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The Long-Term Effects of Youth Unemployment

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The Long-Term Effects of Youth Unemployment

Executive Summary

The era of high employment has taken a sharp downward turn. The U.S. economy was cooling rapidly even before terrorism entered the picture. Employee layoffs are now measured in the hundreds of thousands. Many of these employees were entry-level workers just starting their careers. The Labor Department's statistics on teenage and young adult employment reflect a substantial rise in unemployment rates.

With unemployment rising in nearly every community, there is a compelling question before us: what are the long-term effects of unemployment spells? This is a difficult but very important question, particularly when shaping policies that may create unemployment among young workers. The effects of early unemployment can last much longer than many recognize. In fact, the effects of even relatively brief periods of unemployment can be felt (and measured) for years, not months.

The range of policies that could lead to unemployment among young workers is fairly easy to identify. Many policies that increase the cost of employing entry-level workers either have a proven record of causing job loss (e.g., minimum wage hikes) or carry clear risks of undermining employment levels (e.g., mandated benefits, increased payroll taxes, etc.). Other potential culprits could include tax, expenditure and monetary policies that cause unemployment to rise. It is well known that young people have the highest unemployment rates and their labor market success is quite sensitive to the state of the overall economy.

In this new research, Dr. Thomas A. Mroz of the University of North Carolina at Chapel Hill and Dr. Timothy Savage of Welch Consulting Economists show that policies causing youth unemployment can harm young adults for several years into the future. Far from being a fleeting annoyance, early unemployment has measurable, persistent effects that can be linked to the stagnation of human capital that occurs when an individual is not working, in training or in school.

Data Source

Using the National Longitudinal Survey of Youth (NLSY) Drs. Mroz and Savage study young men and their labor market reactions over time. The NLSY tracked the employment, education and demographic status of young men from the ages of 14 to 19 beginning in 1979 through 1993. Several factors describing the sample workforce change as the sample ages. From 1979 to 1993 the percentage of the sample experiencing any unemployment during the year decreased from 30% to 19%. Annual hours worked increased from an average of 628 in 1979 to 2,026 in 1993. Not surprisingly, average level of education and training increased over time, while the number in school decreased steadily. These statistics all show that human capital increased steadily over the sample period for the average male of that age. The core subject of the research, however, is an examination of the effects of a period of unemployment on future employment.

Lost Jobs Lead to Decreased Wages

Early unemployment delays gains in experience and training that usually lead to increased earnings. Prior work experience has been found to have a large and positive effect on future earnings, which is disrupted by an unemployment spell.

A 13-week unemployment spell last year

Annual Weeks of Unemployment During the Year - for Study Sample

1979	3.32
1986	4.20
1993	2.83

Any Training During the Year
for Study Sample

1979	3%
1986	12%
1993	18%

reduces wages this year by 3.4%, or about $900 (in 1993 dollars) for a full-time employee. A similar unemployment spell as long as four years ago reduces average hourly earnings by over 1%. At full-time in 1993, this amounted to over $300.

A six-month unemployment spell experienced as long as four years ago reduces wages by 2.3%, equivalent to forgoing about one-quarter of a year of schooling.

Past Unemployment and Future Unemployment

In addition to suffering from lower wages after experiencing an unemployment spell, many are subject to increased likelihood of future unemployment. Not only do they have higher chances of being unemployed, but also those spells are shown to be longer for those who were previously unemployed.

Those previously unemployed as long ago as four years have a higher probability of being unemployed in the present year. A 13-week unemployment spell last year increases the duration of a contemporaneous unemployment spell by over 1.5 weeks annually. A term of unemployment last year decreases annual hours worked this year by approximately 5 hours annually for every week unemployed.

The "Catch-Up" Response

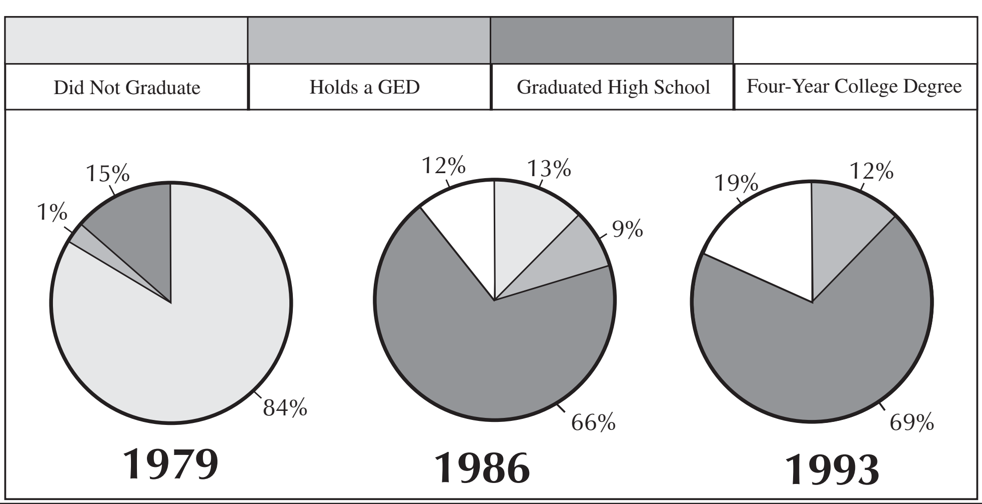
One of the primary findings of this research shows that during the period following a spell of unemployment, young men attempt to "catch up" to where they would be had they not been involuntarily unemployed. These young men attempt to replace the human capital gap created by a spell of unemployment. Prior unemployment is shown to have a positive effect on the contemporaneous likelihood of training. This effect lasts for only a short period as young men attempt to increase their economic value.

Conclusion

The results produced by Drs. Mroz and Savage show that policies causing youth unemployment (even unintentionally) lead to tougher roads for those youths that are most vulnerable. Those experiencing unemployment at an early age have years of lower earnings and an increased likelihood of unemployment ahead of them. Policies that may cause job loss can inadvertently lead to decreased wages, increased chances of unemployment and longer future unemployment spells for the most vulnerable.

Richard S. Toikka | *Chief Economist*

High School Graduation Rate - for Study Sample



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I. Introduction

The long-term effects of youth unemployment on later labor market outcomes are critical factors in the evaluation of government policies that affect the youth labor market. Adverse impacts may take the form of lower wage rates and weakened labor force participation in the future. If these adverse effects are large and persist through time, policies such as raising the minimum wage or increasing unemployment benefits will have sizable but hidden costs. Most analyses of the potential impacts of labor market policy, however, focus only on contemporaneous employment effects. This focus may be quite shortsighted, particularly for young people.

This research presents policy-relevant estimates of the effects of youth unemployment on labor market outcomes later in life. We jointly model the endogenous schooling, training and labor market decisions and outcomes of young men over time using a sample from the 1979 National Longitudinal Survey of Youth (NLSY). The econometric framework used in this study includes detailed controls for the endogeneity of a wide range of human capital behaviors, including prior unemployment.

13 weeks of unemployment experienced as long as four years ago reduces average hourly earnings by over 1 percent...a reduction of over $300.

A spell of unemployment can lead to suboptimal investments in human capital among young people in the short run. A general dynamic model of human capital investment and accumulation predicts a rational "catch-up" response to an involuntary unemployment spell. The estimates presented here provide strong evidence of this catch-up response. First, prior unemployment has a significant positive effect on whether a young man trains today. Second, unemployment as long ago as five years has a significant positive effect on whether a young man works today and on how many hours are worked. While there is little evidence of long-lived persistence of unemployment spells on the incidence and duration of future unemployment spells, there is short-term persistence. It is important to recognize that this evidence on increased training and employment by the previously unemployed youth should not be considered an indication of higher productivity of these youth relative to those youth who did not experience an unemployment spell. Rather, the observed increases in these productivity enhancing activities should be considered as attempts by the previously unemployed youths to replace a fraction of the human capital investments that the unemployment spells impeded. Despite this catch-up response and an absence of long-lived persistence in unemployment spells, there is evidence of long-lived "blemishes" from unemployment. After controlling for the observed human capital stock, 13 weeks of unemployment experienced as long as four years ago reduces average hourly earnings by over 1 percent. In terms of 2,000 hours worked at the sample's average nominal wage in 1993, this is a reduction of over $300. The unemployed youth clearly suffered because of their unemployment experiences, but they undertook activities to diminish the severity of these losses.

The remainder of this paper is divided into five sections. The next section examines the existing literature on the long-term effects of youth unemployment. The third section presents a simple analytic model of human capital accumulation that yields two interesting propositions about unemployment, training and potential earnings. The fourth section presents an empirical framework to analyze this issue and the data used in this study. The fifth section discusses the estimation results derived from the empirical model. The sixth section concludes.

II. Prior Literature

At the end of the 1970s, the official unemployment rate of youths age 16 to 19 had risen considerably during the past decade. Between 1969 and 1979, the annual rate had risen by over 30% from 12.2 to 16.1%. At the time, policymakers feared that the nation was gripped by an unemployment problem that would "permanently scar" the unemployed young. Policymakers accorded much less importance, however, to the fact that the labor force participation rate for this age group had also risen considerably from 49.4 to 57.9%.

In 1997, the US unemployment rate for 16- to 19-year-olds was 16.0% or nearly four times as high as the rate of the adult (20 and above) population. For black teenage males, the rate was over 36%. Surprisingly, these rates have changed very little in two decades. This is remarkable in light of the very different labor market conditions faced by young people in 1979 and in 1997. High youth unemployment rates are not unique to the US, however. In 1995, the annual unemployment rate for 16- to 24-year-olds in the European Union (EU) was 20.8% or nearly double the rate for the above-24 population.[1] The three highest rates were 41.7% in Spain, 33.5% in Italy and 29.9% in Finland. In Japan during 1997, the unemployment rate for 15- to 24-year-olds was twice that of those over 24. If it has longer-term impacts, especially on future earnings, youth unemployment would be an important social and economic issue.

Early empirical analyses of the long-term effects of youth unemployment focused on the extent to which early unemployment spells affect the incidence and duration of future unemployment spells.[2] These analyses found evidence of strong persistence in unemployment. In contrast to these analyses, other studies made a distinction between true state dependence and unobserved heterogeneity.[3] They showed that a failure to control for heterogeneity might spuriously indicate persistence by hypothesizing that individuals differ in certain unobserved characteristics. If these characteristics are correlated over time, measures of state dependence will proxy for this serial correlation in the absence of suitable controls. Youths with weak preferences for working and training, for instance, will tend to work and train less over time, other things equal. Observed variables such as prior unemployment are, therefore, statistically endogenous in regression analyses, and unbiased measures of their effects cannot be obtained.

A 1982 National Bureau of Economic Research (NBER) volume on the youth labor market approached the subject of youth unemployment, in part, by drawing on the search theoretic framework of Mortensen (1970) and Lippman and McCall (1976).[4] Many of the analyses in this volume posit that an extensive process of mixing and matching among workers and firms characterizes the youth labor market. Young people find it optimal to change jobs frequently because of low reservation wages and low opportunity costs. High rates of turnover, possibly punctuated by unemployment spells, are a common characteristic of this market and not a problem *per se*.[5]

Corcoran (1982) examines persistence in employment status by examining whether current employment status is influenced by prior employment status.[6] She finds the odds that a young woman works this year are nearly eight times higher if she worked last year than if she did not. Corcoran also examines the effect of prior education and work experience on hourly earnings, finding that both positively affect wages for the first few years out of school.[7] Ellwood (1982) examines persistence in employment patterns using annual weeks of unemployment and annual weeks worked.[8] After controlling for unobserved heterogeneity, he finds no persistence in unemployment and slight evidence of persistence in work behavior. He also examines the effect of prior education and work experience on hourly earnings, finding that both have a significant and positive effect for the first few years out of school. In both the Corcoran and Ellwood studies, the cost of forgone participation appears to be lower future wages rather than persistent nonparticipation in the labor market.[9] Using normal maximum likelihood methods to control for endogeneity, Meyer and Wise (1982) jointly model the choices of schooling and annual weeks worked. They also jointly model the schooling decision and wages. They find that hours of work during high school positively affect weeks worked after graduation and that early labor force experience positively affects wages. They jointly model only two of the several outcomes of interest, however. While they recognize that schooling, experience and wages should be modeled and estimated jointly, they leave this task to future research.[10]

Research on the youth labor market did not end with the NBER volume, however.[11] Michael and Tuma (1984) examine the labor market effects of early labor force experience.[12] Regressing wages and schooling on lagged experience, they find that early employment does not affect wages or schooling likelihood two years later. They treat early experience as exogenous, however, and do not control for possible unobserved heterogeneity. Ghosh (1994) also examines the effects of early experience.[13] Using proxies such as test scores to control for heterogeneity, he regresses hours worked and wages at ages 22 and 23 on early schooling and labor force experience. He finds that early experience has positive long-run effects on hours worked and wage rates. While he has the advantage of a longer time horizon, Ghosh also treats early decision-making as exogenous. He finds larger effects than Michael and Tuma, however. This indicates that additional panel-years of data are necessary to uncover these long-term impacts.

It is difficult to pinpoint specific policy conclusions that might be drawn from the results in these studies. Several treat early labor force participation and schooling decisions as exogenous. In a model of lifetime decision-making, the inclusion of jointly chosen variables such as years of schooling or work experience yields results that are difficult to interpret behaviorally. Contrasting the results from Michael and Tuma with those of Ghosh, a policymaker would not be able to determine whether programs that encourage labor force participation among high school students benefit the participants with higher wages in later years.

The current literature on the long-term effects of youth unemployment contains many shortcomings. These include the use of small or non-random samples; the failure to control adequately for unobserved heterogeneity and endogeneity; insufficient time horizons to evaluate the full impacts of early unemployment; the imposition of unnecessarily restrictive statistical assumptions; and an absence of specific and meaningful policy conclusions.

This research addresses these deficiencies directly. It uses a large sample representative of the young male US population in 1979. The labor market, schooling and training decisions and outcomes of this sample are followed for 16 years. We jointly model and estimate these outcomes using a permanent/transitory error-components specification for unobserved determinants. This specification controls for the contaminating effects of unobserved heterogeneity and endogeneity. The estimates from this research can be used to gauge the long-term impacts of policies that affect the youth labor market.

III. A Conceptual Framework

Consider the following simple analytic model of human capital investment that closely follows Ben-Porath (1967).[14] In this model, the present and the future are directly linked through the human capital accumulation process. An exogenous shock that perturbs the optimal time-path of investment in one period persists through time via the human capital stock. The model is used to examine the effects of this shock on future behaviors and outcomes.

In this model, individuals live with certainty for three periods and may train in each of the first two periods.[15] Individuals invest in human capital by purchasing inputs d_t to a human capital production function and by training. Training occurs on the job and is considered to be general. There is an implicit time-cost to training, and the share of time spent training is $s_t \in [0,1]$. There are no savings, no human capital depreciation and no decisions regarding hours of work other than the choice of s_t. Earnings E_t are obtained by renting the human capital stock (HC_t) at a constant rate w: $E_t = wHC_{t-1}$.[16] This is always possible except when experiencing involuntary unemployment. Disposable income (or net earnings) is the difference between earnings and human capital investment: $E_t - I_t$. At the beginning of the first period, an individual chooses production function inputs d_1, d_2, s_1 and s_2 for both periods to maximize the present discounted value of disposable income. These four choices yield an optimal time-path of human capital investment and accumulation.

Involuntary unemployment perturbs an individual's optimal time-path of human capital accumulation. This is because it prevents on-the-job training, resulting in an under investment in human capital after the unemployment spell takes place. An involuntary unemployment spell in the first period, therefore, is equivalent to an exogenous reduction in that period's optimal human capital stock.[17] Those who experience the spell enter the second period with a stock of human capital HC_1 that is constrained below the optimal stock. Crucially, having experienced the shock, individuals are able to re-optimize at the beginning of the second period. This reoptimization yields a new optimal time-path of human capital investment. In this model, the only lasting effect of an involuntary unemployment spell is that it initially constrains an individual to less-than-optimal human capital accumulation. The model can be used to examine the spell's effect on future behaviors. It can also be used to examine how a spell affects observable outcomes such as earnings and provides a mechanism through which these effects may be mitigated by optimal behavior. The model provides two interesting implications.[18]

Proposition 1:

The "Catch-Up" Response

Upon experiencing an involuntary unemployment spell in the first period, young people will unambiguously increase the time spent training and their expenditure on human capital inputs in the second period.

(This follows because $\frac{\partial s_2}{\partial HC_1} < 0$ *and* $\frac{\partial d_2}{\partial HC_1} < 0$.)

This proposition states that young people exhibit an optimal "catch-up" response to an involuntary unemployment spell that exogenously reduces their human capital acquisition in the first period.[19] The exogenous spell initially perturbs a young person's optimal time-path of human capital investment. Reoptimization that takes the spell into account, however, yields a new optimal time-path. This re-optimization produces two unambiguous effects on future behavior. The first is that a young person will increase the share of time spent training. The second is that a young person will increase expenditure on human capital. These behavioral responses are obtained because the return to training in the third period is strictly increasing the previous period's human capital stock. These changes in optimal second period choices are referred to as a "catch-up" response.

Proposition 2:
Convergence

The effect of the unemployment spell on potential earnings diminishes over time.

(This follows because $\left|\frac{\partial E_2}{\partial \overline{HC_1}}\right| > \left|\frac{\partial E_3}{\partial \overline{HC_1}}\right|$.)

In the second period, individuals unambiguously increase the share of time spent training. They also increase their expenditure on human capital inputs. These behavioral responses compensate for the human capital involuntarily forgone in the first period. By the third period, this compensatory training behavior results in a convergence in the unperturbed and perturbed human capital stocks. Therefore, the behavior directly mitigates the unemployment spell's effect on potential earnings over time. This model demonstrates persistence in the sense that the effect of a spell in a single period lasts beyond that period. Optimizing behavior, however, mitigates that effect over time.

...an exogenous unemployment spell results in sub-optimal human capital acquisition that directly affects future decisions and outcomes.

This conceptual model is simple but useful. It directly links the present and the future through the process of human capital investment and accumulation. By establishing equivalence between an involuntary unemployment spell and an exogenously constrained human capital stock, one can examine the effects of such unemployment on future behavior and outcomes.[20]

IV. The Empirical Specification and the Data

The chief goal of this research is to provide policy-relevant predictions of the long-term effects of youth unemployment on future labor market outcomes. The preceding conceptual model provides a link between prior unemployment and the future through the human capital accumulation process. In this model, an exogenous unemployment spell results in sub-optimal human capital acquisition that directly affects future decisions and outcomes. Here we address crucial econometric, data and empirical issues.

We model jointly the endogenous schooling, training and labor market decisions and outcomes of young people over time. Each year, a young person chooses whether to train, to attend school and to participate in the labor market. Conditional on his labor force participation, he chooses how many hours to work annually. A young man may also experience unemployment, either voluntary or involuntary, during the year. Hourly earnings as well as schooling, training and labor force participation may be affected by an unemployment spell. The system of equations is estimated jointly using the semiparametric, full information maximum likelihood method suggested for single equations by Heckman and Singer (1984) and extended to simultaneous equations by Mroz and Guilkey (1992) and Mroz (1998). This discrete factor integration method allows complex correlation across equations and over time. It explicitly models and controls for the contaminating effects of heterogeneity and endogeneity.

By using this semiparametric, full information maximum likelihood (FIML) procedure, we are able to control effectively for the endogeneity of a wide range of the youths' previous decisions and outcomes on their later behaviors and outcomes. For example, we are able to model a wide range of endogenous behavioral determinants including previous unemployment, schooling and work experience. The estimates reported in this study, then, should be interpreted as the impacts of an exogenously induced change in the endogenous determinants. By controlling for endogeneity for this wide range of employment, training and wage determinants, the estimates reported here should provide more relevant predictions for policy evaluations than those found in any of the previous studies on the impacts of youth unemployment.

Modeling the Outcomes of Interest

In a study of this type, there are many potentially endogenous human capital variables that are used as right-hand side regressors. They include the stocks of education and work experience and prior unemployment. To account for this potential endogeneity, up to seven behavioral outcomes are jointly modeled every year for each young person in the sample. These outcomes are (log) average hourly earnings; whether or not a young man works; annual hours worked if working; whether or not a young man is unemployed; annual weeks of unemployment if unemployed; school attendance; and training. Log average hourly earnings are specified to be Mincer-type earnings functions. They depend upon polynomials in age and cumulative work experience, the stock of education and demographic variables.[21] Earnings may also be affected by prior unemployment.[22] Annual hours of work depend upon local labor market conditions, polynomials in age and labor force experience, education, prior unemployment and demographic variables. Annual weeks of unemployment depend upon local labor market conditions, polynomials in age and labor force experience, education, prior unemployment and demographic variables. Training is a dummy variable that takes the value one if a young person took part in any government-sponsored or vocational training in a particular year.[23] It depends upon polynomials in age and labor force experience, education, local labor market conditions, demographic variables and prior unemployment. Schooling is a dummy variable that takes the value one if a young person participated in any secondary or postsecondary education in a particular year. It depends upon polynomials in age and labor force experience, demographic variables and prior unemployment. Each of these equations also includes a linear time trend.

The Likelihood Function

To derive the likelihood function for the system of equations to be estimated, we use the following observed sequence for each young person i at each year t:

$$\{s_{it},\ tr_{it},\ work_{it},\ hw_{it},\ un_{it},\ wu_{it},\ w_{it}\}$$

s_{it}	DV	school attendance
tr_{it}	DV	vocational training
$work_{it}$	DV	working
hw_{it}		number of annual hours worked
un_{it}	DV	experiencing any unemployment
wu_{it}		number of annual weeks of unemployment
w_{it}		average hourly earnings

DV = Dummy Variable

Let ε_{it} be a vector with seven elements that contain unobserved determinants of the above outcomes. These unobserved determinants are specified to have an error-component structure: $\varepsilon_{it} = \rho\mu_i + \eta_{it} + u_{it}$, where Δ is a vector of factor loads. Assume u_{it} is a mean-zero iid normal error vector. The only substantive restriction this error-components structure places on the density of e_{it} is that all correlation across equations and through time enter solely through the factors μ_i and η_{it}. It is precisely a permanent/transitory error specification. The factor μ_i captures unobserved determinants that do not vary as young people age, such as ability. The factor η_{it} captures time-specific unobserved determinants that may vary across time, such as preferences for work.[24]

As an example of a discrete outcome, consider vocational training, tr_{it}. As with the other three dummy variable outcomes modeled in this study, a latent index specification is used.

Equation 1

$$tr_{it}^{*} = x_{tr,it}'\alpha_{tr} + \sum_{\tau=1}^{5}\beta_{tr,\tau} wu_{it-\tau} + \rho_{tr}\mu_i + \eta_{tr,it} + u_{tr,it}$$

where $tr_{it} = 1$ if $tr_{it}^{*} > 0$ and $= 0$ otherwise

At each point in time, a young man trains if the value of his latent index is positive. The decision to train is influenced by a vector of observed variables, $x_{tr,it}$. This vector of variables, briefly discussed earlier, includes background characteristics together with demographic and (potentially endogenous) human capital variables.[25] This decision is also influenced by permanent and transitory factors that are not observed. Crucially, the decision to train is also influenced by prior unemployment $wu_{it-\tau}$ for up to five years.[26] This study focuses on the estimates of the ∃'s, the impacts of prior unemployment, for each of the seven outcomes:
$\beta_{o,t}$ for o = s, tr, work, hw, un, wu, w, and $\tau = 1,\ldots,5$.[27]

As an example of a continuous outcome, consider annual hours worked.[28]

Equation 2

$$h_{it} = x_{hit}'\alpha_h + \sum_{\tau=1}^{5}\beta_{h,\tau} wu_{it-\tau} + \rho_h\mu_i + \eta_{hit} + u_{hit}$$

Every year for each young man, annual hours of work are influenced by a vector of observed variables and unobserved error terms. As with the other outcomes, hours of work are also influenced by prior unemployment for up to five years.

A researcher can control for the contaminating effects of heterogeneity and endogeneity by integrating out the unobserved factors, μ_i and η_{it}. For example, if the factors were assumed to have a normal distribution, one could use multivariate normal maximum likelihood. The discrete factor integration method used here assumes that the underlying continuous distributions of the factors can be approximated by discrete distributions with mass points and probability weights that are estimated jointly with the other parameters in the system. Integration is greatly simplified since it requires only summing the suitably weighted products of density functions and univariate integrals. Further, the researcher does not have to make an *a priori* assumption about the distribution of the factors since the discrete approximation is driven by the data.

Conditional upon the factors, the contribution to the likelihood of individual i at time t is:

Equation 3

$$
\begin{aligned}
&\mathrm{L}_{it}\left(\Theta \mid \mu_i, \eta_{it}\right) = \\
&\left[\Pr\left\{\mathrm{work}_{it} = 1 \mid \mu_i, \eta_{it}\right\} \cdot \mathrm{f}_h\left(\mathrm{h}_{it} \mid \mu_i, \eta_{it}\right) \cdot \mathrm{f}_w\left(\ln \mathrm{w}_{it} \mid \mu_i, \eta_{it}\right)\right]^{\mathrm{work}_{it}} \cdot \\
&\left[\Pr\left\{\mathrm{work}_{it} = 0 \mid \mu_i, \eta_{it}\right\}\right]^{(1-\mathrm{work}_{it})} \cdot \\
&\left[\Pr\left\{\mathrm{un}_{it} = 1 \mid \mu_i, \eta_{it}\right\} \cdot \mathrm{f}_{wu}\left(\mathrm{wu}_{it} \mid \mu_i, \eta_{it}\right)\right]^{\mathrm{un}_{it}} \cdot \\
&\left[\Pr\left\{\mathrm{un}_{it} = 0 \mid \mu_i, \eta_{it}\right\}\right]^{(1-\mathrm{un}_{it})} \cdot \\
&\left[\Pr\left\{\mathrm{tr}_{it} = 1 \mid \mu_i, \eta_{it}\right\}\right]^{\mathrm{tr}_{it}} \cdot \left[\Pr\left\{\mathrm{tr}_{it} = 0 \mid \mu_i, \eta_{it}\right\}\right]^{(1-\mathrm{tr}_{it})} \cdot \\
&\left[\Pr\left\{\mathrm{s}_{it} = 1 \mid \mu_i, \eta_{it}\right\}\right]^{\mathrm{s}_{it}} \cdot \left[\Pr\left\{\mathrm{s}_{it} = 0 \mid \mu_i, \eta_{it}\right\}\right]^{(1-\mathrm{s}_{it})}
\end{aligned}
$$

where f_h is the annual hours worked density, f_w is the log wage density, f_{wu} is the annual weeks of unemployment density, and Θ is a vector of parameters to be estimated.

Approximating the distributions of μ_i and η_{it} with mass points μ_{ik}, for k = 1,...,K, and η_{itm}, for m = 1,...,M, the contribution to the likelihood function of individual i is:

Equation 4

$$
L_i(\Theta, \Gamma) = \sum_{k=1}^{K} p_{1k} \prod_{t=1}^{T} \sum_{m=1}^{M} p_{2m} L_{it}\left(\Theta \mid \mu_{ik}, \eta_{itm}\right)
$$

$p_{1k} = \Pr\{\mu_i = \mu_{ik}\}$ for $\mu_{ik} \in \Re$, $p_{2k} = \Pr\{\eta_{it} = \eta_{itm}\}$ for $\eta_{itm} \in \Re^7$, and Γ is the vector containing the parameters of the discrete distributions.

Identification

This study treats training, school attendance, work experience and unemployment as potentially endogenous variables that evolve as the young men in the sample age. The dynamic structure of this model secures the identification of the effects in ways that cannot be achieved in static analyses.[29] Within this dynamic structure, lagged exogenous variables satisfy the conditions for instrumental variables. To see this, consider the unemployment rate in the local labor market. At any point in time, such a variable is exogenous to young people. In 1985, variation in this rate has a direct impact on 1985 labor market choices. Similarly, variation in 1983 has a direct impact on 1983 choices. Because of the timing of decision-making, however, the 1983 rate has no direct impact on 1985 decisions except through the accumulated stock of human capital as of 1985. Consequently, the 1983 rate is an instrumental variable in 1985. This argument, of course, applies to different years and to the other exogenous variables in this study. Therefore, there are numerous instruments available, and the dynamic maximum likelihood procedure allows these to be exploited efficiently.

Identification in this model is also secured with theoretical exclusion restrictions and through nonlinearities in the likelihood function. Variables described later in this section that use exogenous state-level data provide these theoretical exclusion restrictions. These variables directly affect the schooling and training decisions and labor supply, but have no direct impact on wages other than through the human capital stock. They are, therefore, excluded from the wage equation.

The Data

The primary data for this research are taken from the National Longitudinal Survey of Youth (NLSY) and its geocode supplement. We use young men who were 14 to 19 years old in 1979 drawn from both the representative sample and the over-samples of blacks and Hispanics. This yields a sample size of 3,731 in 1979 that is followed through 1994. Of this, 2,286 are from the representative sample and 1,445 are from the two over-samples.

When constructing this sample, we applied the following two selection criteria.[30] First, a young man remains in the sample until his first non-interview date, after which he leaves the sample regardless of whether he is interviewed at some future date.[31] Second, those young men (not in the initial military sub-sample) who enter the armed forces permanently leave the sample upon entry.[32]

Table 1 contains variable descriptions and summary statistics for the time-invariant characteristics of our sample. The first column of numbers contains the sample means for the entire sample. The next two columns contain the means for the representative and over-sample portions respectively. The variable afqt is derived from the 1980 Armed Forces Qualification Test (AFQT).[33] The scores from this test are regressed against age dummies to purge pure age effects.[34] Each value is then mean-differenced using the mean for the entire sample.

The first seven rows of Table 2 contain the unweighted means for the entire sample in 1979, 1986 and 1993 of the outcomes that are jointly modeled in this study. As shown in Figure 1, average annual weeks of unemployment appear quite anti-cyclical over this 16-year period, peaking in the recessions of the early 1980s and early 1990s. Figure 1 shows averages both for the entire sample and conditional upon any unemployment during the year. Average school attendance declines monotonically throughout the 16-year period. Average participation in vocational training rises to a maximum of 18.0% in 1993 but declines slightly in 1994. Average annual hours of work rise monotonically from 628 in 1979 to 2,034 in 1991. They decline somewhat in 1992 and 1993 but return to their 1991 level by 1994. Real average hourly earnings (in logs) rise monotonically from 1979 to 1993.[35] The remaining rows in Table 2 contain the time-varying unweighted averages for other variables used in this study.

There are several sources of state-level data that are matched to the NLSY sample. The first is data taken from the Digest of Education Statistics (DES) on per-student public expenditure at public secondary education institutions. The second is DES data on per-student public expenditure at postsecondary education institutions. The third is data taken from the Integrated Postsecondary Education Data System (IPEDS) on annual tuition prices at the largest or main campus of the state university system.[36] These expenditure and tuition data have been deflated using the CPI-UX1 deflator and show substantial variation through time and across states. For example, in 1979 the New England states spent nearly 25% more per student on secondary education than southern states, while tuition charges at public universities in the South were 80% lower than charges in New England. By 1986, these differentials were 37% and 49%, respectively.

Data on mandated minimum wages are also matched to the NLSY sample. Because certain states, notably California, Massachusetts and Pennsylvania, often have mandates that exceed the federal minimum, we use the larger of the federal or state mandate. These data are also deflated and show considerable variation over time. As shown in Figure 2, the real value in 1982 dollars of the federal minimum wage declines by about 30% from 1979 to 1989, a period during which the federal mandate remained unchanged. It rises in 1990 and 1991 due to legislated increases, but declines thereafter. The real value of the minimum wage in 1991 is about 80% of its 1979 value.

Table 1

Summary Statistics of Time-Invariant Characteristics
(Standard Deviations Omitted for Dummy Variables)

Variable Name	Variable Description	Entire	Represent	Over-sample
		Standard Deviation		
		3731 obs	2286 obs	1445 obs
afqt	Armed forces qualification test score	0.00 28.13	8.14 28.35	-12.88 22.40
mohgc	Mother's highest grade completed	10.86 3.12	11.60 2.63	9.68 3.46
fahgc	Father's highest grade completed	10.96 3.64	11.90 3.38	9.46 3.54
readmat	Age 14: Household received newspapers or magazines	0.81	0.89	0.69
libcard	Age 14: Household had a library card	0.68	0.72	0.61
prot	Age 14: Young man raised protestant	0.50	0.50	0.49
livpar	Age 14: Young man lived with both parents	0.67	0.75	0.55
black	Black in random sample	0.07	0.11	0.00
hispanic	Hispanic in random sample	0.05	0.07	0.00
overblack	Over-sampled black	0.24	0.00	0.69
overhispanic	Over-sampled Hispanic	0.15	0.00	0.31

Table 2

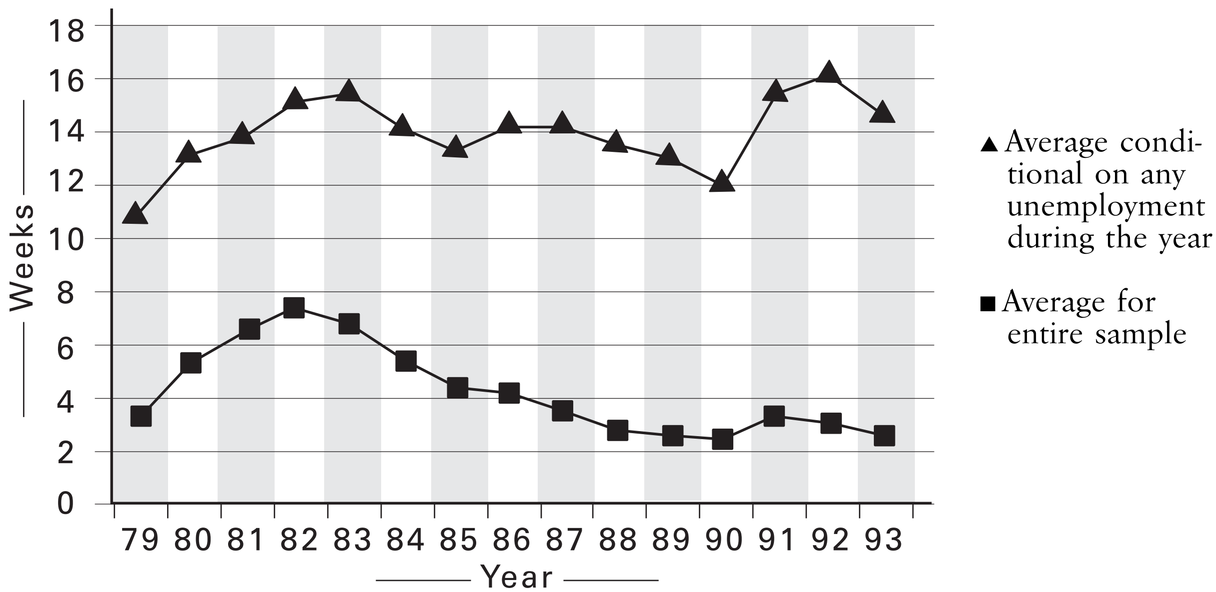
Summary Statistics of Time-Variant Variables
(Standard Deviations Omitted for Dummy Variables)

Variable Name		Variable Description	1979 Mean	1986 Mean	1993 Mean
			Standard Deviation		
			3731 obs	2805 obs	2304 obs
un	DV	Any unemployment during the year	0.30	0.29	0.19
wun		Annual weeks of unemployment (entire sample)	3.32	4.20	2.83
			8.00	9.75	7.97
work	DV	Any work during the year	0.58	0.93	0.93
hw		Annual hours worked	627.97	1814.14	2026.20
			776.92	909.24	904.26
lnw		Log of deflated average hourly earnings from wages and salary	1.31	1.76	2.02
			0.79	0.73	0.66
anysch	DV	Any schooling during the year	0.89	0.20	0.07
train	DV	Any training during the year	0.03	0.12	0.18
age		Age	16.55	23.54	30.52
			1.60	1.63	1.63
exp		Cumulative labor force experience in hours/2000	0.24	4.39	11.29
			0.35	2.55	4.35
hgc		Highest grade in years completed	9.64	12.51	12.96
			1.67	2.23	2.54
geddeg	DV	Holds a general equivalence degree	0.01	0.09	0.12
hsdeg	DV	Holds a high school diploma	0.15	0.66	0.69
coldeg	DV	Holds a four-year college degree	0.00	0.12	0.19
urb	DV	Residence is urban	0.80	0.82	0.81
ne	DV	Residence is Northeastern US	0.20	0.18	0.17
nc	DV	Residence is North-Central US	0.26	0.25	0.26
so	DV	Residence is Southern US	0.36	0.37	0.37
we	DV	Residence is Western US	0.19	0.20	0.20
ur		Local labor market unemployment rate (in percent)	6.31	7.77	7.53
			1.97	2.84	2.60
expsec		Per-pupil public expenditure on secondary institutions (in 1982 dollars)	3107.27	3694.57	4056.55
			732.91	930.58	1042.62
expps		Per-pupil public expenditure on postsecondary institutions (in 1982 dollars)	5735.19	6454.09	6828.19
			1122.29	1135.09	1154.78
ugtuit		Annual undergraduate tuition at main or largest campus of state university (in 1982 dollars)	1142.54	1475.57	2067.79
			391.76	540.10	753.73
mw		The larger of federal or state-level hourly minimum wage (in 1982 dollars)	3.93	3.07	2.97
			0.09	0.07	0.12

DV = Dummy Variable

Figure 1

Average Annual Weeks of Unemployment



V. Estimation Results

This section discusses the key discrete factor maximum likelihood (DFML) estimates using the empirical specification in Section IV.[37] These results are organized into four general topics. The first topic is evidence of a "catch-up" response to unemployment as measured by the effect of an unemployment spell on the probability of training and working and on annual hours worked. The second is evidence of persistence in unemployment. The third is evidence of long-lived "blemishes" of unemployment as measured by forgone average hourly earnings. The fourth discusses other estimates of potential interest, such as demographic characteristics.

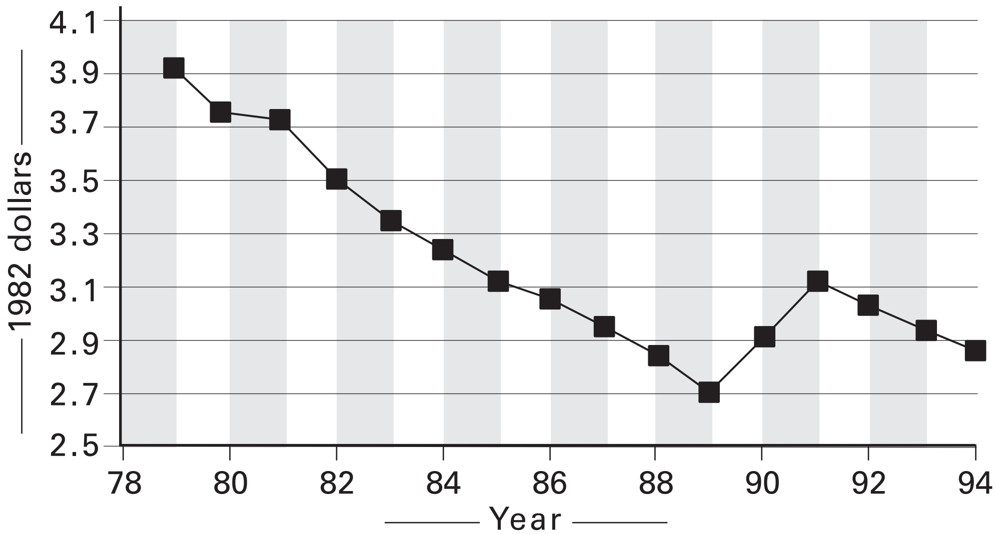
In this section, we compare the DFML estimates to estimates derived from two types of single-equation specifications. The first type of single-equation specification does not control for the endogeneity of prior unemployment. It is either probit or ordinary least squares (OLS).

According to a likelihood ratio test criterion, the probit/OLS specifications, when estimated jointly but independently, are overwhelmingly rejected in favor of the DFML specification. The log-likelihood value for the independent probit/OLS estimates is –217,475.02 based on 224 parameters. The log-likelihood value for the DFML estimates is –209,349.47 based on 304 parameters. This amounts to an improvement of 8,125.55 in the likelihood value for only 80 additional parameters.

The second type of single-equation specification for comparison uses an individual-specific fixed-effects (FE) model to control for possible unobserved heterogeneity.[38] The FE specification is inconsistent in this setting if, for example, unobserved preferences for work change as young people age. In general, we find that the FE point estimates are less precise relative to their DFML counterparts. There is little evidence, however, that the gain in precision with the use of the random-effects DFML specification comes at the expense of consistency. In

Figure 2

Real Value of the Federal Minimum Wage (1979 to 1994),1982 Dollars



several key results, such as the earnings effect of prior unemployment, the FE point estimates are statistically indistinguishable from estimates that do not control for unobserved heterogeneity. One might interpret this as evidence that many of the determinants are not endogenous. The fact that the DFML estimates are often significantly different from the simple estimators but not significantly different from the FE estimates, however, indicates that this would be an incorrect inference. Instead, one should conclude that the FE estimators are often too imprecise to help one make an accurate assessment of the simple, single equation estimates.

A Catch-Up Response

The simple conceptual model discussed earlier presents the notion that individuals may display a catch-up response to an involuntary unemployment spell. This impetus to undertake "extra" training mitigates the effect of the spell on potential earnings over time. The DFML estimates strongly support this notion of a catch-up response. Table 3 displays estimates of the effects of prior unemployment on three separate outcomes: whether a young man trains; whether a young man works; and how many hours a young man works annually conditional upon working.[39]

The estimate in the first row of Table 3 indicates that prior unemployment has a significant and positive effect on the contemporaneous likelihood of training. This training effect, however, is somewhat short-lived. The longer-term effects are at most one-third the size of the immediate effects. Specification tests indicate no statistically significant effect beyond the first year,[40] so we exclude them from the empirical model. The key estimate in this table does indicate a statistically significant effect on training of those having recently experienced unemployment. To our knowledge, this is the first evidence of a "catch-up" response of this type in the literature. Recent unemployment, after controlling for the endogeneity of the unemployment spell, appears to induce young men to undertake more training.

The other estimates in Table 3 buttress the notion of a compensatory behavioral response. It is remarkable that unemployment as long ago as five years has a significantly positive effect on the contemporaneous likelihood of working. Although the initial effect of prior unemployment on annual hours worked is large and negative, the longer-term effect is significantly positive. A 13-week spell experienced as long ago as five years increases hours worked by over 41 hours per year.[41] This effect is quite precisely estimated. A two-standard-error lower bound is over 28 hours per year. The OLS estimates of this latter effect indicate a much larger initial negative effect, -13.2011 (0.6858), and uniformly smaller positive effects on the other lags. For example, the OLS estimate of the fifth lag is 1.4991 (0.6106). Interestingly, with standard errors that are about 15% smaller, the DFML estimates are more precise than their OLS counterparts.[42]

Because the effect of prior unemployment on whether a young man trains is such a key result, the different point estimates of this effect are compared across the three separate specifications.[43] For the DFML specification, the effect of one week of unemployment is equivalent to a 0.44 percentage-point reduction in the local unemployment rate. The standard error of this effect is 0.20.[44] For the probit and conditional logit specifications, the effect (standard error) is 0.33 (0.35) and 0.25 (0.46), respectively. The DFML effect is a third larger than the probit effect and more precisely estimated. The magnitude of the probit effect is washed away by a failure to control for the endogeneity of prior unemployment. On the other hand, the DFML effect is nearly twice the conditional logit effect and much more precisely estimated. Although both methods control for unobserved heterogeneity, there appears to be a large efficiency gain with the random-effects estimator used here. Chamberlain (1984) notes that in certain cases there is a potential for downward bias in the estimates from the conditional logit specification. Such a downward bias may be evident here. The DFML effect is larger and more precisely estimated than either the probit or conditional logit effect.

Taken as a whole, the estimates in Table 3 provide strong evidence of a catch-up response to unemployment. They indicate that unemployment experienced by a young man today significantly increases the likelihood of his undertaking training in the near future and the

Table 3

Evidence of Catch-Up Response

(The Effect of One Week of Unemployment on Training, Work Participation and Work Hours)

DFML estimates with standard errors in parentheses.

Outcome	*Lag of Annual Weeks of Unemployment*				
	1	**2**	**3**	**4**	**5**
Any Training*	**0.0051** (0.0011)				
Any Working*	0.0000 (0.0022)	**0.0056** (0.0027)	**0.0076** (0.0027)	0.0033 (0.0028)	**0.0056** (0.0023)
Annual Hours Worked	**-5.1986** (0.5470)	**3.7056** (0.5670)	**3.5521** (0.5397)	**3.5707** (0.5356)	**3.1980** (0.4987)

*during the year

Bold-faced indicates significance at the 5% level

likelihood of his working for up to five years. Unemployment today also significantly increases the number of hours he will work (conditional upon working) for up to five years.

Persistence in Unemployment

Like many previous studies, here we examine how the duration of prior unemployment affects the incidence and duration of future unemployment. In general, the literature shows that controlling for unobserved heterogeneity greatly reduces measured persistence in unemployment. The evidence presented here generally supports that particular finding. Many of these previous studies also find that no persistence remains after the use of controls for unobserved heterogeneity. This study disagrees with that finding. We find that there is strong and statistically significant evidence of persistence in unemployment.

Table 4 displays estimates of the effects of prior unemployment on the probability of experiencing unemployment and on annual weeks of unemployment. Unemployment as long as four years ago has a positive and significant effect on the likelihood of a contemporaneous spell of unemployment. This effect is quite pronounced for the first lag. In terms of a relative effect, it is equivalent to a 2.7088 (0.4582) percentage-point increase in the local unemployment rate.[45] There is over a 22-fold decrease in this effect after the first year. By the second lag, the effect is equivalent to a mere 0.1205 (0.0637) percentage-point increase in the local unemployment rate. By the fourth lag, the relative effect has all but vanished: 0.1125 (0.0613). This lag structure indicates that the effect of contemporaneous unemployment on the probability of experiencing future unemployment is initially very large and significant. This effect then fades very rapidly.

The positive effect of prior unemployment on the duration of a current spell is quite short-lived but significant.[46] A 13-week spell experienced last year increases the duration of a contemporaneous unemployment spell by over 1.5 weeks annually.[47] With OLS regressions of current unemployment on prior unemployment, Ellwood (1982) finds strong evidence of state dependence in weeks of unemployment. With the use of FE specifications, however, he finds that all evidence of state dependence vanishes upon controlling for unobserved heterogeneity. In this study, the OLS and FE estimates are qualitatively similar to those in Ellwood's study: 0.2402 (0.0087) and 0.0212 (0.0132), respectively. The OLS estimate indicates strong persistence, while the use of an FE specification eliminates all persistence. This inference is due to a large decrease in the point estimate (over a 90 percent decline in the point estimate). Given the standard error of this FE estimate, however, one cannot exclude the possibility of

Table 4

Evidence of Persistence

(The Effect of One Week's Prior Unemployment on the Incidence and Amount of Unemployment)

DFML estimates with standard errors in parentheses.

Outcome	*Lag of Annual Weeks of Unemployment*				
	1	**2**	**3**	**4**	**5**
Any Unemployment*	**0.1056** (0.0039)	**0.0047** (0.0023)	**0.0076** (0.0022)	**0.0044** (0.0022)	0.0033 (0.0019)
Annual Weeks of Unemployment*	**0.1254** (0.0060)				

*during the year

Bold-faced indicates significance at the 5% level

considerable persistence in unemployment spells. On the other hand, the DFML estimate does rule out an absence of persistence. A Hausman (1978) test of any difference between the FE and DFML estimates rejects the null hypothesis of no difference. This indicates that additional controls for unobserved heterogeneity probably are necessary. One way to achieve this is to allow for an equation-specific heterogeneity factor, which is a goal for future research. With these additional controls, we expect the magnitude of persistence to decline. It is important to note that this is the only important instance where a DFML estimate appears substantively and statistically different from an FE estimate.

Long-Lived Blemishes

One of the most important measures of the long-term impact of youth unemployment is the effect of a spell on future earnings. Forgone work experience may reverberate throughout a young person's life.

Perhaps this is because each job leapfrogs into future employment, and early unemployment would delay some of the first jumps. It may also be because lost experience, as posited by dual labor market theorists, permanently tracks young people into jobs characterized by low wages and little room for advancement.[48] Ellwood (1982), for example, finds that prior work experience has a large and positive earnings effect. Forgone experience, therefore, represents lost earnings. This observation is, in fact, the motivation for the theoretical model discussed earlier.

Table 5 displays DFML estimates of the effects of prior unemployment on log average hourly earnings. This earnings equation, as with the others in this study, controls extensively for the observed human capital stock. Even with these controls, there is evidence that the impact of prior unemployment on earnings is rather more long-lived than previous studies have shown.

The initial earnings effect of unemployment is large and quite precisely estimated. A 13-week unemployment spell experienced last year reduces wages by 3.4%.[49] In terms of 2,000 hours worked at the average nominal wage rate in 1993, this is a reduction of nearly $900.[50] A two-standard-error lower bound amounts to a 2.3% reduction in hourly earnings or over $600. A six-month spell experienced as long ago as four years reduces wages by 2.3%. To put this magnitude into context, this reduction is equivalent to forgoing one quarter of a year of school. As predicted by the theoretical model, the earnings effect of prior unemployment tapers off over time. Because it fully disappears after four years, the impact of unemployment on earnings is not permanent, as suggested by a scar analogy. The magnitude and duration of this effect, however, make it much more than a simple blemish. Unemployment experienced by a young man today will depress his earnings for several years to come.

Ideally, one would also like to obtain the effect of reduced human capital on earnings. If the theoretical model is correct and one could

Table 5

Evidence of Long-Lived Blemishes

(The Effect of One Week of Prior Unemployment on Hourly Wages)

DFML estimates with standard errors in parentheses.

Outcome	*Lag of Annual Weeks of Unemployment*				
	1	**2**	**3**	**4**	**5**
Log Average Hourly Earnings	**-0.0026** (0.0004)	**-0.0015** (0.0004)	**-0.0012** (0.0004)	**-0.0009** (0.0004)	0.0002 (0.0004)

Bold-faced indicates significance at the 5% level

perfectly observe the human capital stock, there would be no independent effect of prior unemployment on earnings. The results presented here do not include this additional avenue for how unemployment can reduce earnings. In future extensions of this work, we will simulate the change in the human capital stock due to unemployment in order to obtain the "total" earnings effect. Given the evidence of a rational catch-up response, a crucial result would be whether this total earnings effect is smaller than the effects presented here.

It is important to note that the negative earnings effect of prior unemployment remains after extensive controls for the observed (and potentially endogenous) human capital stock. At first glance, this effect suggests that unemployment does not simply represent forgone human capital, as suggested by dual labor market theorists. There is a more plausible argument, however, for the magnitude and duration of this earnings effect. The human capital variables used in this study are imperfect measures of young men's human capital stock. The "residual" earnings effect that we find could be capturing these imperfectly measured human capital variables.

Table 6 contains the OLS and FE estimates of the earnings effect of prior unemployment. For comparison, it also contains the DFML estimates from Table 5.[51] The OLS and DFML estimates are virtually identical for the first lag. The OLS estimate implies a 3.6% or $960 reduction in earnings for a 13-week unemployment spell. There are some important differences between the two sets of estimates, however. The OLS estimates indicate little change in the effect for the second lag, whereas the DFML effect declines by nearly half. The DFML estimate for the third lag is two-thirds that of the OLS estimate. As in the literature, we find that the use of controls for unobserved heterogeneity reduces the earnings effect of prior unemployment. Interestingly, when comparing the significance of the estimates, the OLS effects appear shorter-lived. The OLS estimates of the fourth and fifth lags are –0.0009 (0.0007) and –0.0007 (0.0006), while the DFML are –0.0009 (0.0004) and 0.0002 (0.0004). Although the point estimates for the fourth lag are identical, the DFML estimates are considerably more precise than their OLS counterparts.[52] This gain in precision results in a statistically significant impact of the fourth lag. Despite the similarity of the estimates, a likelihood ratio test overwhelmingly rejects the OLS specification in favor of the DFML specification.[53] There is a considerable gain in precision with the use of the random-effects specification.

The FE estimates tend to indicate a shorter-lived earnings effect than that implied by OLS. Again, this is largely due to the precision of the estimates. The rounding used to present these

Table 6

Comparison of Blemish Estimates
(The Effect of One Week of Unemployment on Hourly Wages)

Outcome	*Method*	*Lag of Annual Weeks of Unemployment* 1	2	3	4	5
Log Average Hourly Earnings	OLS	**-0.0028** (0.0005)	**-0.0027** (0.0006)	**-0.0019** (0.0007)	-0.0009 (0.0007)	-0.0007 (0.0006)
	FE	**-0.0018** (0.0006)	**-0.0021** (0.0006)	**-0.0010** (0.0005)	-0.0007 (0.0005)	-0.0003 (0.0005)
	DFML	**-0.0026** (0.0004)	**-0.0015** (0.0004)	**-0.0012** (0.0004)	**-0.0009** (0.0004)	-0.0002 (0.0004)

Bold-faced indicates significance at the 5% level

results in tables "overstates" the significance of the FE estimate for the third lag. With one degree of freedom, the p-value of the null hypothesis of zero is 0.0703. As with the random-effects specification, use of the FE specification reduces the magnitude and duration of the negative earnings effect of prior unemployment. A test of whether the FE and OLS estimates differ, however, fails to reject the null hypothesis of no difference.[54] This is not surprising given the similarity of the point estimates in the first two rows of Table 6 and the somewhat large standard errors for the FE model. The DFML estimates, while consistent with the FE estimates,[55] do appear statistically different from the OLS estimates. Again, the precision of the DFML estimates helps to reject the OLS approach and provides more accuracy than the FE procedure.

The results in Table 6 indicate that that there is a considerable gain in precision with the use of random-effects DFML specification. What is crucial is that this additional precision does not come at the expense of consistency. The DFML specification overwhelmingly rejects the OLS specification. The FE specification cannot, however, reject the DFML specification in this case. With the results from Table 5, we find the negative effect of prior unemployment to be large, to be persistent and to taper off slowly over time, even when controlling for unobserved heterogeneity and (imperfectly) for the human capital stock. These are exactly the impacts implied by the theoretical model.

VI. Conclusions

This research provides several new insights to our understanding of the youth labor market and, in particular, the long-term impacts of youth unemployment on later labor market outcomes. First, there is strong evidence of a catch-up response to unemployment. That is, a spell experienced today increases the likelihood that a young person trains in the near future. It also increases for many years to come the likelihood of working and the amount of time spent working among those young people who work. A dynamic model of human capital accumulation predicts this catch-up response. This theoretical implication is new to the literature. The evidence presented here of this response is also new.

Second, results here are consistent with the finding that controls for unobserved heterogeneity greatly reduce measured persistence in unemployment. A spell experienced today does not ignite a long-term cycle of recurring spells of greater length in the future. However, this research disagrees with the finding of no persistence once controls are used. Evidence here indicates that there is some persistence in unemployment. The duration of a spell today increases the likelihood of another spell in the near future. It also increases the length of the spell should it be experienced.

Third, despite a catch-up response, unemployment significantly reduces earnings for up to four years. The magnitude and duration of this effect are simply too great to allow unemployment to be considered a mere blemish, the analogy accorded it elsewhere in the literature. The earnings effect appears to vanish after four or five years, so neither can it be considered a permanent scar.

Finally, we find that the use of the discrete factor maximum likelihood (DFML) specification increases the precision of the effects examined in this study. In several important cases, this gain in precision is considerable and results in different behavioral implications. Since there is little evidence that one should reject the more efficient DFML specification in favor of the less efficient fixed-effects specification, this gain in precision does not come at the expense of consistency.

Appendix 1:

A Conceptual Framework

Consider first the most general model that is identical to Ben-Porath except that is expressed in discrete time. Here the human capital production function has as an argument the lagged stock of human capital. Formally, the components of the model are:

The Law of Motion :

$HC_t = HC_{t-1} + hc_t$

where HC_t is the human capital stock at time t, hc_t is the flow during time t and $HC_0 = HC_0$ is exogenous and positive.

The Human Capital Production Function :

$hc_t = f\,(s_t, d_t, HC_{t-1})$

where s_t is the share of time spent training and d_t is the amount of purchased inputs. By assumption, $f_i > 0$, $f_{ii} < 0$ and $f_{ij} > 0$ for $i \neq j$.

The Potential Earnings and Human Capital Investment Functions :

$E_t = wHC_{t-1}$ is potential earnings.

$I_t = ws_t\, HC_{t-1} + p_t\, d_t$ is the cost of human capital investment, where p_t is the price of the purchased inputs and I_3 is optimally zero.

$$\max_{s_1, s_2, d_1, d_2} \sum_{t=1}^{3} \beta^{t-1}(E_t - I_t)$$

The Agent's Program :

$E_t - It \geq 0\ \forall t$

subject to the human capital production function, the law of motion and

$$\max_{s_2, d_2} w(1 - s_2)\overline{HC_1} - p_2 d_2 + \beta w\left(\overline{HC_1} + f(s_2, d_2, \overline{HC_1})\right).$$

Given an exogenous constraint in the first period, the second period re-optimization is:

This program implies the following first and second order conditions for an interior optimum.

First order conditions :

$$\text{wrt } s_2 : -w\overline{HC_1} + \beta w f_1(s_2, d_2, \overline{HC_1}) = 0 \Rightarrow f_1(s_2, d_2, \overline{HC_1}) = \beta^{-1}\overline{HC_1}$$

$$\text{wrt } d_2 : -p_2 + \beta w f_2(s_2, d_2, \overline{HC_1}) = 0 \Rightarrow f_2(s_2, d_2, \overline{HC_1}) = \beta^{-1}\frac{p_2}{w}$$

Second Order Conditions :

The negative definite Hessian is $H = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix}$, where

$$h_{11} = \beta w f_{11}(s_2, d_2, \overline{HC_1}) < 0$$
$$h_{22} = \beta w f_{22}(s_2, d_2, \overline{HC_1}) < 0$$
$$h_{12} = h_{21} = \beta w f_{12}(s_2, d_2, \overline{HC_1}) > 0$$
and $|H| > 0$.

These first order conditions have familiar interpretations. The first states that the optimal time-share equates the marginal product of time with the discounted constrained human capital stock last period. The second states that the optimal level of purchased inputs equates the marginal product of the purchased inputs with their discounted relative price.

The comparative dynamics are:

$$\begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \cdot \begin{bmatrix} \partial s_2 / \partial \overline{HC_1} \\ \partial d_2 / \partial \overline{HC_1} \end{bmatrix} = \begin{bmatrix} -w\left[1 - \beta f_{13}(s_2, d_2, \overline{HC_1})\right] \\ w\beta f_{23}(s_2, d_2, \overline{HC_1}) \end{bmatrix}$$

The term $-w\left[1 - \beta f_{13}(s_2, d_2, \overline{HC_1})\right]$ cannot be signed without a restriction on the cross-partial derivative. Consequently, the comparative dynamics results are indeterminate.

Suppose the model excludes the lagged stock of human capital from the production function: $hc_t = f(s_t, d_t)$.The comparative dynamics are:

$$\begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \cdot \begin{bmatrix} \partial s_2 / \partial \overline{HC_1} \\ \partial d_2 / \partial \overline{HC_1} \end{bmatrix} = \begin{bmatrix} -w \\ 0 \end{bmatrix} \Rightarrow \begin{matrix} \partial s_2 / \partial \overline{HC_1} = \beta^{-1} \dfrac{f_{22}(s_2, d_2)}{|H|} < 0 \\ \partial d_2 / \partial \overline{HC_1} = -\beta^{-1} \dfrac{f_{12}(s_2, d_2)}{|H|} < 0 \end{matrix}$$

Prediction 1 follows immediately since these dynamics imply:

$$\partial s_2 / \partial \overline{HC_1} = \beta^{-1} \frac{f_{22}(s_2, d_2)}{|H|} < 0$$
$$\partial d_2 / \partial \overline{HC_1} = -\beta^{-1} \frac{f_{12}(s_2, d_2)}{|H|} < 0$$

Prediction 2: $\left|\frac{\partial E_2}{\partial \overline{HC_1}}\right| > \left|\frac{\partial E_3}{\partial \overline{HC_1}}\right|.$

Proof of Prediction 2:

Given $E_t = wHC_{t-1}$:

$$\frac{\partial E_2}{\partial \overline{HC_1}} = w$$

$$\frac{\partial E_3}{\partial \overline{HC_1}} = w + w\left(f_1(s_2,d_2)\,{}^{\partial s_2}\!\Big/_{\partial \overline{HC_1}} + f_2(s_2,d_2)\,{}^{\partial d_2}\!\Big/_{\partial \overline{HC_1}} \right)$$

$$= \frac{\partial E_2}{\partial \delta} + w\left(f_1(s_2,d_2)\,{}^{\partial s_2}\!\Big/_{\partial \overline{HC_1}} + f_2(s_2,d_2)\,{}^{\partial d_2}\!\Big/_{\partial \overline{HC_1}} \right) \Rightarrow$$

$$\left|\frac{\partial E_2}{\partial \overline{HC_1}}\right| > \left|\frac{\partial E_3}{\partial \overline{HC_1}}\right|.$$

Model Limitations

This model is a simple but useful tool. It directly links the present and the future through the process of human capital investment and accumulation. By establishing equivalence between an involuntary unemployment spell and an exogenously constrained human capital stock, it can examine the spell's effects on future behavior and outcomes. It looks at only two behaviors and does not address job search or time voluntarily spent not working.

The duration of unemployment spells will vary by the intensity and duration of job search. While the duration of search is potentially observable, intensity is not. Search intensity is a component of the unobserved heterogeneity that makes unemployment a potentially endogenous variable in statistical analyses. It is unclear, however, what in particular search theory would contribute to this simple framework. The inverse relationship between search intensity and duration is unlikely to yield unambiguous theoretical predictions. In this case, the answers to the questions posed here are entirely empirical. On the other, this simple model uses a standard human capital framework to analyze these issues. Most mainstream labor economists probably accept that one mechanism through which current unemployment can affect future behavior is the human capital stock. Notwithstanding this acceptance, a model like this has not been found in the youth labor market literature. Further, even if all youth unemployment is simply time spent watching television, it may still be relevant to ask whether there are long-term consequences, especially for future earnings.

Finally, the model is expressed in terms of involuntary unemployment. Much of the literature on job search views the distinction between quits and layoffs to have little economic content. See, for example, McLaughlin (1991). As is trenchantly noted by Gottshalk and Maloney (1985), however, much of this debate is tautological. To summarize their argument, even coerced decisions can be viewed as voluntary since they result from re-optimization under an alternate set of constraints. In this case, all unemployment may be considered voluntary. It is not possible to distinguish the nature of unemployment using NLSY data. Total unemployment, however, is identically the sum of its involuntary and voluntary components. Isolating one of these components is sufficient to distinguish them empirically, since the other is identically the residual. Local variation in labor market conditions over time and exogenous changes in mandated minimum wages over time are potentially suitable instruments to make this empirical distinction.

Appendix 2:

MAXIMUM LIKELIHOOD DISCRETE FACTOR ESTIMATES

Log-likelihood function value:	-209349.46980153
Norm of the first partials:	0.25968693311196
Number of parameters:	304

School Attendance:

	Coefficient	Standard Error	T-Ratio
1 cons_sch	-3.87566	4.84406	-0.80009
2 afqt	0.0084	0.00093	9.17103
3 readmat	-0.05404	0.05479	-0.98643
4 libcard	0.11635	0.04127	2.81901
5 livpar	0.00051	0.04267	0.01186
6 prot	-0.06327	0.03999	-1.58238
7 black	0.10052	0.05087	1.97596
8 hisp	0.00325	0.05799	0.05597
9 nc	0.12637	0.07802	1.61973
10 so	0.08224	0.10392	0.79139
11 we	0.14955	0.09832	1.52109
12 urb	0.03830	0.05499	0.69648
13 ur	0.00246	0.00679	0.36196
14 mw	0.12492	1.11761	0.11178
15 mwage	-0.11693	0.04154	-2.81491
16 mwhgc	0.21617	0.03990	5.41817
17 ugtuit	0.01782	0.40485	0.04403
18 expsec	-0.08271	0.33484	-0.24702
19 expps	-0.26580	0.18256	-1.45601
20 age	-0.04182	0.20350	-0.20552
21 age	20.00642	0.00207	3.10687
22 exp	-0.19865	0.02066	-9.61394
23 exp	20.00806	0.00119	6.79929
24 hgc	-0.27871	0.12204	-2.28375
25 geddeg	-0.39679	0.09006	-4.40602
26 hsdeg	-0.46427	0.07536	-6.16061
27 coldeg	-1.24216	0.07790	-15.94587
28 lag1sc	3.57426	1.02815	3.47641
29 lag1wu	-0.00456	0.00240	-1.90295
30 lag2wu	-0.01199	0.00222	-5.39411
31 lag3wu	-0.00465	0.00247	-1.88570
32 lag4wu	-0.00710	0.00256	-2.77620
33 lag5wu	0.00100	0.00250	0.40034
34 year	0.01895	0.01481	1.27954
35 rhod11	0.52003	0.40206	1.29340
36 rhod12	0.20577	9.19403	0.02238

Training:

	Coefficient	Standard Error	T-Ratio
37 cons_tra	-3.52691	1.42106	-2.48189
38 afqt	0.00198	0.00036	5.47660
39 readmat	0.01538	0.02275	0.67589
40 libcard	0.04639	0.01673	2.77321
41 livpar	-0.01311	0.01781	-0.73641
42 prot	0.04133	0.01654	2.49850
43 black	0.01309	0.02285	0.57308
44 hisp	0.05302	0.02392	2.21615
45 nc	0.12488	0.03136	3.98262
46 so	-0.03409	0.04201	-0.81153
47 we	0.06259	0.03992	1.56813
48 urb	-0.01061	0.02009	-0.52832
49 ur	-0.01158	0.00283	-4.08527
50 mw	0.02562	0.27412	0.09345
51 mwage	0.01820	0.01103	1.65029
52 mwhgc	-0.03443	0.01586	-2.17125
53 ugtuit	-0.56616	0.17017	-3.32707
54 expsec	0.23997	0.13463	1.78238
55 expps	-0.35428	0.07210	-4.91363
56 age	-0.01378	0.06328	-0.21776
57 age2	-0.00128	0.00071	-1.79427
58 exp	0.03900	0.00750	5.19970
59 exp2	-0.00066	0.00037	-1.77210
60 hgc	0.14701	0.04924	2.98547
61 geddeg	0.19982	0.03630	5.50453
62 hsdeg	0.15336	0.02812	5.45423
63 coldeg	0.14329	0.03476	4.12235
64 lag1wu	0.00512	0.00107	4.79397
65 year	0.02634	0.00569	4.62568
66 rhod21	-0.46464	0.34470	-1.34797
67 rhod22	-0.97735	43.65679	-0.02239

Probability of Working:

	Coefficient	Standard Error	T-Ratio
68 cons_wo	11.46497	5.82073	1.96968
69 afqt	0.00239	0.00144	1.65507
70 readmat	-0.12169	0.05935	-2.05017
71 libcard	-0.17147	0.05493	-3.12171
72 livpar	0.06122	0.05175	1.18305
73 prot	-0.03928	0.05595	-0.70206
74 black	-0.16617	0.06672	-2.49052
75 hisp	-0.02538	0.07903	-0.32109
76 nc	0.51632	0.09872	5.23000
77 so	0.46939	0.13497	3.47776
78 we	0.39760	0.12121	3.28015
79 urb	0.04878	0.06426	0.75903
80 ur	-0.02956	0.00815	-3.62939
81 mw	-0.87971	1.38690	-0.63430
82 mwage	-0.02871	0.04769	-0.60197
83 mwhgc	0.14778	0.06643	2.22449
84 ugtuit	-0.19835	0.50119	-0.39576
85 expsec	1.64269	0.40119	4.09451
86 expps	0.19765	0.26212	0.75405
87 age	-0.10187	0.22129	-0.46036
88 age	20.00030	0.00220	0.13761
89 exp	0.58686	0.02406	24.39186
90 exp2	-0.01906	0.00163	-11.70383
91 hgc	-0.36775	0.19973	-1.84119
92 geddeg	-0.00031	0.08365	-0.00376
93 hsdeg	0.30864	0.07582	4.07041
94 coldeg	0.87297	0.17756	4.91649
95 lag1wu	0.00000	0.00223	0.00164
96 lag2wu	0.00562	0.00270	2.08194
97 lag3wu	0.00760	0.00270	2.81153
98 lag4wu	0.00328	0.00276	1.18838
99 lag5wu	0.00564	0.00226	2.49618
100 year	-0.06957	0.01799	-3.86649
101 rhod31	-2.62852	1.93673	-1.35719
102 rhod32	0.44534	19.89101	0.02239

Probability of Experiencing Unemployment:

	Coefficient	Standard Error	T-Ratio
103 cons_un	-0.03571	4.31150	-0.00828
104 afqt	-0.00274	0.00078	-3.50847
105 readmat	0.01410	0.04271	0.33007
106 libcard	0.00724	0.03447	0.20996
107 livpar	-0.00892	0.03629	-0.24593
108 prot	-0.00743	0.03559	-0.20876
109 black	0.07670	0.04529	1.69348
110 hisp	-0.02426	0.05021	-0.48318
111 nc	0.27288	0.06741	4.04786
112 so	0.37273	0.08899	4.18839
113 we	0.36924	0.08416	4.38714
114 urb	0.08643	0.04085	2.11599
115 ur	0.03900	0.00589	6.61892
116 mw	0.21816	1.01960	0.21397
117 mwage	-0.00631	0.03517	-0.17951
118 mwhgc	-0.00670	0.04143	-0.16176
119 ugtuit	0.59839	0.33417	1.79068
120 expsec	1.28459	0.27546	4.66346
121 expps	0.45129	0.14320	3.15148
122 age	-0.33927	0.16396	-2.06918
123 age2	0.00613	0.00173	3.54345
124 exp	-0.05615	0.01577	-3.56073
125 exp2	0.00097	0.00091	1.07619
126 hgc	-0.06293	0.12691	-0.49586
127 geddeg	0.17034	0.06903	2.46757
128 hsdeg	-0.18550	0.05437	-3.41188
129 coldeg	-0.08611	0.08327	-1.03413
130 lag1wu	0.10564	0.00386	27.37078
131 lag2wu	0.00470	0.00227	2.07458
132 lag3wu	0.00763	0.00223	3.42158
133 lag4wu	0.00439	0.00217	2.02306
134 lag5wu	0.00326	0.00189	1.72603
135 year	0.01894	0.01223	1.54916
136 rhod41	1.84964	1.36835	1.35173
137 rhod42	1.64577	73.50535	0.02239

Annual Hours Work (positive):

	Coefficient	Standard Error	T-Ratio
138 cons_hw	587.13216	1450.37654	0.40481
139 afqt	-0.35387	0.26091	-1.35628
140 readmat	-11.57867	15.78446	-0.73355
141 libcard	-17.61843	12.62251	-1.39579
142 livpar	16.95630	13.55862	1.25059
143 prot	25.13084	11.94246	2.10433
144 black	20.29885	16.46725	1.23268
145 hisp	39.40818	16.64559	2.36748
146 nc	-23.15641	22.51307	-1.02858
147 so	-72.66200	28.21766	-2.57505
148 we	-116.30386	27.68230	-4.20138
149 urb	-34.99261	12.43418	-2.81423
150 ur	-10.71445	1.59915	-6.70008
151 mw	729.65197	204.12255	3.57458
152 mwage	-50.58476	7.46421	-6.77698
153 mwhgc	66.22437	9.95174	6.65455
154 ugtuit	-53.97291	103.67005	-0.52062
155 expsec	-105.62966	84.52265	-1.24972
156 expps	-256.11669	44.76337	-5.72157
157 age	138.81654	34.70743	3.99962
158 age2	-1.00970	0.36321	-2.77997
159 exp	259.70522	4.29925	60.40715
160 exp2	-7.67411	0.15754	-48.71074
161 hgc	-125.05534	30.03580	-4.16354
162 geddeg	-48.20647	23.41476	-2.05881
163 hsdeg	13.09957	18.32814	0.71472
164 coldeg	202.92814	27.12306	7.48176
165 lag1wu	-5.19855	0.54704	-9.50307
166 lag2wu	3.70562	0.56697	6.53587
167 lag3wu	3.55212	0.53968	6.58195
168 lag4wu	3.57065	0.53563	6.66623
169 lag5wu	3.19795	0.49868	6.41283
170 year	-14.82232	4.13917	-3.58099
171 sdhw	480.24645	3.29214	145.87655
172 rhoc11	-1553.58598	1145.16909	-1.35664
173 rhoc12	41.90863	1873.03774	0.02237

Annual Weeks of Unemployment (positive):

	Coefficient	Standard Error	T-Ratio
174 cons_wu	8.21141	16.73142	0.49078
175 afqt	-0.01169	0.00428	-2.73316
176 readmat	0.19673	0.20549	0.95739
177 libcard	0.11914	0.18466	0.64520
178 livpar	-0.11095	0.17721	-0.62610
179 prot	-0.03977	0.19353	-0.20547
180 black	0.78061	0.24000	3.25254
181 hisp	0.24234	0.27903	0.86852
182 nc	0.52267	0.33824	1.54527
183 so	-0.13183	0.44017	-0.29951
184 we	-0.29831	0.40563	-0.73542
185 urb	-0.27833	0.21798	-1.27685
186 ur	0.18926	0.02661	7.11218
187 mw	-2.87530	2.88504	-0.99662
188 mwage	0.22678	0.11366	1.99516
189 mwhgc	-0.19683	0.15548	-1.26589
190 ugtuit	0.82362	2.08167	0.39565
191 expsec	-0.42912	1.48407	-0.28915
192 expps	0.70790	0.87098	0.81276
193 age	-0.76724	0.69301	-1.10712
194 age2	0.00290	0.00872	0.33209
195 exp	-0.13399	0.09904	-1.35288
196 exp2	0.00278	0.00729	0.38149
197 hgc	0.43480	0.51359	0.84660
198 geddeg	0.50036	0.36901	1.35593
199 hsdeg	0.04657	0.28278	0.16469
200 coldeg	0.18255	0.67398	0.27085
201 lag1wu	0.12539	0.006042	0.75047
202 year	0.04855	0.07772	0.62468
203 sdwun	5.73274	0.05516	103.93607
204 rhoc21	5.34087	3.95794	1.34941
205 rhoc22	1.58481	70.78341	0.02239

Log of Hourly Average Earnings:

	Coefficient	Standard Error	T-Ratio
206 cons_lnw	2.62223	0.93913	2.79217
207 afqt	0.00292	0.00019	15.16630
208 readmat	0.03498	0.01068	3.27419
209 libcard	-0.01570	0.00889	-1.76662
210 livpar	-0.00935	0.00913	-1.02375
211 prot	0.00057	0.00903	0.06330
212 black	-0.09571	0.01116	-8.57476
213 hisp	-0.02199	0.01244	-1.76796
214 nc	-0.20156	0.01163	-17.32885
215 so	-0.19232	0.01095	-17.56550
216 we	-0.09299	0.01185	-7.84903
217 urb	0.05734	0.00940	6.09789
218 ur	-0.00525	0.00124	-4.23621
219 mw	-0.03744	0.15993	-0.23411
220 mwage	0.01283	0.00560	2.28868
221 mwhgc	-0.02353	0.00774	-3.03850
222 age	0.09228	0.02636	3.50100
223 age2	-0.00252	0.00028	-9.09554
224 exp	0.05114	0.00388	13.17102
225 exp2	-0.00095	0.00017	-5.60064
226 hgc	0.12174	0.02461	4.94751
227 geddeg	-0.09378	0.01845	-5.08239
228 hsdeg	0.02171	0.01386	1.56597
229 coldeg	0.05935	0.02120	2.79964
230 lag1wu	-0.00258	0.00035	-7.28413
231 lag2wu	-0.00150	0.00035	-4.31057
232 lag3wu	-0.00122	0.00037	-3.25609
233 lag4wu	-0.00089	0.00038	-2.35692
234 lag5wu	0.00017	0.00035	0.47842
235 year	-0.00579	0.00262	-2.21244
236 sdlnw	0.33085	0.00179	184.44830
237 rhoc31	0.02835	0.03622	0.78271
238 rhoc32	-3.15645	140.99964	-0.02239

Heterogeneity Information:

First Permanent Linear Heterogeneity

Point	Probability Weight	Mass Point
1	0.03031	0.00000
2	0.57626	0.29680
3	0.18826	0.56837
4	0.00022	0.55201
5	0.19377	0.00650
6	0.01118	1.00000

Second Permanent Linear Heterogeneity

Point	Probability Weight	Mass Point
1	0.00000	0.00000
2	0.07806	0.59725
3	0.38797	0.73825
4	0.41077	0.85998
5	0.05575	0.99933
6	0.06745	1.00000

Nonlinear Transitory Heterogeneity

Discrete Outcomes:

Point	Probability Weight	Mass Point
1	0.48781	0.00000
2	0.01352	0.08736
3	0.00946	-0.69859
4	0.13645	-0.89421
5	0.02539	-0.02587
6	0.18150	3.37158
7	0.14587	-2.14653
1	0.48781	0.00000
2	0.01352	-0.06395
3	0.00946	0.00248
4	0.13645	0.00798
5	0.02539	0.08306
6	0.18150	0.04233
7	0.14587	23.03659
1	0.48781	0.00000
2	0.01352	2.13002
3	0.00946	-2.71315
4	0.13645	0.27321
5	0.02539	3.31889
6	0.18150	-0.07333
7	0.14587	-23.74037
1	0.48781	0.00000
2	0.01352	0.91121
3	0.00946	-0.00232
4	0.13645	-5.07658
5	0.02539	-0.11587
6	0.18150	-4.09336
7	0.14587	-0.14282

Continuous Outcomes:

Point	Probability Weight	Mass Point
1	0.48781	0.00000
2	0.01352	-852.60479
3	0.00946	380.51455
4	0.13645	467.45793
5	0.02539	9.52708
6	0.18150	18.04989
7	0.14587	-199.31782
1	0.48781	0.00000
2	0.01352	25.05534
3	0.00946	37.03057
4	0.13645	33.30497
5	0.02539	3.31579
6	0.18150	0.33636
7	0.14587	17.69780
1	0.48781	0.00000
2	0.01352	1.78335
3	0.00946	-3.63258
4	0.13645	-0.14938
5	0.02539	-1.70794
6	0.18150	0.04858
7	0.14587	0.04401

Standard Deviation of First Permanent Heterogeneity: 0.19592711346330

Standard Deviation of Second Permanent Heterogeneity: 0.10483843345877

Standard Deviation of Nonlinear Transitory Heterogeneity:

Equation	Standard Deviation
1.	1.6879633082053
2.	8.7983976221015
3.	9.0903886447375
4.	2.5636254816402
5.	216.49280991229
6.	14.791782913723
7.	0.4956357638527

Appendix 3:

Selected Estimates from Single-Equation Specifications

Table A.1

Estimates of Catch-Up Response

Table format follows that in main text

CL indicates the Chamberlain (1980) Conditional Logit

Outcome	*Method*	*Lag of Annual Weeks of Unemployment*				
		1	**2**	**3**	**4**	**5**
Probability of Training	Probit	**-0.0035** (0.0010)				
	CL	**0.0067** (0.0023)				
Probability of Working	Probit	**-0.0080** (0.0004)	**-0.0041** (0.0004)	0.0028 (0.0021)	0.0007 (0.0022)	**0.0037** (0.0018)
	CL	**-0.0079** (0.0036)	**-0.0076** (0.0036)	0.0059 (0.0038)	0.0002 (0.0037)	0.0031 (0.0037)
Annual Hours Worked	OLS	**-13.2011** (0.6858)	**0.2750** (0.7023)	0.0143 (0.6925)	**1.4044** (0.6106)	**1.4991** (0.6106)
	FE	**-7.6357** (0.5752)	**1.3330** (0.5490)	0.8022 (0.5280)	**1.3269** (0.5092)	**1.3879** (0.4989)

Bold-faced indicates significance at the 5% level

Table A.2

Estimates of Persistence

Table format follows that in main text
CL indicates Chamberlain (1980) logit

Outcome	*Method*	*Lag of Annual Weeks of Unemployment*				
		1	**2**	**3**	**4**	**5**
Probability of Unemployment	Probit	**0.0489** (0.0016)	0.0019 (0.0015)	**0.0070** (0.0015)	**0.0036** (0.0015)	**0.0034** (0.0014)
	CL	**0.0455** (0.0026)	**-0.0150** (0.0025)	**-0.0050** (0.0024)	**-0.0085** (0.0024)	**-0.0140** (0.0024)
Annual Weeks of Unemployment	OLS	**0.2402** (0.0087)				
	FE	0.0212 (0.0132)				

Bold-faced indicates significance at the 5% level

Table A.3

Estimates of Blemishes

Table format follows that in main text

Outcome	*Method*	*Lag of Annual Weeks of Unemployment*				
		1	**2**	**3**	**4**	**5**
Log Average Hourly Earnings	OLS	**-0.0028** (0.0005)	**0.0027** (0.0006)	**-0.0019** (0.0007)	**0.0009** (0.0007)	**-0.0007** (0.0006)
	FE	**-0.0018** (0.0006)	**-0.0021** (0.0006)	-0.0010 (0.0005)	-0.0007 (0.0005)	-0.0003 (0.0005)

Bold-faced indicates significance at the 5% level

Endnotes

1 The EU is currently composed of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, The Netherlands, Portugal, Spain, Sweden and the United Kingdom. Source: Eurostat.

2 See Stevenson (1978) and Becker and Hills (1980). These studies viewed youth unemployment as involuntary. They predicted dire consequences for those young people who experienced unemployment early in their working lives. On the other hand, dual labor market theorists held that early unemployment would permanently track young people into jobs with low pay and little room for advancement. Drawing on the human capital models of Ben-Porath (1967) and Blinder and Weiss (1976), still other analyses posited that early spells would deprive the young of labor force experience during that portion of the life cycle when it yields the highest return. The lifetime earnings profiles of unemployed youths would permanently shift down.

3 See Heckman (1979), Heckman and Borjas (1980) and Flinn and Heckman (1982).

4 While much of the volume is descriptive, Corcoran (1982), Ellwood (1982) and Meyer and Wise (1982) present detailed analyses of the long-term effects of early work and schooling decisions on later labor market outcomes.

5 See Freeman and Medoff (1982) and Freeman and Wise (1982).

6 With a sample of 634 young females from the National Longitudinal Survey of Young Women, she uses the conditional logit model suggested by Chamberlain (1980). Chamberlain (1984, pp. 1274-1278), however, notes that this specification is not consistent in this context because it assumes that there can be no occurrence dependence. Occurrence dependence is exactly what Corcoran is measuring.

7 The sample is 2,067 young women from the Population Study of Income Dynamics who have finished school.

8 The sample is 298 young males from the National Longitudinal Survey of Young Men. To control for unobserved heterogeneity, he uses an individual-specific fixed-effects specification (FE specification).

9 If unobserved tastes vary as young people age, however, neither of these studies controls appropriately for heterogeneity. Variables such as schooling or prior unemployment remain endogenous, and estimates of their effects on outcomes such as hourly earnings are biased. Furthermore, evidence (Lewis, 1986 and Robinson, 1989) indicates that the FE specification exacerbates problems of measurement error in a manner that biases estimates toward zero.

10 Since their data omit high school dropouts, young people for whom early unemployment may have large effects later in life, their results could understate the true long-term effects of early unemployment. Further, recent Monte Carlo evidence (Mroz and Guilkey, 1992 and Mroz 1998) indicates that the normality assumption, when invalid, often induces greater bias than ignoring the endogeneity in models of the type used by Meyer and Wise.

11 See also Lynch (1985), Lynch (1989), Narendranathan and Elias (1993) and Raphael (1996).

12 The sample they use is 14- and 15-year-olds from the National Longitudinal Survey of Youth (NLSY). While this age range may appear quite young, they note that a quarter of the male sample works on average 12 hours per week.

13 His sample is 14- and 15-year-olds from the NLSY. He specifies a recursive system whereby labor force participation (either a dummy variable or actual average hours of work) is influenced by exogenous characteristics and unobserved ability. Participation and unobserved ability affect the level of schooling, which in turn influences hours worked and wages at age 22 and 23.

14 Ben-Porath uses a continuous-time framework, while the model described here is in discrete time. See Appendix 1 for a complete presentation of this model.

15 Because training is costly and there is no future gain, it is optimal not to train in the third period.

16 As with Ben-Porath, there is an initial positive stock of human capital that is exogenous.

17 The timing of these events is as follows. Individuals choose an optimal time-path at the start of the first period by maximizing their objective function with respect to d_1, d_2, s_1 and s_2. Having made their optimal purchases of d_1, the involuntary spell perturbs their optimal time-path of human capital accumulation. While the d_1 choice has already been made, young people can re-optimize in the second period. It is second period choices that are of interest.

18 See Appendix 1 for proof of these propositions.

19 Although the comparative dynamics in the parentheses are negative, the effects of the spell on subsequent human capital investments are positive. To see this, note that the spell constrains the first period human capital stock below its optimal value. The comparative dynamics measure the effects of a slight relaxation in this constraint, as the constrained stock approaches the optimal stock from the left on the real line. Therefore, the effects of the spell on optimal second period behaviors are the opposite sign of the comparative dynamics. That is, the effects of the spell on these human capital investment behaviors are positive.

20 This model looks at only two behaviors and does not address job search or time voluntarily spent not working. These and other limitations are discussed in Appendix 1.

21 The stock of education is measured by highest grade completed, whether a young man possesses a high school diploma or a general equivalence degree (GED) and whether he possesses a four-year college degree.

22 If the mechanism through which unemployment affects wages is exclusively forgone human capital, there should be no effect of prior unemployment on wages after perfectly controlling for the human capital stock. Perfectly controlling for the human capital is unlikely, however, because the human capital variables are only proxy measures.

23 The NLSY questionnaire was substantially altered in 1987 when management of the NLSY was transferred to the Bureau of Labor Statistics (BLS), and no training questions were asked in this year. In 1988, the questionnaire asked whether any training had occurred in either 1987 or 1988.

24 This specification is linear in the permanent heterogeneity factor and is nonlinear in the transitory heterogeneity factor. The linear heterogeneity factor is a restricted form of the nonlinear heterogeneity factor. See Mroz (1998). The inclusion of a permanent nonlinear heterogeneity is a possible extension to this specification.

25 These variables are listed in Tables 1 and 2 in the data section.

26 The choice of a five-year lag structure is somewhat arbitrary. There is some evidence that unemployment longer ago than five years is influential for two outcomes.

27 While of lesser focus, the estimates of the ∀s for each equation are quite interesting and relevant. They are also discussed.

28 The decision to work, wages and unemployment are modeled only for those young men not in school. Further, annual hours of work and wages are modeled only if a young man chooses to work, while weeks of unemployment are modeled only for those who experience a spell of unemployment during the year.

29 For a thorough discussion of identification in models of this type, see Mroz and Surette (1998).

30 By 1986, these selection criteria affect nearly 25% of the sample. By 1994, nearly 40% is affected.

31 The average length of a non-interview spell is greater than three years. Given the age of this sample, the failure to observe outcomes for this length of time could induce bias in estimates of interest. If the attrition process is random, this selection procedure does not bias the estimates. See MaCurdy, Mroz and Gritz (1998) for a detailed analyses of attrition from the NLSY.

32 Despite the role that training plays in the armed forces, those young men who enter the military report no training. Future extensions of this research may also model a young man's (endogenous) decision to enter the military and his accumulated years of military experience.

33 Approximately 90% of the original cohort was administered the AFQT test.

34 For those in the sample not administered the test, a predicted value is assigned using the race-specific mean residual from the age regression.

35 Average hourly earnings are defined as total annual earnings from wages and salary divided by annual hours worked. They are deflated using the CPI-UX1 price index with a base year of 1982.

36 Alex Cowell provided us with the tuition price data.

37 A complete set of DFML estimates may be found in Appendix 2. These estimates are obtained from a model that uses two permanent linear heterogeneities, each with six mass points, and a vector of transitory nonlinear heterogeneities with seven mass points. This amounts to 80 additional parameters over a model with no heterogeneity.

38 In the case of a dummy variable outcome, the Chamberlain (1980) conditional logit model is used. In the presence of occurrence dependence or lagged endogenous variables, this conditional logit estimator is inconsistent. Appendix 3 contains selected results for the single-equation specifications used for comparison. A complete set of single-equation results is available from the author on request.

39 In all equations, prior unemployment is measured as weeks per year. The other variables used in these equations are listed in Tables 1 and 2, together with a linear time trend and squares in age and experience.

40 Specification testing fails to reject the hypothesis that only the first lag is significant. The results presented in this table come from a model that excludes the second, third, fourth and fifth lags from the training equation. The estimates are accordingly omitted from the table. With a specification that uses all five lags, the DFML estimates (standard errors) on the remaining four lags are: 0.0014 (0.0018); -0.0009 (0.0017); 0.0010 (0.0016); and -0.0009 (0.0016), respectively.

41 This effect is obtained by multiplying the point estimate by 13: 3.1980*13 = 41.574.

42 The OLS standard errors are not robust, as they do not account for the correlations of disturbances across years. A portion of this additional efficiency in the DFML specification comes from the implicit seemingly unrelated regression (SUR) covariance structure.

43 These comparisons require a normalization of the different point estimates since they are derived from different probability specifications. For this normalization, I use the estimated coefficient of the local unemployment rate in the training equation. For the DFML specification, the normalization is 0.0051/(–0.0116) = –0.4396. For probit, it is 0.0035/(–0.0106) = –0.3302. For conditional logit, it is 0.0067/(–0.0263) = –0.2548. The negative sign indicates that these relative effects can be expressed in terms of a reduction in the local unemployment rate.

44 The standard errors of these normalized effects are obtained using parametric bootstrapping with 10,000 replications drawn from the distribution implied by the covariance matrix of the estimates.

45 The DFML estimate of the local unemployment rate in this equation is 0.0390. The standard errors of these effects are obtained using parametric bootstrapping with 10,000 replications.

46 Testing fails to reject the hypothesis that this effect is zero beyond the first lag. These exclusions are imposed for the specification used for these estimates. With the specification that uses all five lags of annual weeks of unemployment, the DFML estimates (standard errors) on the remaining four lags are 0.0251 (0.0146); 0.0204 (0.0144); 0.0025 (0.0136); and 0.0027 (0.0131), respectively. These are quite small, relative to the one-year lag.

47 This measure is 13*0.1254 = 1.6302.

48 For a discussion of these issues, see Cain (1976).

49 This measure is –0.0026*13 = –0.0338.

50 The average nominal wage rate in 1993 is 13.19/hour. At 2,000 hours, this yields average earnings of 26,380.

51 The OLS and FE estimates in Table 6 appear in Appendix 3 as Table A.3. Unlike the other tables in Appendix 3, this table is in the main text because of the importance of these particular effects.

52 With more significant digits, the DFML standard error is 0.00038 while the OLS standard error is 0.00068.

53 Recall that there is an improvement of 8125.55 in the likelihood value for only 80 additional parameters.

54 The test used here bootstraps the difference in the two estimates using 1,000 replications. The value of the test statistic is 4.5447. With five degrees of freedom, the p-value of the null hypothesis of no difference is 0.4739.

55 A Hausman (1978) test of any difference between the FE and DFML estimates yields a test statistic of 8.3368. With five degrees of freedom, the p-value of the null hypothesis of no difference is 0.1386.

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