the behavior of wages. My model is able to generate observed declines in job finding and separation rates without adding the complexity of a second type of career match.

The paper proceeds as follows. [Section 2](#) presents the model. [Section 3](#) describes how the parameters of the model are chosen. [Section 4](#) presents the results from the calibrated model and compares them to the standard [Jovanovic \(1979\)](#) model. The lasting consequences of starting a worker's career in a bad economy are explored in [Section 5](#) and the effects of minimum wages are explored in [Section 6](#). [Section 7](#) concludes.

## 2 Model

### 2.1 Economic Environment

The basis for the model is a discrete time version of [Jovanovic's \(1979\)](#) model. I consider the optimal decision problem of a risk-neutral worker who maximizes the present discounted value of her consumption. I will consider the problem of a single worker who must choose between productive opportunities which I call jobs. For most of what is done in the paper, describing the firm side of the problem is not important<sup>1</sup>. Preferences are given by:

$$U = \sum_{\tau=0}^{\infty} \beta^{\tau} c_{\tau}$$

A single consumption good is produced with only labor from the worker. The average output for a worker in a job is given by its quality,  $\mu$ . The value of  $\mu$  is uncertain. The quality of each job is drawn from a known distribution. I follow [Moscarini \(2005\)](#) in restricting the support of  $\mu$  to two values:  $\mu_h$  and  $\mu_l$  where  $\mu_h > \mu_l$ .  $\mu_h$  is a “good” job where  $\mu_l$  denotes a “bad” job. The probability that any job is good is:

$$p_0 = Pr(\mu = \mu_h) = 1 - Pr(\mu = \mu_l) \in (0, 1)$$

Workers learn about the quality of the job in two ways. First, the output produced is

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<sup>1</sup>The firm side of the model can be introduced by either following [Jovanovic \(1979\)](#) in introducing firms that compete for the workers and pay competitive wages or following [Moscarini \(2005\)](#) in introducing a matching technology and wage bargaining. These options are discussed in more detail later in the paper.

observed in each period. Output from of job of quality  $\mu$  is given by:

$$x_t = \mu + z_t$$

$z_t \sim N(0, \sigma^2)$  is an independent random realization of output noise that keeps the true value of  $\mu$  hidden. Hence, output in each period is distributed  $N(\mu, \sigma)$  for a worker with job quality  $\mu$ . As the match continues, the worker observes realizations of output and updates her belief about the quality of the job by conducting a probability ratio tests using Bayes' rule.

Workers can also learn about job quality from an initial signal that is proportional to their labor market experience. For each period that the worker is employed she receives one unit of experience until she reaches the maximum experience level denoted by  $T$ . This labor market experience provides jobless workers with an initial signal about the quality of a new opportunity. Workers with no past experience get no signal so their beliefs about the quality of the job are just the prior probability. Workers with  $\tau$  units of experience get a signal that is equivalent to observing  $\alpha\tau$  periods of output from their prospective job.  $\alpha$  is restricted to be in  $[0, 1]$ . In the case where  $\alpha = 0$  no learning about future jobs occurs. This is the standard [Jovanovic \(1979\)](#) model. When  $\alpha = 1$  all experience in learning carries over to future jobs.

Jobs can be dissolved in two ways. First, workers can quit if the value of a job is below their reservation level. Second, jobs are subject to a separation shock that dissolves the match with probability  $\delta > 0$  each period.  $\delta$  captures reasons for job separations not captured by the endogenous quits that arise from learning in the model. Possible examples include plant

closures, natural disasters, or geographic relocation by the worker.

A jobless worker gets a flow value of leisure denoted by  $b$ . Assumptions on  $b$  must be made so that the worker has an interesting decision problem. First, assume that  $b$  is high enough so that it is optimal for workers to quit the job if they are certain that  $\mu = \mu_l$ . Additionally, assume that it will be optimal for workers to accept a job that they have no information about. A sufficient restriction for these assumptions to hold is  $b \in [\mu_l, (1 - p_0)\mu_l + p_0\mu_h]$ . This condition holds for all  $\alpha$ . However, when  $\alpha > 0$  it can be weakened as workers get an additional value of experience from working and get an initial signal about a job opportunities' quality when unemployed. In each period, jobless workers receive an offer with exogenous probability  $\lambda$ . It is possible to endogenize this parameters but it is not done as this paper seeks to understand how labor market experience influences individuals workers behavior. Taking  $\lambda$  as given simplifies the exposition.

## 2.2 Information and Wages

Given the normality assumption on output noise a sufficient statistic for any worker's output history is her posterior belief,  $p$ , that the job is "good." For any belief, the expected distribution of output is given by:

$$g(x; p) = p \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu_h}{\sigma}\right)^2} + (1-p) \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu_l}{\sigma}\right)^2}$$

With probability  $p$  output is drawn from a normal distribution with mean  $\mu_h$  and variance  $\sigma$  while with probability  $1 - p$  it is drawn from a normal with mean  $\mu_l$  and the same variance.

To update beliefs the worker and firm use Bayes' Rule to perform a probability ratio test.

Given any current belief,  $p$ , and output for a given period,  $x$ , the posterior,  $p'$ , is given by:

$$f(p, x) \equiv p' = Prob(\mu = \mu_h | p, x) = \frac{pe^{-\frac{1}{2}\left(\frac{x-\mu_h}{\sigma}\right)^2}}{pe^{-\frac{1}{2}\left(\frac{x-\mu_h}{\sigma}\right)^2} + (1-p)e^{-\frac{1}{2}\left(\frac{x-\mu_l}{\sigma}\right)^2}}$$

Here the numerator is proportional to the joint probability of observing output  $x$  and the match being good where the denominator is the total probability of observing output  $x$ .

Normality of the output noise implies that the entire history of output realizations is not needed; average output is sufficient to compute the posterior distributions. This is important as jobless workers receive an initial signal of differing amounts of output. First, consider a worker who receives signals in two consecutive periods. The distribution of total output for the next two periods given current probability  $p$  is:

$$\begin{aligned} g(x_1, p) + g(x_2, p) &= p \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_1-\mu_h}{\sigma}\right)^2} + (1-p) \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_1-\mu_l}{\sigma}\right)^2} \\ &\quad + p \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_2-\mu_h}{\sigma}\right)^2} + (1-p) \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_2-\mu_l}{\sigma}\right)^2} \\ &= p \frac{1}{\sqrt{2}\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_1+x_2-2\mu_h}{\sqrt{2}\sigma}\right)^2} + (1-p) \frac{1}{\sqrt{2}\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_1+x_2-2\mu_l}{\sqrt{2}\sigma}\right)^2} \end{aligned}$$

Where the second equality comes from the summing of normal distributions. Averaging the two observations together we get that the average output from two observations is given by:

$$\bar{g}(\bar{x}; p, 2) = p \frac{1}{\frac{\sigma}{\sqrt{2}}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\bar{x}-\mu_h}{\sigma/\sqrt{2}}\right)^2} + (1-p) \frac{1}{\frac{\sigma}{\sqrt{2}}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\bar{x}-\mu_l}{\sigma/\sqrt{2}}\right)^2}$$

The function  $\bar{g}(x; p, n)$  denotes the distribution of average output  $x$  given prior probability  $t$  and the number of periods the output is observed for  $n$ .

Similarly, for a worker who observes  $t$  periods of output, the distribution of the average output per period,  $\bar{x}$  is given by:

$$\tilde{g}(\bar{x}; p, t) = p \frac{1}{\frac{\sigma}{\sqrt{t}} \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{\bar{x} - \mu_h}{\frac{\sigma}{\sqrt{t}}} \right)^2} + (1 - p) \frac{1}{\frac{\sigma}{\sqrt{t}} \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{\bar{x} - \mu_l}{\frac{\sigma}{\sqrt{t}}} \right)^2}$$

Additionally, the average value of output along with the number of periods of output observed is sufficient to determine the posterior probability. That is, the order of the observations is irrelevant. Suppose a worker with probability  $p$  receives two signals  $x_1$  and  $x_2$ . The worker has the same posterior if she updates with  $x_1$  followed by  $x_2$  as she does if she simply updates with the sum of the two. That is:

$$\begin{aligned} f(f(p, x_1), x_2) &= \frac{p e^{-\frac{1}{2} \left( \frac{x_1 \mu_h + x_2 \mu_h + \mu_l^2}{\sigma} \right)^2}}{p e^{-\frac{1}{2} \left( \frac{x_1 \mu_h + x_2 \mu_h + \mu_l^2}{\sigma} \right)^2} + (1 - p) e^{-\frac{1}{2} \left( \frac{x_1 \mu_l + x_2 \mu_l + \mu_h^2}{\sigma} \right)^2}} \\ &= \frac{p e^{-\frac{1}{2} \left( \frac{x_1 + x_2 - 2\mu_h^2}{\sqrt{2}\sigma} \right)^2}}{p e^{-\frac{1}{2} \left( \frac{x_1 + x_2 - 2\mu_h^2}{\sqrt{2}\sigma} \right)^2} + (1 - p) e^{-\frac{1}{2} \left( \frac{x_1 + x_2 - 2\mu_h}{\sqrt{2}\sigma} \right)^2}} = \bar{f}(p, x_1 + x_2, 2) \end{aligned}$$

Where  $\bar{f}(p, x, n)$  is used to denote the posterior after prior  $p$  is updated with total observed output of  $x$  after  $n$  periods. Using the same strategy, the posterior after observing the

average output from  $t$  periods is computed as:

$$\tilde{f}(p, \bar{x}, t) = \frac{pe^{-\frac{1}{2}\left(\frac{\bar{x}-\mu_h}{\sigma}\right)^2}}{pe^{-\frac{1}{2}\left(\frac{\bar{x}-\mu_h}{\sigma}\right)^2} + (1-p)e^{-\frac{1}{2}\left(\frac{\bar{x}-\mu_l}{\sigma}\right)^2}}$$

Workers value their expected output each period. Given the probability that the match is good is  $p$ , expected output is given by:

$$\pi(p) = p\mu_h + (1-p)\mu_l$$

## 2.3 Worker's Decision Problem

The value functions for employed and unemployed workers can now be defined. The value functions for workers with less than  $T$  units of experience are described first. An employed worker's value function depends on her belief about the quality of the match  $p$  and experience  $\tau$ . Let  $V(p, \tau)$  be the value function for a worker entering a period with an employment opportunity that is of type  $\mu_h$  with probability  $p$  and  $\tau$  units of experience and let  $U(\tau)$  be the value function for an unemployed worker with experience  $\tau$ . An employed worker must decide whether to keep the job and work in the period or quit to search for a new one. If she remains employed she gets expected output  $\pi(p)$  and her discounted future value. After production, her discounted future value is described in two parts. She is exogenously separated from her job with probability  $\delta$ . In this case, she enters unemployment next period with  $\tau + 1$  units of experience. If she is not exogenously separated from her job she will

observe her output  $x$  and update her priors entering next period with value  $V(f(p, x), \tau + 1)$ .

If she quits her job she gets value  $U(\tau)$ . We can write the employed value function as:

$$V(p, \tau) = \max \left\{ U(\tau), \pi(p) + \beta\delta U(\tau + 1) + \beta(1 - \delta) \int_{-\infty}^{\infty} V(f(p, x), \tau + 1)g(x; p)dx \right\}$$

Unemployed workers with experience  $\tau$  receive leisure value  $b$  and get a new job offer for next period with probability  $\lambda$ . If they get a job offer they observe a signal equivalent to  $\alpha\tau$  periods of output. If average output from the signal is  $\bar{x}$  they enter the next period with value  $V(\tilde{f}(p0, x, \alpha\tau), \tau)$ . If they do not get an offer they remain unemployed with experience  $\tau$ . Hence, the value function can be written as:

$$U(\tau) = b + \beta\lambda \int_{-\infty}^{\infty} V(\tilde{f}(p0, x, \alpha\tau), \tau)\tilde{g}(x; p0, \alpha\tau)dx + \beta(1 - \lambda)U(\tau)$$

In the case where workers have reached the maximum possible experience workers no longer accumulate experience when employed. Hence, their value functions are given by:

$$V(p, T) = \max \left\{ U(T), \pi(p) + \beta\delta U(T) + \beta(1 - \delta) \int_{-\infty}^{\infty} V(f(p, x), T)g(x; p)dx \right\}$$

$$U(T) = b + \beta\lambda \int_{-\infty}^{\infty} V(\tilde{f}(p0, x, \alpha T), T)\tilde{g}(x; p0, \alpha T)dx + \beta(1 - \lambda)U(T)$$

### 3 Parameterization

To parameterize the model we will assume that there is a large number of identical workers facing the same decision problem described above. Each of these workers faces a different history of idiosyncratic shocks. Averaging outcomes across workers, aggregate data can be constructed from the model. Parameters are chosen to match employment statistics in the U.S. economy. To numerically solve the model there are ten parameters that must be chosen: the maximum amount of experience  $T$ , the discount factor  $\beta$ , the job offer rate  $\lambda$ , the average output from a “good” match  $\mu_h$ , the average output from a “bad” match  $\mu_l$ , the probability that a match is “good”  $p_0$ , the variance of output noise  $\sigma$ , the proportion of experience used for new matches  $\alpha$ , the exogenous separation rate  $\delta$ , and the value of leisure  $b$ . The model period is set to be one month.  $\mu_h$  is normalized to one.  $T$  is chosen to be large enough so that it will not impact individual decisions. I set  $T = 480$ . Because the model period is one month,  $\beta$  is set to 0.9966 which corresponds to an annual interest rate of 4%.

Remaining parameters are chosen to match features of the decline in job finding and separation rates in the U.S. [Figure 1](#) shows the decline in the job separation rate with age in the U.S. for workers aged 18-57<sup>2</sup>. The separation has a sharp initial decline for 8-10 years followed by a gradual decline.

[Figure 2](#) shows the decline in the job finding rate. Similarly, the job finding rates fall

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<sup>2</sup>This data was constructed by Robert Shimer using CPS monthly microdata from 1976 to 2005. The procedure used follows [Shimer \(2007\)](#) to create a time series of job separation and finding rates for individuals of each age. The time series is then averaged to create average unemployment, job finding, and job separation rates for each age group. For additional details, please see [Shimer \(2007\)](#) and his webpage <http://robert.shimer.googlepages.com/flows>.

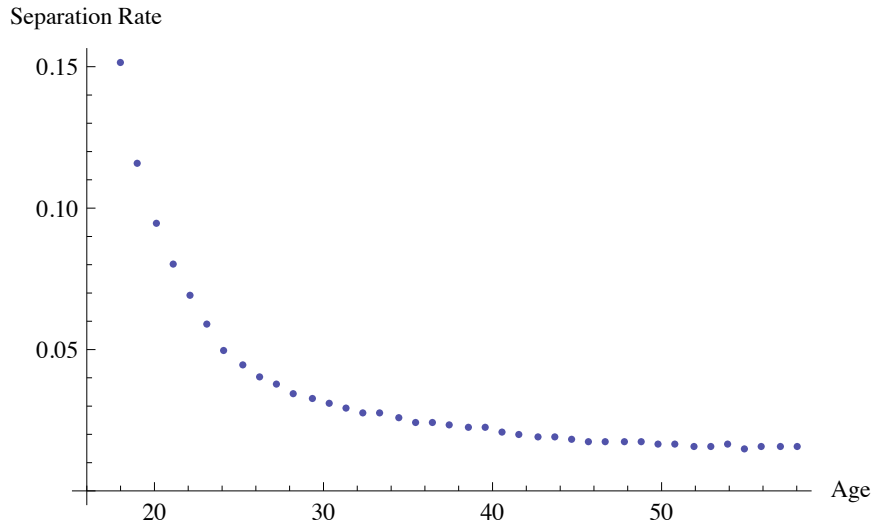


Figure 1: Average job separation rate by age for the U.S. economy.

fastest for the first 8-10 years, but the initial decline is less dramatic than the separation rate and finding rates continue to decline at a greater rate for the remainder of the workers' careers. Taken together the steeper decline in the separation rate implies that the unemployment rate declines with age.

$\lambda$  is chosen to match the worker's rate of job offers. In the data, 16-year-old workers have the highest job finding rate of 0.612. According to the model, these workers with no experience should accept any job offered to them. Hence, to match this feature of the data, I set  $\lambda = 0.61$ .

Workers with an infinite amount of experience are able to perfectly distinguish between good and bad jobs. In this case, they accept only good jobs so their job finding rate is given by  $p_0\lambda$ . The job finding rates data implies that the lowest job finding rate is 0.283 for 58 year old workers. Assuming that they are perfectly distinguishing between good and bad

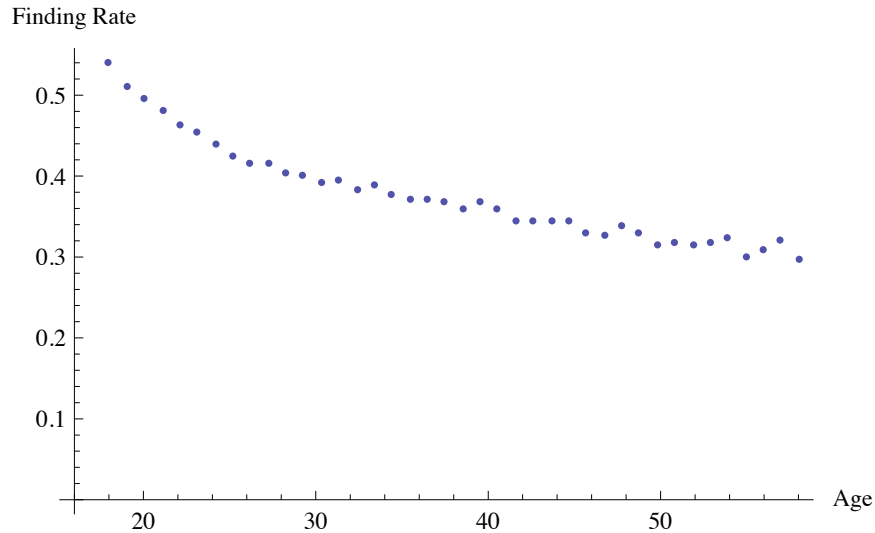


Figure 2: Average job finding rate by age for the U.S. economy.

job offers, I set  $p_0 = 0.46$ . In this sense,  $p_0$  determines the magnitude of total decline in the job finding rate over individual’s life cycle.

I next choose the output for “bad” matches,  $\mu_l$ . Job search behavior is determined by the signal to noise ratio for output  $\frac{\mu_h - \mu_l}{\sigma}$ . Hence given the normalization of  $\mu_h$ , for any choice of the  $\mu_l$  there is a value of  $\sigma$  that generates identical search behavior. Hence, this parameter is chosen to determine the dispersion of wages in the model.  $\mu_l$  provides a lower bound on possible wage realizations while  $\mu_h$  is the upper bound.  $\mu_l = 0$  is chosen so that increase by 66% over the life cycle. This implies that most of wage life cycle wage growth in the data is accounted for by sorting and learning in the model, but there is still room for other factors like human capital accumulation to play a role.

Next,  $\sigma$  is the amount of output noise. Higher values of  $\sigma$  imply that workers learn slowly about the quality of their matches. In the limit,  $\sigma = 0$  implies that workers perfectly observe

the quality of the match with one observation while as  $\sigma \rightarrow \infty$  workers have no learning.  $\sigma = 2$  is chosen so that the peak of job separations matches that found in the data. Higher values of  $\sigma$  imply that workers learn more slowly. This slower learning means that it takes longer to distinguish bad matches and therefore workers are willing to stay in initial matches longer before quitting.

$\alpha$  determines the amount of experience that carries over in learning about new job opportunities. It is natural to restrict  $\alpha$  to be in  $[0, 1]$ .  $\alpha = 0$  is analogous to the standard [Jovanovic \(1979\)](#) model where individuals learn nothing about future jobs and the employment is a pure renewal process.  $\alpha = 1$  is the limit where all learning carries over to future jobs. Higher values of  $\alpha$  imply that workers learn faster about future jobs and therefore have a steeper decline in both job finding and separation rates. With the model period set to be a month, we set  $\alpha = \frac{1}{30}$ . This corresponds to getting on average one month worth of information about a new job for every two years of labor market experience. This parameter is chosen so that the model matches the curvature in the decline in separation rates. Higher values of  $\alpha$  predict a steeper initial decline followed by less learning later. This parameter is sensitive to the choice of  $\sigma$ . The chosen value of  $\sigma$  implies that individuals learn quickly by observing output so to have enough curvature on the separation rates we choose a low value of  $\alpha$ .

$\delta$  is the rate of exogenous job separations. It determines the level of job separations in the model. Using data on average monthly job finding probabilities by age in the population, the lowest observed number in the data is 0.014 for 59 year olds. This should be an upper

bound on the value of  $\delta$ . I choose  $\delta = 0.009$  so that the level of separations for experienced workers matches the data.

The final parameter that must be set is  $b$ . This parameter determines the relative desirability of being employed in a “bad” job compared to searching for a new job. Higher values of  $b$  make unemployment more attractive.  $b = 0.3e$  is set to match the average level of job finding rates over the career. The model is not highly responsive to changes in the value of  $b$ .

Name	Parameter	Value
Max Experience	$T$	480
Discount Factor	$\beta$	0.9966
Job Offer Rate	$\lambda$	0.61
“Good” Output	$\mu_h$	1
“Bad” Output	$\mu_l$	0
Probability of Good Job	$p_0$	0.46
Output Noise	$\sigma$	2
Experience Rate	$\alpha$	$\frac{1}{30}$
Exogenous Separation Rate	$\delta$	0.009
Value of Leisure	$b$	0.35

Table 1: Calibrated values of the model parameters.

**Table 1** summarizes the chosen parameters and their values.

## 4 Simulation Results

After computing the value functions and reservation probabilities for workers at each experience level I simulate employment outcomes for individual workers. When simulating the model, 80% of workers start off employed while 20% start off unemployed. This matches the

steady state level of unemployment that is generated from a job finding rate of 0.15 and a job separation rate of 0.61. Starting with some workers employed avoids having higher than normal initial levels of unemployment. When generating outcomes I keep track of employment, job finding, job separation, wages, tenure, and total experience. I simulate the model for 10,000 workers and calculate average outcomes from the date that workers enter the labor force. To compare these average outcomes with labor force data I construct average outcome by age by entering workers into the labor market by the age at which workers get their first full time employment from the data. [Topel and Ward \(1992\)](#) compute the percentage of workers who enter the labor force at a given age by assuming that workers enter when they attain their first employment that lasts at least 2 quarters. This measure leaves out workers who take summer jobs and then return to school. [Table 2](#) replicates their table showing the percentage of workers who enter the labor force at each age. When constructing the data from the model I assume that all workers in the  $\leq 18$  category enter at age 18 and that all workers in the  $\geq 25$  category enter at age 25.

$\leq 18$	19	20	21	22	23	24	$\geq 25$
29.6	24.9	18.8	11.4	8.1	4.8	1.7	0.7

Table 2: Percent of populations first employment spell by age. Taken from [Topel and Ward \(1992\)](#).

For the remainder of the section, I compare results from the calibrated model where  $\alpha = \frac{1}{24}$  to the data and to the model where  $\alpha = 0$ .  $\alpha = 0$  is an interesting benchmark as it corresponds to the standard [Jovanovic \(1979\)](#) model where there is no learning about future matches. This highlights the novel effects of learning in the model. I find that the model is

better able to match employment data than the standard model.

## 4.1 Unemployment

It is well known that young workers face higher unemployment rates than prime aged workers.

The model is able to capture this decline in unemployment with age.

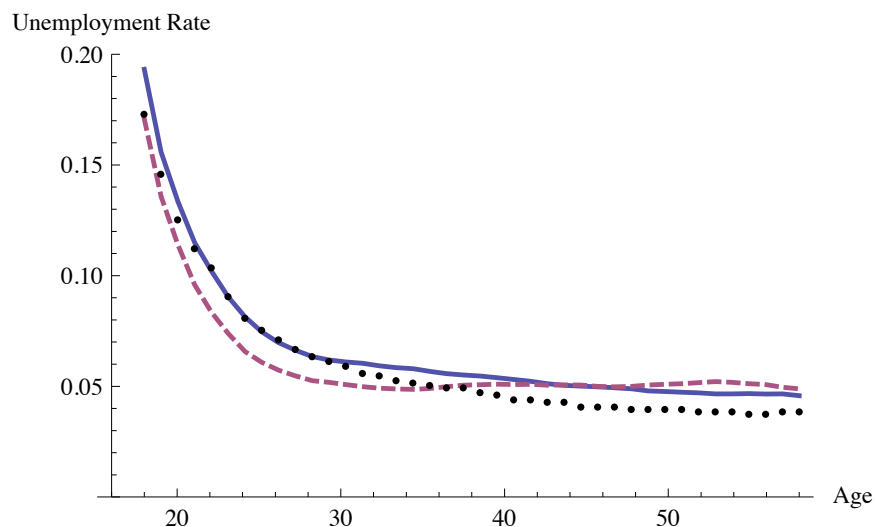


Figure 3: Average unemployment rate by age. Data: dots; Calibrated Model: Line;  $\alpha = 0$  Model: Dashed.

Figure 3 shows the average annual unemployment rate by age. The dots depict the decline in unemployment found in the data where the solid and dashed lines depict the results from the model with  $\alpha = \frac{1}{30}$  and  $\alpha = 0$  respectively. The data show a steady decline in unemployment with age. Unemployment declines from about 17% for 18 year old workers to between 3.5 and 4% for prime aged workers. The calibrated model captures a similar decline over the life cycle, with 18 year old workers experiencing unemployment of 19% and declining to 4.4%. There are two mechanisms in the model that generate this

decline. First, as workers are in the labor market for longer they are more likely to sort themselves into “good” jobs. These jobs have a lower rate of separation. Hence, fewer workers are unemployed. A second mechanism whereby workers are more likely to be in good jobs with more experience is the learning mechanism. Experienced workers are better able to distinguish between “good” and “bad” jobs so are more likely to start off in “good” jobs than inexperienced workers.

The model with  $\alpha = 0$  captures much of the decline in unemployment. Unemployment drops rapidly during the first 10 years of work experience with little to no decline later in life. In this case, only the mechanism is present. The figure shows that workers are able to sort themselves into good jobs within the first 10 years of work. To generate a continued decline in unemployment rates the learning mechanism is necessary.

To compare the fits of the two models with the data I construct a measure of the wellness of fit:

$$Fit = 1 - \frac{\sum_{a=18}^{57} (\varepsilon_a - \bar{\varepsilon})^2}{\sum_{a=18}^{57} (y_a - \bar{y})^2}$$

This is similar to an  $R^2$  measure, where  $\varepsilon_a$  is the difference between the model and the data for age  $a$ ,  $\bar{\varepsilon}$  is the average difference,  $y_a$  is the level of the data for age  $a$ , and  $\bar{y}$  is the average level of the data. So the top give the sum of squared errors between the data and the model and the bottom gives the sum of squared deviations in the data.

Using this metric to compare the two models, both models account for most of the decline in the unemployment rate with age. The calibrated model fits slightly better with a measure of 0.98 while the model with  $\alpha = 0$  fits has a measure of 0.88.

## 4.2 Labor Market Flows

While both the calibrated model and the  $\alpha = 0$  model capture the decline in unemployment they have different implications for labor market flows. It is well known that turnover declines with age. Job separations exhibit a sharp initial drop and continue to decline with age. It is also the case that job finding rates decline. The two models ability to capture the decline in separation rates is shown in [Figure 4](#)

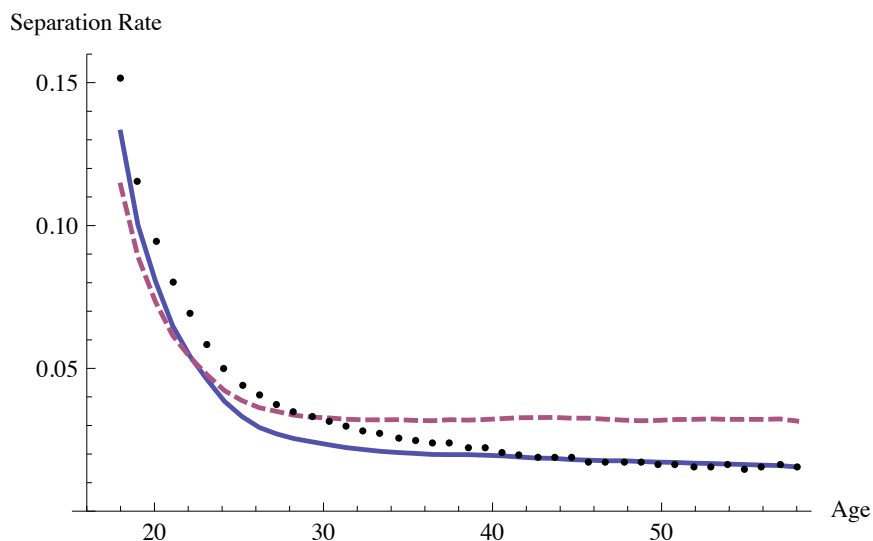


Figure 4: Average job separation rate by age. Data: dots; Calibrated Model: Line;  $\alpha = 0$  Model: Dashed.

[Figure 4](#) shows the decline in separations for both models compared with the data. Both models have an initial decline in the separation rate that is steeper than the data. The calibrated model accounts for nearly the entire magnitude of the decline. In contrast, the model with  $\alpha = 0$  is unable to capture the entire variation in the separation rate with age as the separation rate becomes flat after the first 10 years. The mechanism for this is again the same as with unemployment. Both models are characterized by the selection of individuals

into “good” matches as they spend more time in the labor market. However, the calibrated model is able to capture the continued decline in the separation rate as workers learn about the quality of future matches where the effects from selection have already ended.

In computing the fit of both models with the data it is clear that the calibrated model outperforms the standard model. In the calibrated case the fit is 0.96 where when  $\alpha = 0$  the fit is 0.80. So while the  $\alpha = 0$  model fits the data quite well, the full calibration is able to account for almost all of the variation in the data.

Job finding rates also decline with age. They, however, decline more slowly as the more rapid decrease in separations leads to declining unemployment over the life cycle. New to the model is the ability to account for this decline in job finding rates. Since experience allows individuals to learn about the quality of new matches, experienced workers can be selective about which jobs they choose to accept.

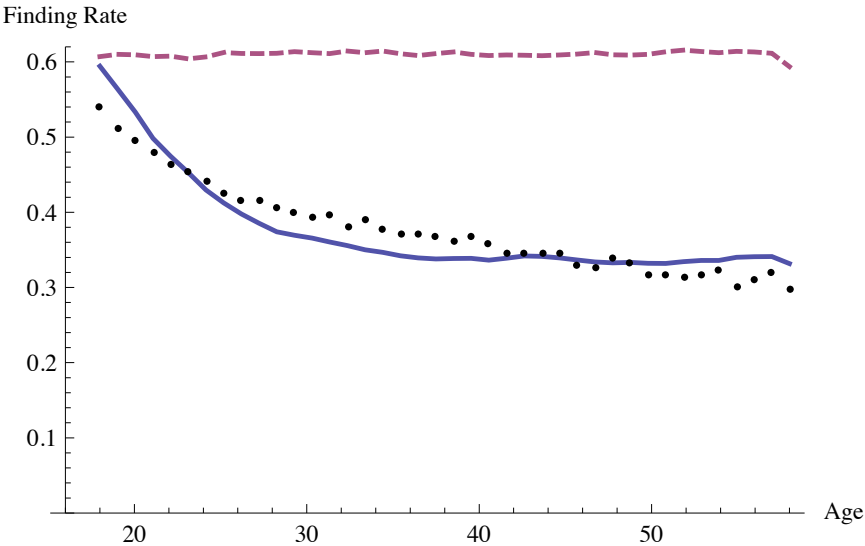


Figure 5: Average job finding rate by age. Data: dots; Calibrated Model: Line;  $\alpha = 0$  Model: Dashed.

figreffig: Find shows the decline in job finding rates. The solid line shows that the decline from the calibrated model is initially steeper with less decline later in the career than found in the data. Despite the difference in shape of the decline, the model with learning is able to match the decline in finding rates better than the model without. The dashed line shows the model when  $\alpha = 0$ . In this case, the job finding rate is simply  $\lambda = .61$  as the worker is willing to accept any job offered since she is unable to distinguish between them. The standard model is unable to deliver any decline in the separation rates.

Comparing the fit between the two models reveals that the calibrated model has a fit of 0.82 compared to a fit of  $0.03 \approx 0$  in the standard model. The negative outcome from the standard model is a result of noise from the simulations. It should deliver an exact zero as job finding rates are  $\lambda$  for all ages.

### 4.3 Separations by Tenure

One of the primary motivations for [Jovanovic's \(1979\)](#) paper was to be able to explain the declining hazard rate of unemployment with tenure. This model continues to capture the negative relationship between separations and tenure. The primary explanation for this feature in the model is that within any job, workers learn their productivity as tenure increases.

[Figure 6](#) depicts the average monthly separation rate by year of tenure for agents in the two models. It shows that the probability of separation is more than twice as high during the first year on a job than during any other year. As tenure accumulates, the job separation

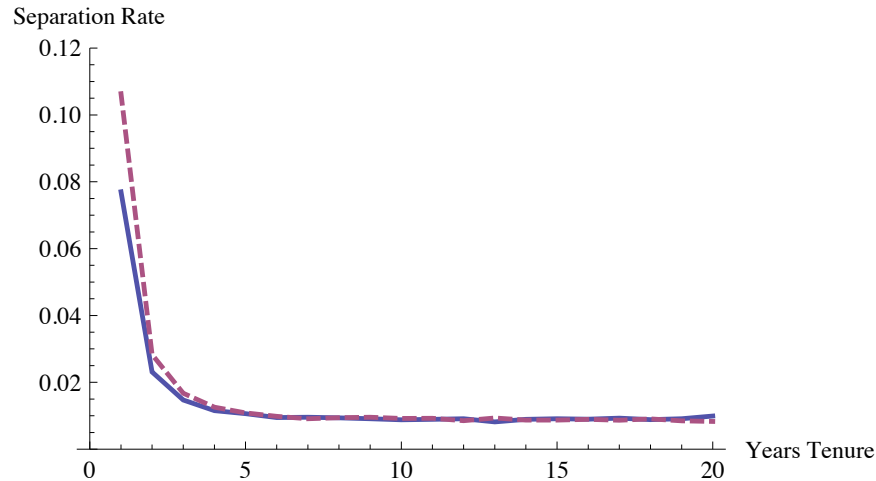


Figure 6: Average separation finding rate by years of tenure from the model. Calibrated Model: Line;  $\alpha = 0$  Model: Dashed.

rate continues to decline slowly after the first five years. The decline in both models is very similar to that found in Moscarini (2003), which compares well with the data.

#### 4.4 Wage Distribution

An additional feature of this model is that it provides a theory of wage changes over the life cycle. Since workers earn their expected product at any given task, wages will change based on how good on average individual's matches are for a given level of experience. As first shown in Moscarini (2005), the wage distribution generated by these models have fat right tails which is in line with the empirical wage distribution. Both the calibrated and standard models have the same ability to generate fat right tails found in the data.

## 4.5 Wage Growth

Topel and Ward (1992) document a number of features of wage profiles during worker's first 10 years of experience. They document that the first 10 years of the career account for two-thirds of lifetime wage growth and that gains in wages at job changes average about 10 percent. These job changes can explain about one-third of wage growth. Moreover, wages on the job approximate a random walk. The model qualitatively replicates the behavior of wages over the cycle.

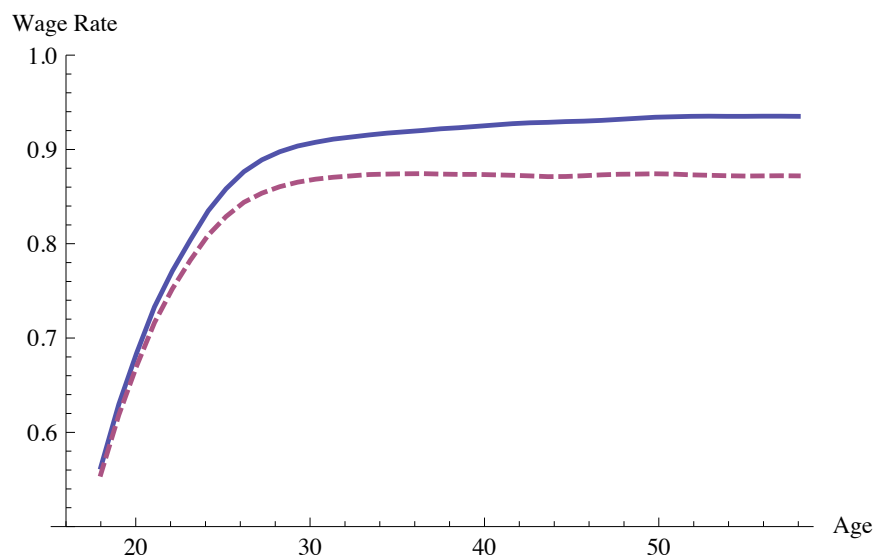


Figure 7: Average wages by age. Calibrated Model: Line;  $\alpha = 0$  Model: Dashed.

Figure 7 shows the average annual wages by age from both models. I calibrate the  $\alpha = \frac{1}{30}$  model so that wages grow by 66%; the pattern of wage growth from the model is endogenous. The model generates rapid wage growth during the first 10 years of experience and then levels off. Wage growth in during the first 10 years in the calibrated model accounts for about 89% of total wage growth instead of the 66% found in the data. The standard model does not

generate as much wage growth as the calibrated model. Wages grow rapidly for the first 10 years then stop growing completely. The standard model delivers wages that grow by only 55% over the life cycle. The first ten years accounts for 93% of total wage growth. Again, the secondary learning effect is crucial to deliver continued wage growth in the model.

## 5 Lasting Effects

In this section, I evaluate the model's predictions on the effects of a worker who graduates in a bad economy. Thus far I have assumed that the job offer rate  $\lambda$  is constant throughout the individual's working life. However, recent research shows that job finding rates vary substantially over the business cycle. [Shimer \(2007\)](#) decomposes fluctuations in unemployment since 1948 and finds that three-quarters of the fluctuations are accounted for by changes in job finding rate. Similarly, [Hall \(2005\)](#) argues that jobs are difficult to find during recessions because of low job finding rates rather than high job separations.

Given the fluctuations in job finding rate, I consider the effects of a worker who enters the labor force in a bad economy by evaluating the effect of facing low job finding rates for the first two years of work. In particular, I assume that for the first two years after entering the labor force the exogenous job offer rate is half the calibrated value followed by an unexpected permanent change back to the level in the original calibration. In this section, workers enter the labor market unemployed with no past experience. Career earnings and employment outcomes are compared for workers who face this initial low job offer rate with workers who face high job finding rates for their entire career.

First, I find that workers who enter the labor force in bad time have only a modest decrease in accumulated experience over their career. On average, graduating in a bad economy implies a loss of 0.86 months of experience during the first year and 1.8 months during the first two years. After that, the difference in experience grows to just 2.70 months over 40 years in the labor market. Workers who face poor job prospects in their first two years of labor market experience lose a modest amount of experience during these years and almost none after.

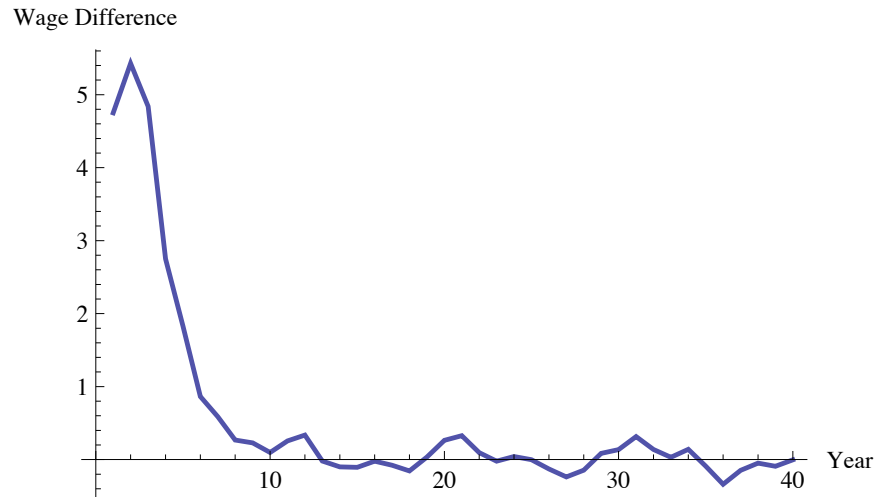


Figure 8: Log difference in wages of workers with normal finding rates to those who graduate in economy by year of labor market experience.

Figure 8 shows the log difference in wages between workers who face the calibrated job offer rate for their entire life and workers who graduate in a bad economy. It shows that wage losses grow to over five percent during the years when workers face diminished job finding prospects then decline to nearly zero in the next eight to ten years. Workers' wage losses grow during the first two years when they face poor job finding prospects. These initial job

losses remain persistent as workers have lower experience from these years, but the wage outcomes converge back to the levels for workers who never face poor job finding prospects. The fluctuations after the first 10 years in the graph are noise from the simulations.

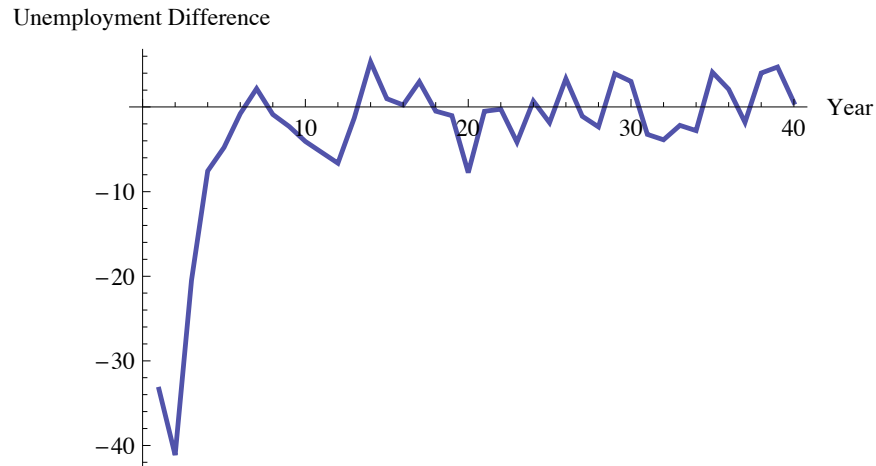


Figure 9: Log difference in unemployment rate of workers with normal finding rates to those who graduate in economy by year of labor market experience.

Next, I examine the employment effects of graduating in a recession. [Figure 9](#) shows the log difference in unemployment between the two models. Graduating in a bad economy implies that unemployment rates are about 40% higher during the downturn. However, once job offer rates return to normal, unemployment rates quickly revert to normal levels. Within two to three years, unemployment has returned to normal levels. Workers who were unable to find a job initially have lower experience and hence have more motivation to quickly find a job and gain experience when prospects improve. Hence, there are no lasting effects on unemployment.

The effects from the model are consistent with a growing empirical literature has studied the effects of unemployment on young workers. [Kahn \(2006\)](#) studies the effects of graduating

from college in a bad economy using NLSY data between 1979 and 1988. She finds large negative wage effects of graduating in a bad economy but no lasting effects on labor supply. Similarly, [Oreopoulos et al. \(2005\)](#) study the effects of graduating college in a recession using Canadian university-employer-employee matched data from 1982 to 1999. They also find significant wage effects that fade after 8-10 years with little impact on time worked by those who faced high unemployment early in their career.

A separate approach is to look at the effects of workers who lose their jobs. [Jacobson et al. \(1992\)](#) find that displaced workers face long term wage losses of 25% per year. However, later research has found that losses for young workers are less severe. [Kletzer and Fairlie \(2003\)](#) find considerable difference in the first few years after displacement but that these effects only last for about five years. [Bender and von Wachter \(2006\)](#) study the effects of early job loss for young workers in Germany and find that initial wage losses are 15% and fade to zero within five years. These experiments show that there are persistent effects from loss of experience early in a workers career. The model is able to generate persistent wage differences as a result of learning.

## 6 Minimum Wages

Finally, I explore the effects of wage restrictions in the model and find that having endogenously determined job finding rates is essential to understand the implications of minimum wages for young workers' employment outcomes. To explore minimum wages, it is necessary to introduce firms into the model. In this section, I follow the convention from [Jovanovic](#)

(1979) that there are competitive firms who compete for the services of a worker. Specifically, workers receive job offers from industries composed of many firms that compete over the services of the worker. Therefore, the worker is paid her expected output in each period. The worker is paid their expected marginal product each period on the job<sup>3</sup>. While the worker flows in the model are calibrated to match the employment data for the U.S. the nature of these flows vary across countries. Cohen et al. (1997) compares French and U.S. labor markets. They find that young workers in France have much higher unemployment rates than those in the U.S. When breaking down the factors that contribute to this difference, they show that the U.S. is characterized by more rapid job finding and separation rates than France. Pries and Rogerson (2005) show that labor market policies can have large impacts on labor market flows. In evaluating the effect of policies, it is important to capture the age dimension of worker flows.

To understand the importance of endogenous job finding rates in predicting the effect of labor market policies, the implications of wage restrictions are examined. The levels of minimum wages vary dramatically across countries. In the U.S., minimum wages are low and have been declining in real terms for much of the last 25 years. In 2002-2003 the ratio of the minimum wage to the median in the U.S. economy was 0.335. In contrast, several European

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<sup>3</sup>Alternately, I could introduce firm worker matches and bargaining as in Moscarini (2005). This model introduces a few more modeling choices if this route is chosen as workers with different levels of experience have different values of unemployment. The main choice is whether to use one matching function for all workers or a separate matching function for each worker type. If one matching function is used, the overall distribution of workers types must be tracked while if multiple are used this is not an issue. This method endogenizes the job offer rate  $\lambda$  and the choices of the matching function have different implications. One matching function implies that distortions on any worker can have effects for all workers search behavior, while having multiple matching functions localizes these effects. There is not clear reason to choose one over the other, though it is interesting to think about how policies alter matching rates.

countries have minimums that are over forty percent of the minimum. In particular, the French minimum wage is 0.62 of the median. While differences in wage dispersion across countries may make these figures difficult to compare directly, minimum wages in Europe are much more restrictive than in the U.S. In the U.S. only about 1.5% of workers are paid the minimum wage compared with 14% in France.

To explore the effects of wage restrictions, I the effects of a high minimum wage in the calibrated model and in the model where  $\alpha = 0$ . Workers begin employed with one unit of experience. To restrict wages in the model, I set a lower bound on the probability of a good match of jobs that workers are allowed to take. A minimum wage of  $\underline{p} = 0.45$  is considered for both the calibrated model and the model with  $\alpha = 0$ . This restriction is similar to the levels of minimum wages in France. I find that the model without learning is unable to generate realistic employment effects from the minimum wage because there is no decline in the job finding rate. In the model with experience, the initial decline in job finding rates for young workers generates the pattern of unemployment found in European countries with high minimum wages.

To compare the effects of the wage restriction, I first evaluate the effects of minimum wages on unemployment. [Figure 10](#) compares the unemployment rate by age for both models with unemployment from the calibrated model with no minimum wage. While unemployment increases in both models, the pattern of the change is dramatically different. The dot-dashed line shows that the employment effects from the calibrated model are large for young workers then converge to the model with no minimum wage. In contrast, the dashed line shows that

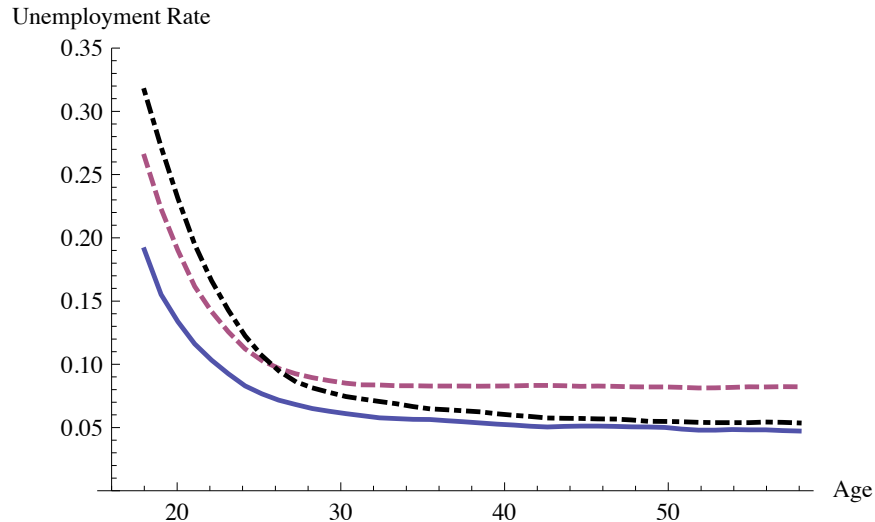


Figure 10: Unemployment rate by age for calibrated model with no minimum wage (solid), calibrated model with minimum (dot-dashed), and  $\alpha = 0$  model with minimum (dashed).

in the model with  $\alpha = 0$  the minimum wage causes unemployment to be uniformly higher throughout the worker's life. The calibrated model much more closely resembles patterns in unemployment in European countries with high minimum wages. In these countries, young workers have higher rates of employment than in the U.S. but prime aged workers have similar unemployment rates.

To understand the origin of the differences in unemployment between the two models, I examine their predictions on job separation and finding rates. [Figure 11](#) shows the effect of minimum wages on job separation rates. Here the pattern is again similar to the unemployment rates. For the calibrated model, the minimum wage causes higher separations. In contrast to the unemployment figure, the differences in separations from the model with no minimum wages lasts less than 10 years. The dashed line shows that minimum wages increase the separation rate in the  $\alpha = 0$  model for all ages. Without a minimum wage workers are

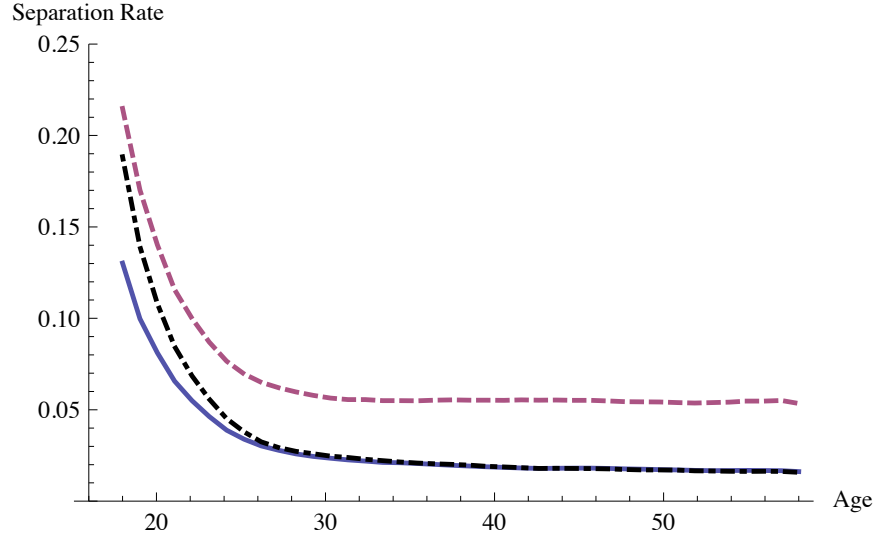


Figure 11: Job Separation rate by age for calibrated model with no minimum wage (solid), calibrated model with minimum (dot-dashed), and  $\alpha = 0$  model with minimum (dashed).

free to gain experience on a job with low productivity. Minimum wage restrictions prevent this early accumulation of experience. These high initial separation rates are important in causing the increase in unemployment for young workers in both models.

Finally, the effects of minimum wages on job finding rates are explored. [Figure 12](#) shows job finding rates for both models. Here the predictions of the two models is drastically different. The calibrated model predicts a decline in job finding rates where job findings remain fixed in the model where  $\alpha = 0$ . The inability of job finding rates to move in the model without experience makes it unable to generate accurate predictions about the effects of minimum wages across countries.

The endogenous decline in finding and separation rates is crucial to understand the pattern of unemployment changes with minimum wages. [Table 3](#) computes average unemployment rates from the model for different age groups. In computing the table it is assumed

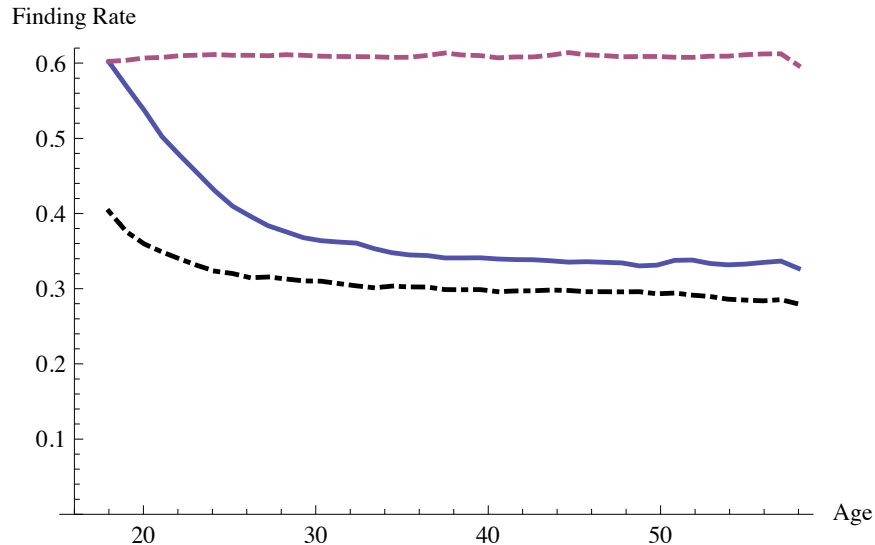


Figure 12: Job Finding rate by age for calibrated model with no minimum wage (solid), calibrated model with minimum (dot-dashed), and  $\alpha = 0$  model with minimum (dashed).

Age	No Minimum	Standard MW	$\alpha = 0$ MW
15-24	11.9	19.4	16.5
25-34	6.2	7.6	8.7
35-44	5.2	6.0	8.3
45-54	4.9	5.5	8.2

Table 3: Unemployment rate by age band from the calibrated model with no minimum wage, the calibrated model with a minimum wage, and the  $\alpha = 0$  model with a minimum wage.

that there are equal numbers people at each age within each age band. Demographic changes are not accounted for. Higher levels of minimum wages are shown to have large effects on unemployment for workers aged 15-24 and modest effects for 25-34 year olds in the model with experience. In contrast, the model where  $\alpha = 0$  is does not generate as large of unemployment differences for young workers and the effects do not completely disappear as workers age.

The patterns of unemployment as a result of minimum wages are consistent with cross-

Age	U.S.	France
15-24	13.0	20.9
25-34	5.8	9.7
35-44	4.6	6.9
45-54	4.1	6.1
55-64	4.2	7.0

Table 4: Unemployment rate by age band for U.S and France. Average value for male workers from 2003-2004 from OECD.

country data. [Table 4](#) shows the average unemployment rate by age band for U.S. and French male workers in 2003-2004. In the U.S. where workers face a modest minimum wage, unemployment is 13% for the youngest age group and converges quickly to under 6%. In contrast, in France where there is a high minimum wage young workers face unemployment rates above 20% that declines slowly with unemployment rates of almost 10% for workers aged 25-34 before to between six and seven percent for older workers. This pattern is consistent across European countries that typically have high minimum wages. These countries have higher rates of unemployment than the U.S. and these differences are concentrated in young workers. Understanding these differences in employment outcomes requires a model that is able to capture key changes in job finding and separation rates over the life cycle.

[Gorry \(2008\)](#) provides a more detailed quantitative analysis of the effects of minimum wages on youth employment outcomes. Taking the decline of job finding and separation rates as a feature of the economy, he shows that minimum wages can account for a significant portion of the differences in employment rates between the U.S. and European countries.

## 7 Conclusion

This paper presents a model of learning that has novel implications for workers job finding rates. Workers' learning about the quality of their match is not only important for observed outcomes while employed like wages and employment durations; it is also important for their behavior while unemployed. This insight motivates the model where experience gives workers both knowledge about the quality of their current job and the ability to distinguish between good and bad jobs when unemployed.

A model with learning about both the quality of the current match and future matches has rich implications for labor market outcomes. It is consistent with the age profiles of unemployment, job finding rates, job separation rates, hazard rates of separation with tenure, wage dispersion, and wage growth. Having a model that has consistent prediction about a broad range of labor outcomes makes it ideal to analyze the effects of policy on these outcomes. This paper explores the effects of graduating in a bad economy and the implications for wage restriction on employment outcomes. The model generates results that are consistent with empirical findings in both cases: early losses of experience have lasting consequences for wages but not for employment and high minimum wages imply high rates of unemployment for younger workers.

The model will be fruitful for further studies on the effects of labor market policies. In particular, the model has implications for optimal unemployment insurance. Current policy in the U.S. has different payments depending on past experience but all workers receive the same duration of unemployment benefits. This model has strong implications for the

duration of unemployment based on past experience. Using this model would allow the effects on making the duration of unemployment benefits dependent on past experience to be studied.

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