Layoffs and lemons over the business cycle

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Abstract

This paper develops a simple model in which unemployment arises from a combination of selection and bad luck. During recessions, the proportion of workers who are laid off due to low productivity declines during recessions, diminishing the adverse signaling effect of an unemployment spell. Wage regressions estimated using the Displaced Workers Supplement support this basic prediction of the model.
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1. Introduction

In the labor economics literature, layoffs are often viewed as a selective weeding process. For example, Laing (1994) and Gibbons and Katz (1991) develop signaling models in which firms may choose to lay off workers when they are discovered to be of low ability.[1] In contrast, macroeconomists have typically focused on the type of unemployment that arises because the wage is set above the market-clearing level, but unemployed and employed workers are otherwise indistinguishable. In these models, unemployed workers are simply those who were unlucky enough to be laid off. For example, Gray's (1978) contracting model and efficiency wage models such as Shapiro and Stiglitz's (1984) model have this feature. These models have the advantage that they account more naturally than models in which unemployment is generated solely from asymmetric information for the striking tendency of unemployment to rise in recessions and fall in booms.[2] In an asymmetric information model, the distribution of worker types would have to fluctuate

with the business cycle to generate procyclical unemployment. However, they also lack the reasonable feature of asymmetric information models that unemployment falls disproportionately on workers who have unexpectedly low productivity. There are few models that fall between these extremes.

In this paper, I consider what happens when layoffs result from a combination of bad luck and selection. One implication of this model is that the proportion of unemployed workers who are laid off due to low productivity varies over the business cycle. The intuition is simple. Suppose that some workers are laid off in every period due to low productivity. However, the number of workers laid off simply due to bad luck is higher in recessions than in booms. In this case, workers laid off during recessions are, on average, less adversely selected than those laid off in booms. Furthermore, if the workers' productivities are not observable to firms then firms draw inferences about the workers' productivities from their past work experience. Since the signaling effect of an unemployment spell varies over the business cycle, so do the wage losses associated with unemployment.

2. Model

Consider the following simple model of unemployment over the business cycle. The model consists of firms and workers. There are two unobservable types: good and bad. Only "good"

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[1] Other more recent literature on signaling adverse selection models of layoffs includes Rodriguez-Planas (2003), van Wachter (2002) and Krashinsky (2002).
[2] In an asymmetric information model, the distribution of worker types would have to fluctuate with the business cycle to generate procyclical unemployment.

type workers contribute to production. The population fraction of good types is given by θ. The total amount of labor available in the economy is normalized to 1.

Firms produce according to the production function,

$$Y_t = A_t F(L_t), \tag{1}$$

where L_t denotes the "productive" labor employed by the firm (defined below), and A_t is an aggregate productivity shock. The production function $F(L_t)$ has diminishing marginal returns to labor.[3]

The labor aggregate entering into the representative firm's production function is defined,

$$L_t = \theta_t l_t, \tag{2}$$

where l_t is the total number of workers hired by the firm and θ_t is the fraction of good types among these workers.

Let us define the marginal price of one unit of L_t as w_t (I define this explicitly below). In this case, the firm chooses L_t to maximize profits in a given period,

$$A_t F(L_t) - w_t L_t, \tag{3}$$

where w_t is the effective wage of productive workers. The first order condition implies,

$$L_t = F'^{-1}\left(\frac{w_t}{A_t}\right), \tag{4}$$

when $F'^{-1}\left(\frac{w_t}{A_t}\right) < \theta$ and $L_t = \theta$ otherwise.

I assume that wages are determined one period in advance, before the next period's productivity is observed. As a consequence, an adverse productivity shock may cause labor demand to fall below $\lambda_t = \theta - F'^{-1}\left(\frac{w_t}{A_t}\right)$.

Every period consists of two parts. In the first part, the productivity shock is observed and workers are hired. The firm then determines the number of workers to hire based on the observed productivity shock, and offers wages to previously employed and unemployed workers equal to $w_t(e)$ and $w_t(u)$ respectively. In the second part of the period, the firm observes workers' productivity and lays off the workers who are observed to be bad types.

The unemployed population therefore consists of a measure $1-\theta$ of "bad" labor (who were laid off) as well as a quantity λ_t of unemployed productive labor (who were never hired). Thus, the unemployment rate u_t in a given period is,

$$u_t = 1 - \theta + \lambda_t, \tag{5}$$

where λ_t is the quantity of unemployed productive labor. This expression implies that the fraction of "good" types among unemployed workers is given by,

$$\theta_t(u) = \frac{u_t - (1 - \theta)}{u_t}. \tag{6}$$

Table 1
Descriptive statistics

Variable	Not in a full-time job		In a full-time job	
	Observations	Mean	Observations	Mean
Dummy for layoffs	2953	0.34	6510	0.37
Tenure at previous Job	2912	4.86	6437	4.90
Weeks unemployed following displacement	2697	57.72	6293	21.47
Dummy for white race	2953	0.84	6510	0.90
Dummy for male gender	2953	0.49	6510	0.70
Education<12	2953	0.27	6510	0.19
Education 13–15	2953	0.16	6510	0.22
Education>=16	2953	0.08	6510	0.13

*The sample includes workers from the 1984, 1986, 1988, 1990 and 1992 CPS Displaced Workers Supplements, and include displacements that occurred in a calendar year at least 4 years previous to the survey, between 3 and 4 years (in time) before the January survey.

I assume that a firm cannot observe a worker's type when hiring, but can observe whether she was employed or unemployed in the previous period. For simplicity, I assume that the labor market is sufficiently large and impersonal that the firm does not retain any private information about workers (i.e. workers' types) between the time periods. I also assume that the firm is only able to verify a worker's employment status one period into the past.

The firm's cost minimization problem implies that the relative wage of the two types of workers must equal the ratio of their productivities,

$$\frac{w_t(u)}{w_t(e)} = \theta_{t-1}(u) \tag{7}$$

Thus, the relative wage of displaced workers is,

$$\frac{w_t(u)}{w_t(e)} = \frac{u_{t-1} - (1 - \theta)}{u_{t-1}}. \tag{8}$$

Given this expression, the marginal price of one unit of L_t is simply $w_t = w_t(e)$.[4]

Expression (8) motivates the empirical model presented in the next section. Notice that the relative wage is increasing in the unemployment rate at the time of the layoff in this model. Although I have assumed a particular model of unemployment (i.e. unemployment due to wage rigidity) this framework is not at all important to the results of the model. The key assumption is simply that business cycle increases in unemployment arise from aggregate shocks rather than an increased number of "lemons" in the labor force.

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[3] The diminishing marginal utility of labor can be thought of as arising from the implicit presence of a quasi-fixed factor of production such as land or capital.

[4] The firm may purchase units of L_t either by hiring previously employed or unemployed workers. The wage differential between the two types of workers implies that the firm is indifferent between employing previously employed workers at a high wage (who are all good types); or employing previously unemployed workers at a lower wage (who are sometimes bad types).

3. Empirical analysis

3.1. Wage change regressions

I estimate a linear regression model of the form,

$$\Delta \log w_t = \beta_0 + \alpha u + \beta x + \varepsilon, \qquad (9)$$

where $\Delta \log(w_i)$ is the difference in the individual's real wage before, α and β are vectors of parameters, x is a vector of other covariates, and u is the state-level unemployment at the approximate time of the job displacement, and is ε an error term. This type of specification is also used, for example, in Gibbons and Katz (1991). This specification has the advantage, relative to a specification in levels, that person-specific fixed-effects are differenced out in the left-hand side variable. I estimate the regression using data from the 1984–1992 Displaced Workers Supplement to the Current Population Survey.[5] The unemployment data are annual and was downloaded from the BLS website.

I only consider job transitions from one full-time job to another in order to eliminate the "quantity" effect of changes in hours worked. Moreover, I include only workers between the ages of 20 and 61. The DWS includes workers who lost their jobs due to a plant closing, slack work, or because a position or shift was eliminated, termed "displaced workers" by the Bureau of Labor Statistics (BLS), as well as workers who were displaced because a seasonal job finished, due to the failure of a self-operated business, and for other reasons. The empirical model (9) is estimated for both the entire sample, as well as for displaced workers alone.

Since the unemployment rate is a highly persistent variable, I focus on workers who were displaced during a calendar year at least 4 years prior to the survey — between 3 and 4 years before the January survey.[6] For these job displacements, the sample correlation between the unemployment rate at the time of the survey and the unemployment rate at the time of the job displacement is approximately 0.4, whereas the correlation would be much higher if more recent job displacements were also included in the sample. To the extent that current unemployment is associated with lower wages for new workers, the correlation between current unemployment and unemployment at the time of the job displacement will bias the estimated coefficient on the previous unemployment rate toward zero.

The other covariates x consist of the demographic variables age, education, minority status and sex, as well as the worker's tenure at his previous job, the time since the worker was laid off, a dummy variable for whether the displacement was a "layoff" and a time trend. I follow Gibbons and Katz (1991) in defining a

Table 2
Wage regressions and hazard function estimates

	Wage change regressions		Hazard function estimates
	(1)	(2)	(3)
Unemployment rate at time of job displacement	0.021 (0.004)	0.019 (0.005)	0.056 (0.011)
Dummy for layoffs	−0.037 (0.015)	−0.026 (0.015)	−0.239 (0.017)
Tenure at previous job	−0.011 (0.001)	−0.011 (0.001)	−0.015 (0.002)
Years since job loss	−0.047 (0.017)	−0.053 (0.018)	
Constant	−15.532 (6.278)	0.019 (0.005)	−1.224 (0.159)
Unemployment rate at time of survey			−0.152 (0.011)
p (Shape parameter for the Weibull Hazard function)			0.739 (0.005)
N	12461	12461	29163
R^2	0.06	0.06	

Note: The dependent variable is the change in real log weekly earnings. The standard errors are in parentheses. The sample includes workers from the 1984, 1986, 1988, 1990 and 1992 CPS Displaced Workers Supplements, and include displacements that occurred in a calendar year at least 4 years previous to the survey, between 3 and 4 years (in time) before the January survey. Specification (1) includes workers displaced for any reason, whereas specification (2) includes only "displaced workers" (as defined by the BLS). The regressions include state and major occupation group dummies. The base categories are 20–24 year old white males. Specification (3) presents estimates of a hazard function model for the hazard of ending an unemployment spell. All of the specifications include dummy variables for education: education <12 years, 13–15 years>=16 years; as well as dummy variables for age: 25–34, 35–44, 45–54, 55–61; and a dummy variable for gender and race.

displacement as a "layoff" so long as it did not occur due to a plant closing. These explanatory variables are included in the wage regression to try to isolate the signaling effect of unemployment from the effects of observable variables such as age and sex. Occupation and state fixed-effects are included in all of the specifications. Table 1 compares descriptive statistics for the sample of displaced workers used in this paper, broken down by whether the worker had a new full-time job at the time of the survey.

Table 2 presents the regression results. I present the results of the model estimated for both the entire sample, as well as for displaced workers alone (as defined by the BLS).

In both specifications, the unemployment rate at the time of the job displacement has a significantly positive effect on the individual's post-displacement relative wage change.[7] Quantitatively, a 1 percentage point increase in the state-level unemployment rate at the time of displacement is associated with about a 2 percentage point increase in the best linear predictor of the percentage change in the worker's relative wages following the displacement.

If workers displaced in the previous three calendar years are included (rather than those displaced in the previous 4 calendar

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[5] The Displaced Workers Supplement (DWS) is only collected in even years. Thus, I use data from the 1984, 1986, 1988, 1990 and 1992 surveys. See Farber (1993, 1997) for a detailed analysis of job loss using the DWS.

[6] Unfortunately, changes to the DWS after 1992 make it less suitable for this study for the more recent data, given the need to focus on job displacements that occurred several years back. Among other things, the survey was changed to include only job displacements that occurred in the 3 calendar years prior to the survey. See Farber (1997) for a detailed discussion of these issues. However, the relatively short panel of the DWS that can be used for this purpose is clearly a limitation of this work.

[7] Notice also that the "layoffs" dummy has a significantly negative coefficient, as in Gibbons and Katz (1991) and Farber (1997).

years) the sign on the unemployment rate is smaller, but remains statistically significant.

3.2. Hazard function estimation

In a more general model, the unobserved factors generating lower post-displacement wages might also lead to longer unemployment spells. To investigate this idea, I estimate a proportional Weibull hazard function model for the probability of the workers exiting unemployment. The hazard function depends on the same variables x as in the wage regression as well as a time-varying regressor for the current unemployment rate and a variable reflecting the unemployment rate at the time of the job displacement.

Displaced workers are viewed as exiting an unemployment spell only when they acquire a new full-time job. If a worker is not observed to find a new full-time job by the survey date, his unemployment spell is viewed as censored. Of the 25,612 observed unemployment spells, 15,111 are observed to end with the worker exiting to a full-time job before the survey date; while the remainder are counted as censored.

The second panel of Table 2 presents the results of this exercise. Qualitatively, the results go in the same direction as the wage change regressions. The coefficient on a given variable indicates the contribution of the variable to the individual's "hazard" of exiting unemployment. The second panel of Table 2 indicates that a higher unemployment rate at the time of the job displacement increases the hazard of exiting unemployment, or decreases the expected length of the unemployment spell. In contrast, a higher current unemployment rate increases the expected length of the unemployment spell. Layoffs are associated with a lower hazard of job exit, as in Gibbons and Katz (1991).The estimated shape parameter for the Weibull Hazard function is 0.73.

4. Conclusion

This paper shows that in a model with unemployment due to bad luck as well as selection, the composition of displaced workers varies over the business cycle, and presents some empirical evidence supporting this claim. As in Gibbons and Katz (1991), it is difficult to know whether the effect is associated with signaling or adverse selection. The workers may receive lower wages because firms take previous unemployment as a signal of low ability or simply because the firms observe that the workers are adversely selected. However, as Gibbons and Katz (1991) note, a symmetric information story must be able to account for both why workers are laid off at all (instead of receiving wage cuts) and why their wages decline on average following layoffs.

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