

THE LONG-TERM EFFECTS OF YOUTH UNEMPLOYMENT

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Abstract

Using National Longitudinal Survey of Youth data on young men, we estimate the long-term effects of youth unemployment on later labor market outcomes. A spell of involuntary unemployment can lead to sub-optimal investments in human capital among young people in the short run. A theoretical model of dynamic human capital investment predicts a rational “catch-up” response to such a spell. Using semiparametric techniques to control for the endogeneity of prior behaviors, our estimates provide strong evidence of this response. We also find evidence of persistence in unemployment. Despite the catch-up response, however, we find the negative effect of prior unemployment on earnings to be large, to be persistent and to taper off slowly over time. The theoretical model predicts each of these three effects. Combining our semiparametric estimates with a dynamic approximation to the lifecycle, we find that unemployment experienced as long ago as ten years continues to affect earnings adversely.

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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 levels of human capital, reduced 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 could have sizeable 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 (NLSY79). The econometric framework used in this study includes detailed controls for the endogeneity of a wide range of human capital behaviors, including prior unemployment.

A spell of unemployment can lead to sub-optimal 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. We find that recent unemployment has a significant positive effect on whether a young man trains today. While there is little evidence of significant long-lived persistence of unemployment spells on the incidence and duration of future unemployment spells, there is short-term persistence.

Despite this catch-up response and an absence of long-lived persistence in unemployment spells, there is evidence of long-lived “blemishes” from unemployment. Dynamic simulations using our approximation to the lifecycle optimization process indicate that a six-month spell of unemployment experienced at age 22 would result in eight percent lower wages, on average, at age 23. This wage effect occurs whether we “assign” unemployment to all working individuals in the sample or if we use increases in local unemployment rates to induce those most at risk of layoff into unemployment. The former scenario represents a “population average” effect, while the latter is a form of a local-average treatment effect. Wages remain over five percent below their non-disturbed level through age 26, and even at ages 30 and 31 wages are two to three percent lower than they otherwise would have been. In 2002 US dollars at 2,000 hours per year, a six-month spell of unemployment at age 22 yields a \$1,400 to \$1,650 earnings deficit at age 26 (about six percent) and a \$1,050 to \$1,150 deficit (about four percent) at age 30, at depending on the type of average effect one considers.

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 several 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

Between 1969 and 1979, the unemployment rate of young people age 16 to 19 in the US had risen by over 30% from 12.2 to 16.1 percent. At the time, policy-makers feared that the nation was gripped by an unemployment problem that would “permanently scar” the unemployed young.¹ Therefore, early empirical analyses of the long-term effects of youth unemployment focused on the extent to which early unemployment spells affected the incidence and duration of future spells.² These analyses found evidence of strong persistence in unemployment.

In contrast, later studies drew a distinction between true state dependence and unobserved heterogeneity.³ Hypothesizing that individuals differ in certain unobserved characteristics, these studies demonstrated that a failure to control for heterogeneity might spuriously indicate causal persistence. If such characteristics are correlated over time, measures of state dependence act as proxies for this serial correlation in the absence of suitable controls. Young people with weak preferences for work, for instance, will tend to work 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 on future spells cannot be obtained.

¹ Policy-makers 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 percent. To contrast the 16.1% rate in 1979, the US unemployment rate for 16- to 19-year-olds was 18.5% in May 2003, which is three times higher than the rate of the above-20 population. For black teenagers, the unemployment rate was over 37% at this time.

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), other analyses posited that early spells would deprive the young of labor force experience during that portion of the lifecycle when it yields the highest return. As a result, the lifetime earnings profiles of unemployed youths would permanently shift down.

³ See Heckman (1979), Heckman and Borjas (1980), and Flinn and Heckman (1981).

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). 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 change jobs frequently due to low reservation wages and low opportunity costs. High turnover rates, possibly punctuated by unemployment spells, are a natural characteristic of this market and, as such, are not a source of concern.⁴

Within the context of this analysis, three of these papers require further discussion. First, Corcoran (1982) examines persistence in employment status by examining whether current employment status is influenced by prior employment status.⁵ 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.⁶ Second, Ellwood (1982) examines persistence in employment patterns using annual weeks of unemployment and annual weeks worked.⁷ After controlling for unobserved heterogeneity with a fixed-effects specification, 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

⁴ See Freeman and Medoff (1982) and Freeman and Wise (1982).

⁵ With a sample of young females from the National Longitudinal Survey of Young Women, she uses the Chamberlain's (1980) conditional logit model. Chamberlain (1984, pp 1274-1278), however, notes that this specification is not consistent in this context because it assumes that there is no occurrence dependence, which is exactly what Corcoran is measuring.

⁶ The sample is young women from the Population Study of Income Dynamics who have finished school.

⁷ The sample is young males from the National Longitudinal Survey of Young Men.

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.⁸ Third, 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.⁹

There are several other papers that fit within the context of this research.¹⁰

Michael and Tuma (1984) examine the labor market effects of early labor force experience.¹¹ 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), who treats early decision-making as exogenous, also

⁸ If unobserved tastes vary as young people age, however, neither of these studies controls appropriately for unobserved 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 fixed-effects specification exacerbates problems of measurement error in a manner that biases estimates toward zero.

⁹ Since their data omit high school dropouts, young people for whom early unemployment may have large effects later in life, their results could under-state the true long-term effects of early unemployment. Further, recent Monte Carlo evidence (Mroz and Guilkey [1992] and Mroz [1999]) 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.

¹⁰ See also Lynch (1985), Lynch (1989), Narendranathan and Elias (1993), Raphael (1996), and the Report on the Youth Labor Force by the US Department of Labor (2000).

¹¹ The sample is 14- and 15-year-olds from the NLSY79. While this age range may appear quite young, they note that a quarter of the male sample works on average 12 hours per week.

examines the effects of early labor force experience.¹² 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 experience and finds that early experience has positive long-run effects on hours worked and wage rates. Finally, in a subsequent NBER volume on the youth labor market, Card and Lemieux (2000) hypothesize that young people adapt to changes in labor market conditions in a variety of ways.¹³ They find that weaker labor market conditions and lower wages increase the likelihood that young men stay at home with their parents, as well as remain in school. Their hypotheses, however, are not ultimately tied directly to a formal model of optimization under uncertainty.

In summary, much of the current literature on the long-term effects of youth unemployment contains 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; the lack of a theoretical foundation; and, the 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, self-selection, and endogeneity. We

¹² His sample is 14- and 15-year-olds from the NLSY79. 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 separately wages at age 22 and 23.

test hypotheses arising from a model of maximizing behavior under uncertainty. The estimates and simulations from this research can help one gauge the long-term impacts of policies that affect the youth labor market.

¹³ The US sample is from the Current Population Survey. The Canadian sample is based on Canadian census data.

III. A CONCEPTUAL FRAMEWORK

Consider the following analytic model of human capital investment. The model is similar to Ben-Porath's (1967) classic model with the addition of random unemployment shocks that affect one's ability to earn and train.¹⁴ In this model, the present and the future are linked through the process of human capital accumulation. An exogenous shock that perturbs the optimal time-path of human capital investment in one period persists through time via its effects on additions to 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 T periods and may train in each of the first $T-1$ periods.¹⁵ For the moment, assume, as in Ben-Porath, that there is no unemployment. At the beginning of period t , an individual's human capital stock is given by H_t . Individuals invest in additional human capital by devoting a fraction of their time, s_t , to human capital production, which we call training. Training occurs on the job and is considered to be general. There are no savings, no human capital depreciation and no decisions regarding hours of work other than the choice of the fraction of time to devote to investments and away from current earnings. Potential earnings, E_t^* , could be obtained by renting the human capital stock at a constant rate w : $E_t^* = wH_t$.¹⁶ It is always possible to obtain these earnings, except when experiencing involuntarily unemployment. Disposable income (or net earnings) is the difference between potential

¹⁴ Ben-Porath uses a continuous-time framework, while the model described here is in discrete time. Unlike Ben Porath, we do not allow the human capital production function to exhibit Harrod neutral technical change. 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 last period.

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

earnings and the opportunity cost of human capital used in the production process, or

$$E_t = (1 - s_t)wH_t.$$

At the beginning of each period, an individual chooses the fraction of his time to devote to the production of new human capital, s_t . Human capital at the start of the next time period is given by $H_{t+1} = H_t + f(s_t^*)$, where s_t^* is the actual amount of time that ends up being devoted to producing new human capital. In the absence of unemployment, $s_t^* = s_t$. We assume that the production function of human capital is increasing in its argument and strictly concave. These investment choices through time yield an optimal time-path of human capital investment and accumulation.

We assume that all unemployment is involuntary and that individuals have rational expectations about the probability of experiencing unemployment. The probability of unemployment does not depend on the individual's choice of s_t . All training and earnings for each time period take place on the single job chosen at the start of the time period (indexed by the value of s_t) before the individual's unemployment status is revealed. When unemployment strikes, it reduces disposable earnings and optimally planned training time on the job by equal percentages. In particular, let $(1 - \lambda)$ be the fraction of the time period that the individual spends unemployed. If he experiences unemployment, then his actual disposable earnings in the time period would be $E_t = \lambda(1 - s_t)wH_t$, and the additions to the human capital stock during the period he is unemployed would be given by $f(\lambda s_t)$.¹⁷ Unemployment, therefore, perturbs an

¹⁷ A simple way to conceptualize this setup is to assume that at the start of the "year" an individual chooses a job for that entire year that allows him to devote the fraction s_t of each working day to producing new

individual's optimal time-path of human capital accumulation by preventing on-the-job training. This results in an under-investment in human capital after the unemployment spell occurs. One can view unemployment at time t , then, as an exogenous reduction in the amount of human capital available at the start of period $t + 1$.

Those who experience an unemployment spell in the preceding period enter the current period with a lower stock of human capital than otherwise identical individuals who did not experience unemployment. Crucially, having experienced the shock, individuals are able to re-optimize at the beginning of this next time period. This re-optimization yields a new optimal time-path of human capital investment. Besides lowering lifetime expected wealth, the only lasting effect of an involuntary unemployment spell is that it constrains an individual to a lower human capital accumulation than he had planned. This model, therefore, 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 training, and it provides a mechanism through which these effects may be mitigated by optimal behavioral responses. The model provides three interesting implications.¹⁸

Proposition 1: The “Catch-up” Response

After experiencing an involuntary unemployment spell in all years except T and $T-1$, an individual will unambiguously increase the time that is spent training in the next period.

This proposition states that a young person will exhibit an optimal “catch-up” response to an involuntary unemployment spell that exogenously reduces his human capital acquisition at time t . An exogenous spell perturbs a young person's optimal time-

human capital. If unemployment occurs, the individual loses the latter $100 \cdot \lambda\%$ of the year's workdays for earning disposable income and for producing human capital.

path of human capital investment. Re-optimization that takes the spell into account, however, yields a new optimal time-path for the human capital investments. This re-optimization produces an unambiguous effect on future behavior: a young person will increase the share of time that is spent training.¹⁹ We refer to this change in subsequent, optimal investment choices as a “catch-up” response.

Proposition 2: The Convergence of Potential Earnings

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

This proposition states that, because of the optimal response to the human capital shock, the 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.

Proposition 3: Excessive Divergence Followed by Excessive Convergence of Disposable Earnings

Observed net earnings immediately after experiencing unemployment are lower than would be implied by solely the reduction in the human capital stock. Furthermore, observed earnings grow faster after the first period following an unemployment spell than would be implied by the convergence of the human capital stocks.

This proposition states that, observed differences in disposable earnings between those who were and those who were not recently unemployed are larger than would be

¹⁸ See Appendix 1 for proof of these propositions.

¹⁹ An alternative view of this “catch-up” response is that those who did not experience unemployment had acquired “too much” human capital at time t because they did not become unemployed. They in turn reduce their production of new capital at $t+1$.

implied by the differences in their human capital stocks. To see this, holding fixed the share of time that is spent training, the reduction in earnings would reflect exactly the lower stock of human capital. The optimal catch-up response, however, implies that a recently unemployed individual increases the share of time that is spent training. Therefore, he necessarily decreases the share of time spent producing disposable earnings, which results in observed earnings that are lower than would be implied solely by the reduction in the human capital stock.

In subsequent time periods, because of the catch-up response, the gap in human capital stocks diminishes between those who had and had not experienced unemployment. Differences in the shares of time spent training, therefore, become less pronounced. The later convergence of disposable earnings reflects both the convergence of the human capital stocks as well as the convergence of the human capital investment decisions.

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 positing 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 In our empirical analysis, we assume that observed hourly wages are net of human capital training costs. Wage rate differentials reflect both differences in human capital stocks and differences in the amount of time spent in on-the-job training.

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

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 future behaviors and outcomes 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 jointly model 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 the unemployment. We jointly estimate this system of equations 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 (1999). This discrete factor maximum likelihood (DFML) 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 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, job changing, 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.

Furthermore, 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 previous studies of 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 explanatory variables. They include the stocks of education and work experience, as well as prior unemployment. In addition, there are potential self-selection issues for the observed working and training outcomes. To account for these potential sources of bias, up to eight 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; whether the individual changed jobs; school attendance; and training. We also specify an initial condition equation to control for the endogeneity of each person's schooling attainment at the start of the panel.

Log average hourly earnings are specified to be Mincer-type earnings functions. They depend upon polynomials in age and in cumulative work experience, the stock of

education and demographic variables.²¹ Hourly earnings may also be affected by prior unemployment.²² We also allow hourly earnings to be affected by recent job changes in order to separate out the effects of experiencing unemployment from those attributable to just changing one's employer. We allow for up to five annual lags for weeks spent unemployed and for job changes.

Annual hours of work depend upon local labor market conditions, polynomials in age and in labor force experience, education, prior unemployment and demographic variables. Annual weeks of unemployment depend upon local labor market conditions, polynomials in age and in 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 in labor force experience, education, local labor market conditions, demographic variables and five years of unemployment and job change histories. Schooling is a dummy variable that takes the value one if a young person participated in any secondary or post-secondary education in a particular year. It depends upon polynomials in age and in labor force experience, demographic variables, and prior unemployment. Each of these equations also includes four time period dummies (for 1979, 1980 to 1982; and 1992 to 1994, with 1983-1991 being the

²¹ The stock of education is measured by highest grade completed, whether a young man possesses a high 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 NLSY79 questionnaire was altered in 1987 when its management 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 either in 1987 or 1988.

excluded category). Complete specifications for all equations, along with point estimates and standard errors, are reported in Appendix 2.

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 in each year t :

$\{is_i, as_{it}, tr_{it}, work_{it}, hw_{it}, un_{it}, wu_{it}, ch_{it}, w_{it}\}$ where:

is_i is initial schooling at the start of the NLSY79 survey

as_{it} is a dummy variable for school attendance in year t

tr_{it} is a dummy variable for any vocational training in year t

$work_{it}$ is a dummy variable for working in year t

hw_{it} is hours worked during year t (if working)

un_{it} is a dummy variable for experiencing unemployment in year t

wu_{it} is the number of weeks unemployed in year t (if unemployed)

ch_{it} is a dummy variable indicating a job change in year t

w_{it} is the logarithm of average hourly earnings in year t (if working)

Let ε_{it} be a vector with nine 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 ρ is a matrix of factor loads and μ_i is a vector of unobserved factors. This represents a permanent/transitory error specification. Assume u_{it} is a mean-zero iid normal error vector. The primary substantive restriction this error-components structure places on the density of ε_{it} is that all correlation across

equations in different time periods enters solely through the linear factors μ_i . Within time periods, the covariance pattern is unrestricted due to the freely-estimated relationships among the elements of η_{it} , though we do impose that the joint distribution does not vary through time. The factors μ_i capture unobserved determinants that do not vary as young people age such as, perhaps, ability.²⁴ The factor η_{it} captures time-specific unobserved determinants that may vary across time such as preferences for work.²⁵ It allows for arbitrary, contemporaneous correlation of outcomes at each point in time that is not captured by the person specific unobserved factor.

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

$$tr_{it}^* = x_{tr,it}' \alpha_{tr} + \sum_{\tau=1}^5 \beta_{tr,\tau} wu_{it-\tau} + \sum_{\tau=1}^5 \gamma_{ch,\tau} ch_{it-\tau} + \rho'_{tr} \mu_i + \eta_{tr,it} + u_{tr,it} \quad \text{Equation 1}$$

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.²⁶ 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 and prior job changes for up to

²⁴ The error structure for initial schooling is modeled only with the permanent heterogeneity factors.

²⁵ This specification we use is linear in two permanent heterogeneity factors and is nonlinear in the transitory heterogeneity factor.

²⁶ These variables are listed in Tables 1 and 2 in the data section and in Appendix 2.

five years.²⁷ This study focuses on the estimates of the β 's, the impacts of prior unemployment, for each of the eight outcomes:

$\beta_{o,\tau}$ for $o = as, tr, work, hw, un, wu, ch, w$ and $\tau = 1, \dots, 5$.

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

$$h_{it} = x'_{hit} \alpha_h + \sum_{\tau=1}^5 \beta_{h,\tau} wu_{it-\tau} + \sum_{\tau=1}^5 \gamma_{ch,\tau} ch_{it-\tau} + \rho'_h \mu_i + \eta_{hit} + u_{hit} \quad \text{Equation 2}$$

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 and job changes 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 normally distributed, one could use multivariate normal maximum likelihood. The discrete factor integration method used in this study assumes that the underlying continuous distributions of the factors can be suitably 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 *a priori* assumptions 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 in year t is:

²⁷ 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 one outcome.

$$L_i(\Theta | \mu_i, \eta_{it}) = \Pr\{as_{it} = 1 | \mu_i, \eta_{it}\}^{as_{it}} \cdot \left[\begin{array}{l} \Pr\{as_{it} = 0 | \mu_i, \eta_{it}\} \cdot \\ \left[\Pr\{work_{it} = 1 | \mu_i, \eta_{it}\} \cdot f_h(h_{it} | \mu_i, \eta_{it}) \cdot f_w(w_{it} | \mu_i, \eta_{it}) \right]^{work_{it}} \cdot \Pr\{work_{it} = 0 | \mu_i, \eta_{it}\}^{(1-work_{it})} \cdot \\ \left[\Pr\{un_{it} = 1 | \mu_i, \eta_{it}\} \cdot f_{wu}(wu_{it} | \mu_i, \eta_{it}) \right]^{un_{it}} \cdot \Pr\{un_{it} = 0 | \mu_i, \eta_{it}\}^{(1-un_{it})} \cdot \\ \left[\Pr\{ch_{it} = 1 | \mu_i, \eta_{it}\}^{ch_{it}} \cdot \Pr\{ch_{it} = 0 | \mu_i, \eta_{it}\}^{(1-ch_{it})} \right. \\ \left. \Pr\{tr_{it} = 1 | \mu_i, \eta_{it}\}^{tr_{it}} \cdot \Pr\{tr_{it} = 0 | \mu_i, \eta_{it}\}^{(1-tr_{it})} \right]^{(1-as_{it})} \end{array} \right] \cdot \quad \text{Equation 3}$$

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

Approximating the distributions of μ_i and η_{it} with mass points μ_{1j} , for $j = 1, \dots, J$, μ_{2k} , for $k = 1, \dots, K$, and η_m (vector) for $m = 1, \dots, M$, the contribution to the likelihood function of individual i is:

$$L_i(\Theta, \Gamma) = \sum_{j=1}^J p_{1j} \sum_{k=1}^K p_{2k} \left(f_{is}(is_i | \mu_{1j}, \mu_{2k}) \right) \cdot \prod_{t=1}^T \sum_{m=1}^M p_{3m} L_{it}(\Theta | \mu_{1j}, \mu_{2k}, \eta_m)$$

where $p_{gr} = \Pr\{\mu_{gi} = \mu_{gr}\}$ for $\mu_{gr} \in R$ and $g = 1, 2$, $p_{3m} = \Pr\{\eta_i = \eta_m\}$ for $\eta_m \in R^8$,

f_{is} is the density for the potentially endogenous initial condition describing schooling completed at the start of the longitudinal survey, and Γ is the vector containing the parameters of the discrete distributions.

Identification

This study treats training, school attendance, work experience, prior job changes, 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

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.

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 non-linearities 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.

Alternative Approaches to Estimation

To assess some of the more important findings in this paper, we also use more standard single-equation approaches to estimate the impact of prior unemployment on

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

particular outcomes of interest.³⁰ For the most part, these alternative approaches provide estimates that are qualitatively similar to those from the discrete factor maximum likelihood approach, and in only one instance do we find evidence of significant differences between the fixed-effect estimates and the DFML estimates. It is important to note that for the labor market and schooling outcomes that we examine, there could be potentially serious sample selection biases. In most instances, only the DFML estimator has the potential to control for such selection biases when compared to the single-equation approaches. Further, since much of our analysis explicitly deals with moderately complex patterns of prior outcomes influencing current outcomes through the process of human capital accumulation, one should discount the relevance of the conditional/fixed-effect logit estimates presented here. Such estimators can exhibit considerable bias when the outcome of interest depends on prior outcomes for the process.³¹

The Data

The primary data for this research are taken from the 1979 National Longitudinal Survey of Youth (NLSY79) and its geocode supplement. We use young men who were 14 to 19 years old in 1979 and are drawn from both the representative sample and the over-samples of blacks and Hispanics. This yields a sample size of 3,731, of which 2,286 are from the representative sample and 1,445 are from the two over-samples. We follow these young men through 1994. When constructing this sample, we applied the following

³⁰ For continuous dependent variables, these are ordinary least squares (OLS) and fixed-effect regressions. For discrete dependent variables, these are probit and Chamberlain's (1980) conditional/fixed-effect logit.

³¹ See Chamberlain (1984, pp 1274-1278).

two selection criteria.³² 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.³³ Second, those young men not in the initial military sub-sample who enter the armed forces permanently leave the sample upon entry.³⁴

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).³⁵ The scores from this test are regressed against age dummies to purge pure age effects.³⁶ Each value is then mean-differenced using the mean for the entire sample.

The first eight 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

³² By 1986, these selection criteria affect nearly 25% of the sample. By 1994, nearly 40% is affected.

³³ 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 analysis of attrition from the NLSY.

³⁴ Despite the role that training plays in the armed forces, those young men who enter the military report no training.

³⁵ Approximately 90% of the original cohort was administered the AFQT test.

³⁶ For those in my sample not administered the test, a predicted value is assigned using the race-specific mean residual from the age regression.

maximum of 18.0% in 1993 but declines slightly in 1994. Average annual hours of work rise monotonically from 481 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 1993.³⁷ Training started out low in 1979, reflecting the young age of the sample at that date. By 1993, over one in six young men reported some type of formal vocational training. The remaining rows in Table 2 contain the time-varying unweighted averages for other variables used in this study.

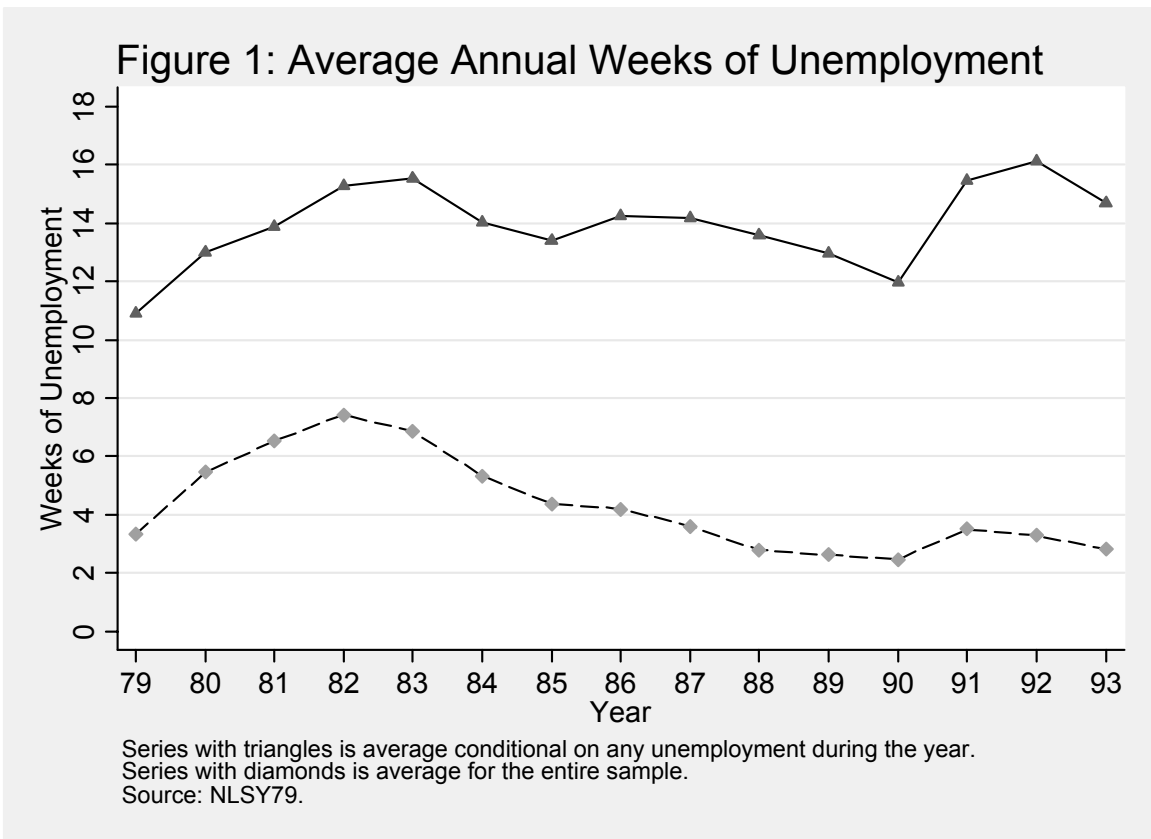
Table 1: Summary Statistics of Time-Invariant Characteristics
(Standard Deviations Omitted for Dummy Variables)

Variable Name	Variable Description	Entire (St. Dev.) 3731 obs	Represent. (St. Dev.) 2286 obs	Over-sample (St. Dev.) 1145 obs
Afqt	Armed forces qualification test score	0.00 (28.13)	8.14 (28.35)	-12.88 (22.40)
Initsch	Initial level of schooling	9.64 (1.67)	9.75 (1.63)	9.45 (1.71)
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

³⁷ 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.

Table 2: Summary Statistics of Time-Variant Variables
(Standard Deviations Omitted for Dummy Variables)

Variable Name	Variable Description	1979 Mean (St. Dev.) 3731 obs	1986 Mean (St. Dev.) 2805 obs	1993 Mean (St. Dev.) 2304 obs
Un	Dummy variable: Any unemployment during the year	0.30	0.29	0.19
Wun	Annual weeks of unemployment (entire sample)	3.32 (8.00)	4.20 (9.75)	2.83 (7.97)
Work	Dummy variable: Any work during the year	0.58	0.93	0.93
Hw	Annual hours worked (entire sample)	627.97 (776.92)	1814.14 (909.24)	2026.20 (904.26)
Lnw	Log of deflated average hourly earnings from wages and salary (in 1982 dollars)	1.31 (0.79)	1.76 (0.73)	2.02 (0.66)
Anysch	Dummy variable: Any schooling during the year	0.89	0.20	0.07
Train	Dummy variable: Any training during the year	0.03	0.12	0.18
Chjob	Dummy Variable: Change job in prior year	0.0027	0.1027	0.0660
age	Age	16.55 (1.60)	23.54 (1.63)	30.52 (1.63)
exp	Cumulative labor force experience in hours/2000	0.24 (0.35)	4.39 (2.55)	11.29 (4.35)
hgc	Highest grade in years completed	9.64 (1.67)	12.51 (2.23)	12.96 (2.54)
geddeg	Dummy Variable: Holds a general equivalence degree	0.01	0.09	0.12
hsdeg	Dummy Variable: Holds a high school diploma	0.15	0.66	0.69
coldeg	Dummy Variable: Holds a four-year college degree	0.00	0.12	0.19
urb	Dummy Variable : Residence is urban	0.80	0.82	0.81
ne	Dummy Variable : Residence is Northeastern US	0.20	0.18	0.17
nc	Dummy Variable : Residence is North-Central US	0.26	0.25	0.26
so	Dummy Variable : Residence is Southern US	0.36	0.37	0.37
we	Dummy Variable : Residence is Western US	0.19	0.20	0.20
ur	Local labor market unemployment rate (in percent)	6.31 (1.97)	7.77 (2.84)	7.53 (2.60)
expsec	Per-pupil public expenditure on secondary institutions (in 1982 dollars)	3107.27 (732.91)	3694.57 (930.58)	4056.55 (1042.62)
expps	Per-pupil public expenditure on post-secondary institutions (in 1982 dollars)	5735.19 (1122.29)	6454.09 (1135.09)	6828.19 (1154.78)
ugtuitt	Annual undergraduate tuition at main or largest campus of state university (in 1982 dollars)	1142.54 (391.76)	1475.57 (540.10)	2067.79 (753.73)
Mw	The larger of federal or state-level hourly minimum wage (in 1982 dollars)	3.93 (0.09)	3.07 (0.07)	2.97 (0.12)

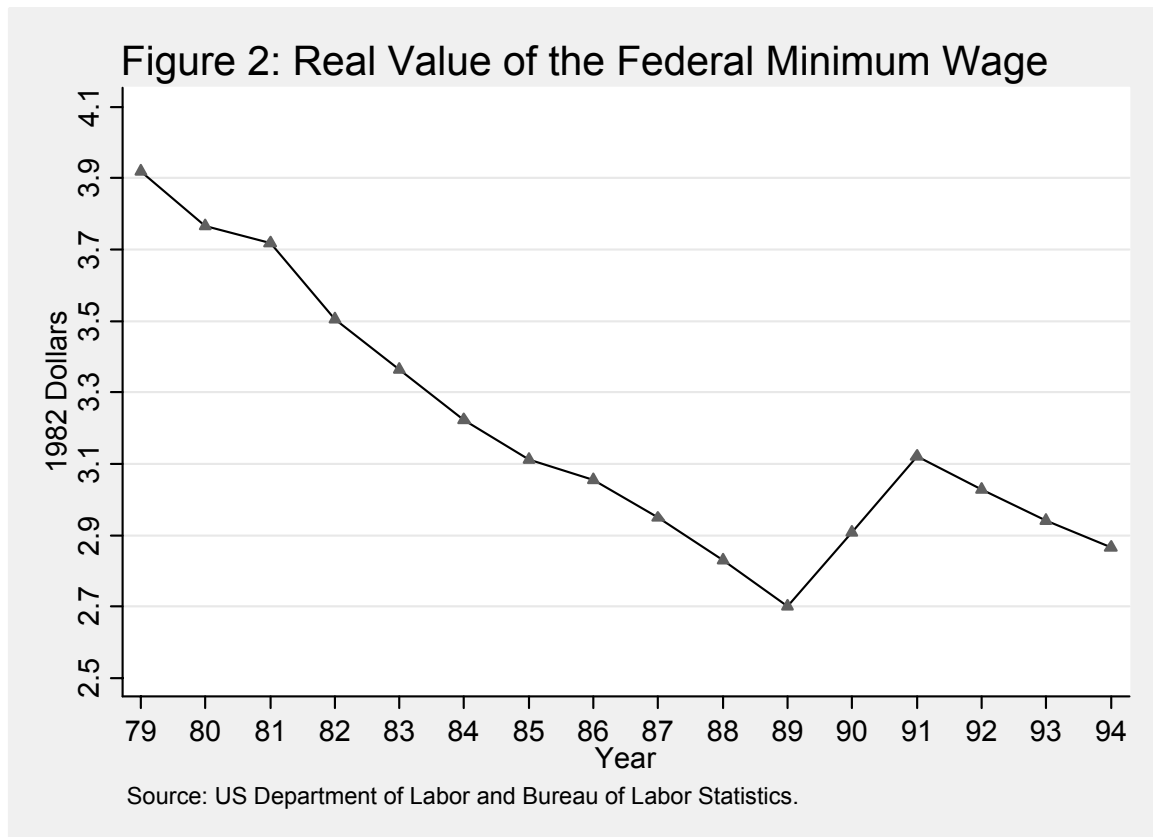


There are several sources of state-level data that are matched to the NLSY sample. The first is data taken from the Digest of Education Statistics (DES) on per-student public expenditure at public secondary education institutions. The second is DES data on per-student public expenditure at post-secondary education institutions. The third is data taken from the Integrated Post Secondary Education Data System (IPEDS) on annual tuition prices at the largest or main campus of the state university system.³⁸ 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

³⁸ We are grateful to Alex Cowell for the tuition price data.

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 declined 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.



V. ESTIMATION AND SIMULATION RESULTS

This section discusses the key DFML estimates using the empirical specification in Section IV.³⁹ 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 section presents simulation evidence of impacts of unemployment on training, later unemployment, work, and wages during the early adult lifecycle.

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 $-230,148.9$ based on 364 parameters. The likelihood value for the DFML estimates is $-220,859.4$ based on 444 parameters. This amounts to an improvement of 9,289.5 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

³⁹ 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 with five and four mass points respectively, and a vector of transitory nonlinear heterogeneities with six mass points. This amounts to 80 additional

heterogeneity.⁴⁰ 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. For most key results, such as the wage effect of prior unemployment, the FE point estimates are statistically indistinguishable from DFML estimates, the latter of which control more parametrically for unobserved heterogeneity and do not ignore possible self-selection biases

A Catch-Up Response

The conceptual model discussed earlier presents the notion that individuals display an optimal 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 (“Any Training”); whether a young man works (“Any Work”); and, how many hours a young man works annually conditional upon working (“Annual Hours Worked”).⁴¹

parameters over a model with no heterogeneity for the 129 possible outcomes we examine (8 outcomes for each of 16 time periods plus one initial condition).

⁴⁰ In the case of a dummy variable outcome, we use a conditional logit model (Chamberlain, 1980). In the presence of occurrence dependence or lagged endogenous variables, this estimator is inconsistent. A complete set of single-equation results with and without fixed effects is available from the authors on request.

⁴¹ 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 the time period dummies and squares in age and experience. See Appendix 2 for complete specifications.

The estimate in the first row of Table 3 indicates that unemployment in the prior period has a significant and positive effect on the likelihood of training in this period. This training effect, however, is somewhat short-lived. The longer-term effects fall to zero quite rapidly, and specification tests indicate no statistically significant effect beyond the first year.⁴² This is the key estimate in this table, which indicates a statistically significant effect of having recently experienced unemployment on training. To our knowledge, this is the first evidence of such a “catch up” response in the literature. Recent unemployment, after controlling for the endogeneity of the unemployment spell, appears to induce young men to undertake more training.

**Table 3: Evidence of Catch-Up Response
(The Effect of One Week of Unemployment on Training, Work Participation, and Hours Worked)**

Standard errors in parentheses

Bold-faced indicates significance at the 5% level

<i>Method</i> Outcome	Lag of Annual Weeks of Unemployment				
	1	2	3	4	5
<i>DFML</i>					
Any Training	0.0035 (0.0013)	0.0011 (0.0015)	-0.0019 (0.0016)	0.0006 (0.0016)	-0.0005 (0.0017)
Any Work	-0.0014 (0.0023)	0.0026 (0.0029)	0.0087 (0.0032)	0.0004 (0.0031)	0.0038 (0.0027)
Annual Hours Worked	-6.1351 (0.5515)	1.4876 (0.5605)	1.3089 (0.5516)	1.3928 (0.5568)	1.2408 (0.5350)
<i>Fixed Effects</i>					
Annual Hours Worked	-8.0821 (0.5673)	1.0700 (0.5488)	0.5976 (0.5315)	1.1307 (0.5229)	0.5965 (0.5264)
<i>OLS*</i>					
Annual Hours Worked	-11.8621 (0.6697)	0.8996 (0.6571)	0.6007 (0.6149)	1.7038 (0.5746)	1.3521 (0.5775)

* Robust standard errors.

⁴² A specification test fails to reject the hypothesis that only the first lag is significant. An empirical

The other DFML estimates in Table 3 buttress the notion of a compensatory behavioral response. There appears to be little response of subsequent work behavior to prior unemployment. Conditional on working, however, the initial effect of prior unemployment on annual hours worked is large and negative, perhaps reflecting the fact that we assigned weeks of unemployment to the calendar year containing the longest part of a spell interrupted at January 1. Each of the four longer-term effects, however, is significantly positive. A 26-week spell experienced as long ago as five years increases hours worked by over 32 hours per year.⁴³

Table 3 also presents estimates from fixed effect (FE) and OLS estimators for hours worked. Both of these estimators yield point estimates that are more negative for the impact of unemployment experienced last year. The OLS estimates of the former effect indicate a much larger initial negative effect (standard error), -11.86 (0.67), than either of the other two approaches. For additional lags, both of these alternative estimates tend to indicate smaller responses that vary considerably from lag to lag. The estimates reported in this table support the notion of increased job training immediately after being unemployed, as was suggested by the theoretical model. They also suggest increases in hours of work after experiencing unemployment, an effect that is not directly captured in our theoretical model.

The effect of prior unemployment on the probability a young man trains is a key result of this study. Therefore, we compare the DFML point estimates of this effect with two more conventional specifications.⁴⁴ For the DFML specification, the effect of one

specification that excluded the four insignificant lags yielded similar estimates to those in Table 3.

⁴³ This effect is obtained by multiplying the point estimate by 26: $1.2408 * 26 = 32.26$.

⁴⁴ These comparisons require a normalization of the different point estimates since they are derived from different probability specifications. For this normalization, we use the estimated coefficient of the local

week of unemployment is equivalent to a 0.41 percentage-point reduction in the local unemployment rate. The standard error of this effect is 0.16.⁴⁵ Using an identical probit specification (for the explanatory variables), we find the same point estimate of 0.41 with a standard error of 0.14. Using an identical conditional/fixed-effects logit, the effect is equivalent to a 0.32 percentage point reduction with a standard error of 0.15. Each of these three procedures implies increased training in response to an unemployment spell, and we consider this to be compelling evidence for the catch-up response derived from the theoretical model. Note, however, that neither the probit nor the conditional logit are consistent if past human capital investments are endogenous, especially if training has an impact on earnings and labor supply decisions.

It is important to note that our specification for training also controls for whether an individual changed jobs during the prior year.⁴⁶ We included this control because it is quite likely that those taking on new jobs might spend some time in formal training programs in order to learn new job skills. If we had failed to control for job changes, an unemployment event might merely be an imperfect signal of a job change and its attendant new-job training. Not one of the three estimation procedures, however, uncovered a significant response of job training to having changed a job in either of the two prior years.

unemployment rate in the training equation because it is an effect that is fairly precisely estimated by each approach. In all instances, higher local unemployment rates appear associated with less training. For the DFML specification, the normalization is $0.00351/(-0.00846) = -0.4149$. For probit, it is $0.0035/(-0.0086) = -0.4070$. For conditional logit, it is $0.0062/(-0.01968) = -0.3147$. The negative sign indicates that these relative effects can be expressed in terms of a reduction in the local unemployment rate.

⁴⁵ The standard errors of these normalized effects assume that the scaling factors are fixed.

⁴⁶ Recall that for the DFML specification, we explicitly model contemporaneous job changing that is not due to an unemployment spell. The job change explanatory variable, however, captures both types of job changes.

Taken as a whole, the estimates in Table 3, as well as the probit and conditional logit results discussed in the text, 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. The DFML estimates also indicate that 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, 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 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 short-lived persistence in unemployment.

**Table 4: Evidence of Persistence
(The Effect of One Week of Unemployment on the Incidence and Duration of Unemployment)**

DFML estimates with standard errors in parentheses

Bold-faced indicates significance at the 5% level

Outcome	Lag of Annual Weeks of Unemployment				
	1	2	3	4	5
Any Unemployment	0.0927 (0.0039)	0.0041 (0.0028)	0.0068 (0.0027)	0.0085 (0.0028)	0.0030 (0.0025)
Annual Weeks of Unemployment	0.1447 (0.0143)	0.0253 (0.0152)	0.0303 (0.0157)	0.00138 (0.0158)	0.0233 (0.0160)

Table 4 displays estimates of the effects of prior unemployment on the probability of experiencing subsequent unemployment and on annual weeks of unemployment if unemployed. The effect for both outcomes is quite pronounced for the first lag, but subsequently diminishes by an order of magnitude or more. Unemployment as long as four years ago, however, has a positive and significant effect on the likelihood of a contemporaneous spell of unemployment.

The positive effect of prior unemployment on the duration of a current spell is short-lived but quite significant. A 26-week spell experienced last year increases the duration of a contemporaneous unemployment spell, if unemployed, by 3.8 weeks annually.⁴⁷ The effect is more than an order of magnitude smaller for all longer lags. With OLS regressions of current unemployment on prior unemployment, Ellwood (1982) finds strong evidence of state dependence in weeks of unemployment. He finds that all evidence of state dependence vanishes, however, upon controlling for unobserved heterogeneity with FE specifications.

In this study, the OLS and FE estimates are qualitatively similar to those in Ellwood's study: 0.2393 (0.0158) and 0.0073 (0.0157) respectively per week unemployed in the prior year. The OLS estimate indicates a strong influence on later unemployment durations, while the use of a FE specification eliminates all evidence of persistence. On the other hand, the DFML estimate rules 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 might be necessary. It is important to note that this is the only important

⁴⁷ This measure is $0.1447 \times 26 = 3.7622$.

instance where a DFML estimate appears substantively and statistically different from an associated FE estimate. The FE estimator, however, cannot control well for possible sample selection bias.

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 one job leapfrogs into another, 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 power. 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.

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

**Table 5: Evidence of Long-Lived Blemishes in Wages
(The Effect of One Week of Prior Unemployment on Log Average Hourly Earnings)**

Standard errors in parentheses

Bold-faced indicates significance at the 5% level

<i>Method</i>	Lag of Annual Weeks of Unemployment				
	1	2	3	4	5
<i>DFML</i>	-0.0018 (0.0004)	-0.0013 (0.0004)	-0.0011 (0.0004)	-0.0008 (0.0004)	0.0002 (0.0004)
<i>FE</i>	-0.0019 (0.0006)	-0.0019 (0.0006)	-0.0010 (0.0005)	-0.0012 (0.0005)	-0.0000 (0.0005)
<i>OLS*</i>	-0.0023 (0.0008)	-0.0019 (0.0008)	-0.0014 (0.0007)	-0.0006 (0.0006)	0.0001 (0.0007)

* Robust standard errors.

The initial earnings effect of unemployment is large and quite precisely estimated. The DFML estimates tend to be slightly smaller than those derived from FE or OLS specifications, so we focus on them. A 26-week unemployment spell experienced last year reduces wages by 4.7 percent.⁴⁹ In terms of 2,000 hours worked at the average wage rate in 1993, this is a reduction of over \$1,543 in 2002 US dollars.⁵⁰ A two standard error *lower bound* amounts to a 2.6% reduction in hourly earnings or over \$850. Further, a 26-week spell experienced as long ago as three years reduces wages by 2.9 percent. To put this magnitude into context, this reduction is equivalent to forgoing one-quarter to one-half of a year of school.⁵¹ As predicted by the theoretical model, the earnings effect of prior unemployment tapers off over time. Because it fully disappears after about 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

⁴⁹ This measure is $-0.0018 \times 26 = -0.0468$.

⁵⁰ The average real wage rate in 1993 is 16.42 per hour in 2002 US dollars. At 2,000 hours, this yields average earnings of \$32,840.

⁵¹ The impact (standard error) of an additional year of school on log wages is 0.0791 (0.0209) in the DFML model.

simple blemish. Unemployment experienced by a young man today will depress his earnings for several years to come.

It is important to note that the negative earnings effect of prior unemployment remains even 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, however, an alternative interpretation for the magnitude and duration of these effects on earnings. 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.

Simulating Unemployment's Total Impact on Human Capital, Training, and Earnings

The above analysis of the earnings effect of prior unemployment above tells only a partial story. A complete analysis would account simultaneously for the effects of reduced human capital on earnings, as was implied by the theoretical model. For example, if the theoretical model were correct and one could perfectly observe the human capital stock, there should no independent effect of prior unemployment on earnings. A complete evaluation of the impacts of unemployment must take into account the various avenues through which it can affect later labor market outcomes. The DFML estimator, since it models the entire early lifecycle of schooling, training, work, and unemployment, provides a rich framework for tracing out the impacts of unemployment. In this section, we use dynamic simulations with the DFML estimates to undertake such an analysis.⁵²

⁵² The estimates presented in Tables 3 through 5 above were partial derivative effects. These simulations are more equivalent to total derivatives.

Before presenting the impacts of experiencing unemployment, it is necessary to define precisely what is meant by “unemployment.” The literature on local average treatment effects, Angrist, Imbens, and Rubin (1994) in particular, highlights the fact that if individuals differ in their responses to a stimulus, there are usually an unlimited number of possible average effects that one could calculate given continuous instrumental or forcing variables. In this study we focus on two of these measures.⁵³

The first measure we analyze is a population average effect. We define this as the average impact in our sample on an outcome of interest if a worker were forced to experience a six-month spell of unemployment at age 22.⁵⁴ In practice, we start with all individuals in our sample who were 14 to 16 years old in 1979, and we simulate outcomes for them until age 21 using the complete set of DFML estimates. Then, for each “individual” at age 22 who was not simulated to be in school or out of the labor force, we “force” them to experience no unemployment at that age and complete their simulated lifecycle for up to 10 additional years. We do this 50 times for each individual and use this as a baseline simulation for individuals who were “forced” not to experience unemployment. Next, starting at age 22, we force the same group of “individuals” to experience 26 weeks of unemployment and a 50% reduction of their labor market experience for that year. We also force a job change. Again, we complete the simulated lifecycle for up to 10 additional years for this group. Our population average effect, therefore, corresponds to those workers who, at age 22, were forced to experience 26

⁵³ Heckman (1990) discusses alternative measures of the effect.

⁵⁴ We do not use data from the “poor” white subsample in the NLSY in this study because of the peculiar selection issues that might arise. Appropriate weights for aggregating the stratified but random samples we use are not available. Consequently, we do not adjust our estimates to reflect the distribution of teenagers in the US at the time of the NLSY survey in 1979. The major consequence of this is that our sample greatly over-represents blacks and Hispanics.

weeks of unemployment. We refer to this effect as “Forced Unemployment” in the graphs discussed below.

We also consider one particular form of the local average treatment effect. To do this, we again examine each of the above “individuals” at age 22. At that age, we ask, for individuals who were not in school and were working but did not experience any unemployment, whether an increase of two standard deviations in the local unemployment rate would induce them into unemployment.⁵⁵ This defines a select group of individuals who, because of their particular configuration of exogenous explanatory variables up to age 22 and the configurations of their permanent and transitory heterogeneity at age 22, were susceptible to becoming unemployed because of a worsening local labor market. After selecting this group of individuals, as above we “force” them to experience 26 weeks of unemployment, lose one half of their age-22 job experience for that year, and experience a job change. Here, each individual’s “treatment effect” is identical to the effect for them in the calculation of the population average effect. In fact, the only difference between these two ways of measuring the effects of unemployment is in the set of individuals used to define the “average” impact. The local average effect captures the effect of unemployment on those most likely to be adversely impacted by worsening economic conditions. We refer to this effect as “Induced Unemployment” in the graphs discussed below.

Figure 3 displays simulation results for the impact of forced and induced unemployment at age 22, described above, on job training behavior through age 31. The

⁵⁵ A two standard deviation increase is 5.2 percentage points. For each “individual” we draw a complete set of all random numbers that would enter their simulations throughout these early lifecycle simulations and use the same set of random numbers under each of the two scenarios. This reduces the sampling variability of the estimated effects and is simple to do with pseudo random number generators.

top graphs display the level of training at each age and the lower graphs display the change in the fraction of training at each age in response to the unemployment event. The left hand graphs correspond to the population average effect and the right hand graphs are for the local average treatment effect. The series with triangles on the level graphs are for those who experienced unemployment at age 22. Later graphs follow the same format. In the first two years after experiencing unemployment, there is a one- to two-percentage point increase in the incidence of training (about a 10 to 20% increase) for both unemployment effects. This is precisely the type of catch-up response suggested by the theoretical model. At age 25 and later, however, there is a slightly lower tendency for those who experienced unemployment at age 22 to train. While not displayed here, examination of the simulation results for school attendance indicates a one- to three-percentage point reduction in school attendance rates in the mid-twenties among those who experienced unemployment at age 22. By age 30, however, there are no appreciable differences in school attendance rates for either type of unemployment effect.

Figure 4 displays simulation results for the impact of forced and induced unemployment at age 22 on employment rates through age 31. For both types of “treatment” effects, there is evidence of long-lived persistence in the effect of unemployment. From ages 25 to 31, employment rates for those who experienced unemployment at age 22 are about two percentage points below the baseline rate. There is some evidence that this persistence is shorter for those who were most likely to be affected by worsening local labor market conditions. While not presented here, an examination of the simulated hours of work (conditional on working) indicates a 75-hour

per year reduction in hours of work for those experiencing unemployment, with slightly smaller impacts for the local average treatment.

Figure 5 presents simulation results for “state dependence” in unemployment. Those who experienced unemployment at age 22 are at least 10 percentage points more likely to experience unemployment at age 25, but by age 30 the difference in unemployment rates becomes quite small. An examination of the simulated duration of unemployment reveals about one to two additional weeks per unemployed person year at age 23 for those who experienced unemployment at age 22. It falls to essentially zero from age 24 to age 31. Again, the difference between the two types of unemployment effects is relatively small.

Figure 6 contains simulation results for the impact of forced and induced unemployment at age 22 on the log of average hourly earnings through age 31. After experiencing unemployment at age 22, wages at age 23 are eight to nine percent below their baseline level. According to the theoretical model, an immediate, and excessive, decline in wages would be expected if individuals chose jobs with high levels of on-the-job training after experiencing unemployment.⁵⁶ Immediately after age 23, however, the wage differential begins to shrink. The simple theoretical model also predicted this effect. By age 27, the wage difference due to forced or induced unemployment falls to about half its size at age 23. Nevertheless, wages for those who experienced forced or induced unemployment at age 22 are still three to four percent lower by age 31. Again, the difference between the two types of unemployment effects we consider is fairly small.

⁵⁶ Informal training of this type might not be captured by our more formal measure of vocational training.

The simulation results presented here are generally consistent with the predictions of the theoretical model.⁵⁷ There is evidence of increased job training after experiencing unemployment. Furthermore, wages appear to fall precipitously in the first year after experiencing unemployment, which could reflect a combination of a relative loss in human capital as well as an increase in the share of time that is spent training. This wage gap rapidly diminishes, but remains substantial even nine years after either forced or induced unemployment at age 22. This is precisely the pattern of wages one would expect if there were real costs to unemployment at younger ages.

⁵⁷ Unlike the somewhat small and relatively short-lived effects implied by the (partial-derivative) point estimates, however, these simulation results indicate fairly long-lived impacts of unemployment.

Figure 3: Unemployment Impacts on Training

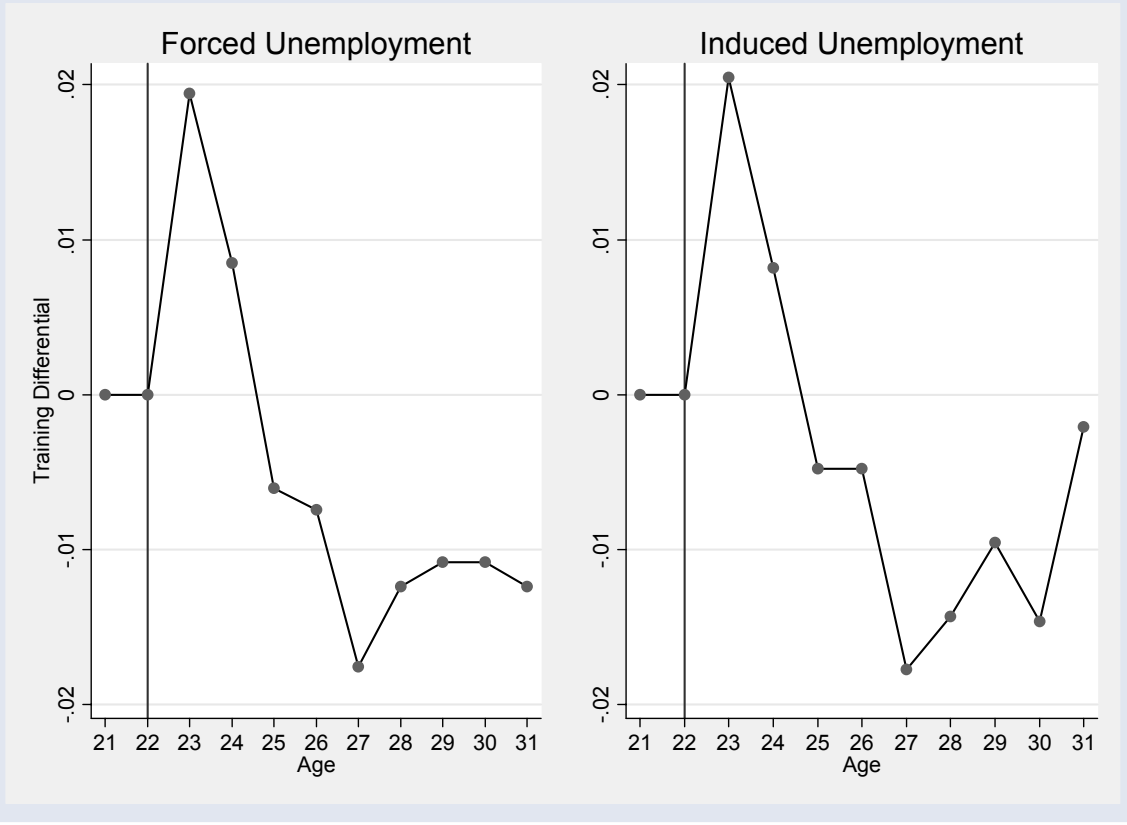
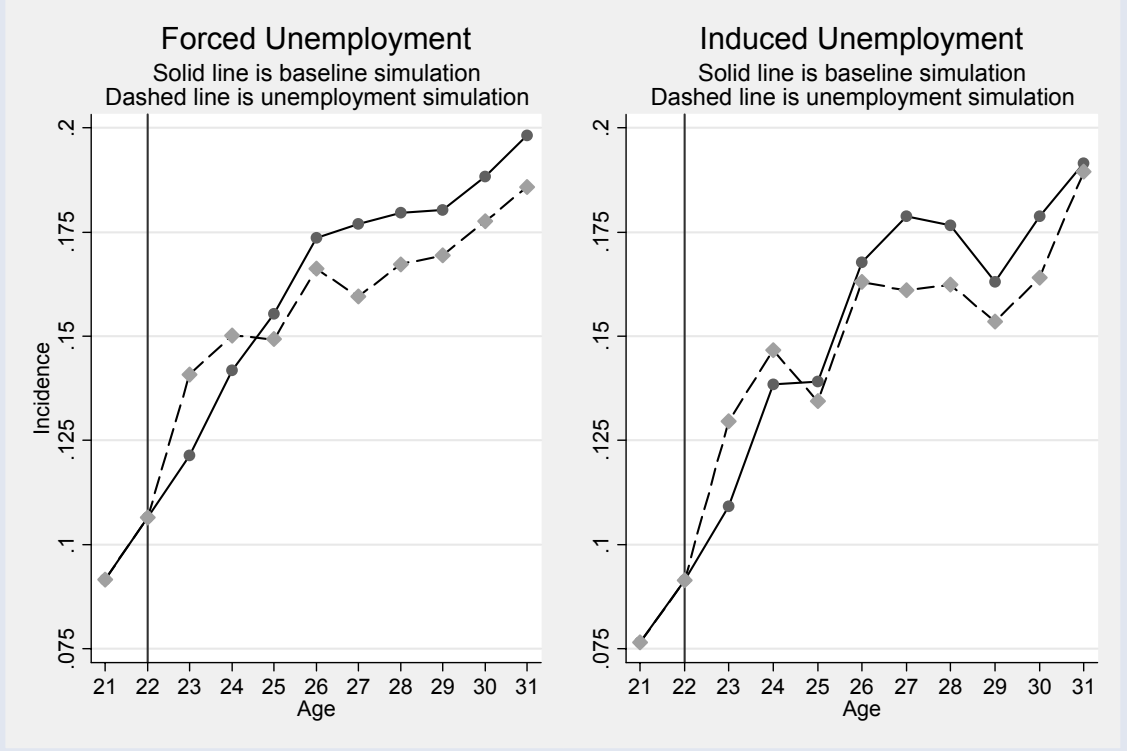


Figure 4: Unemployment Impacts on Employment

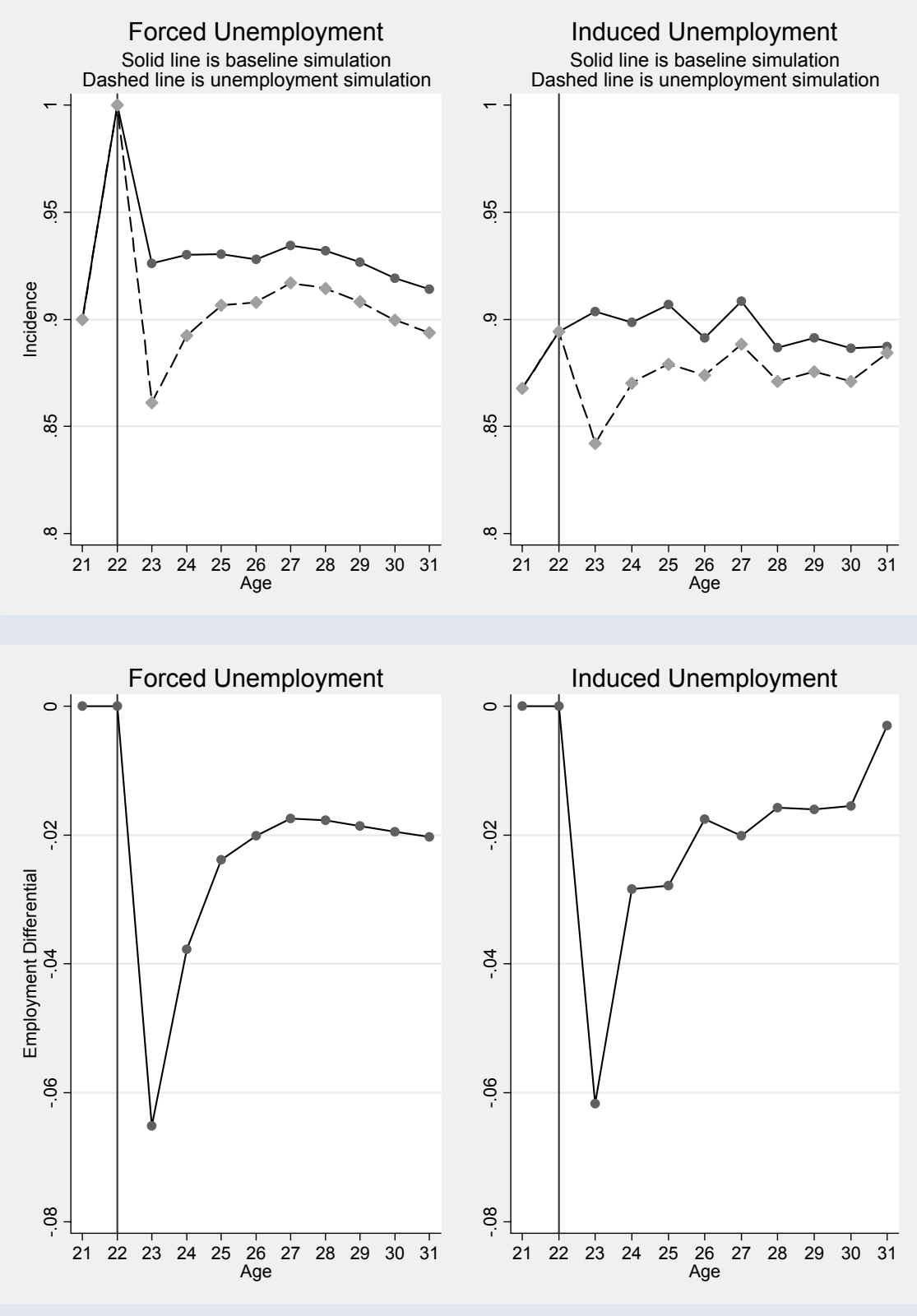


Figure 5: Unemployment Impacts on Subsequent Unemployment

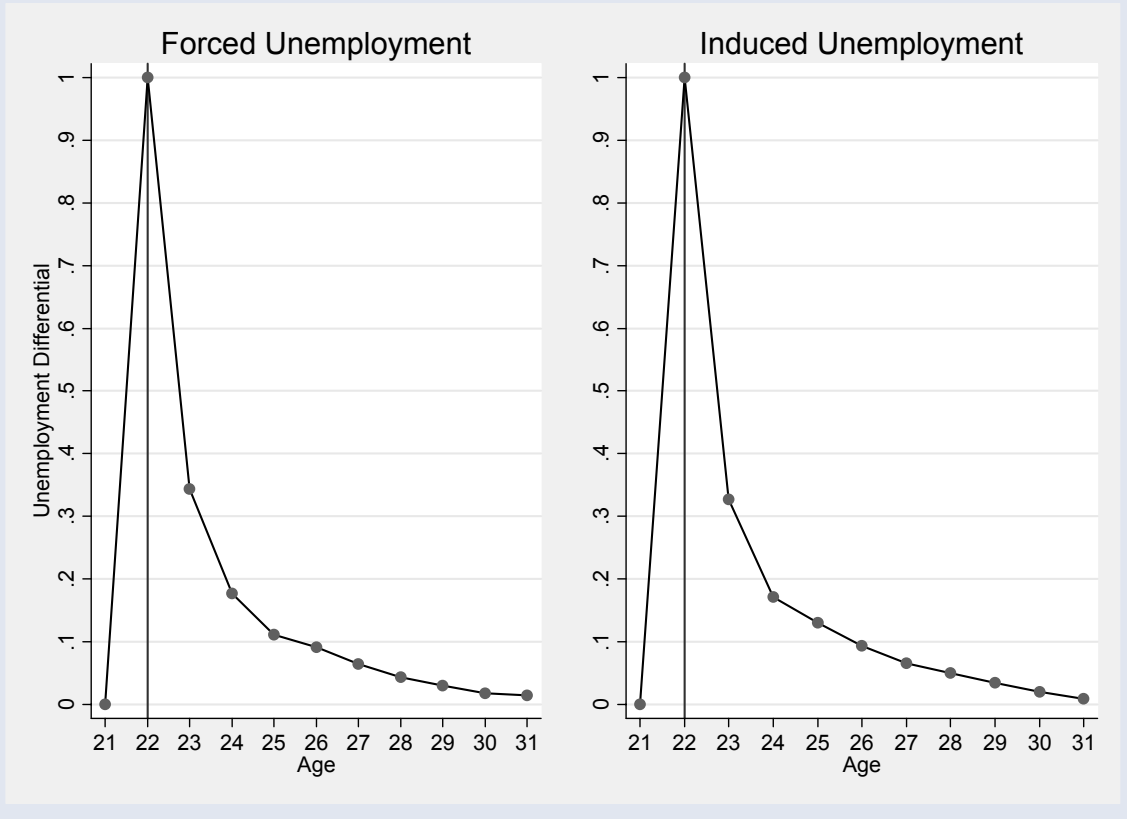
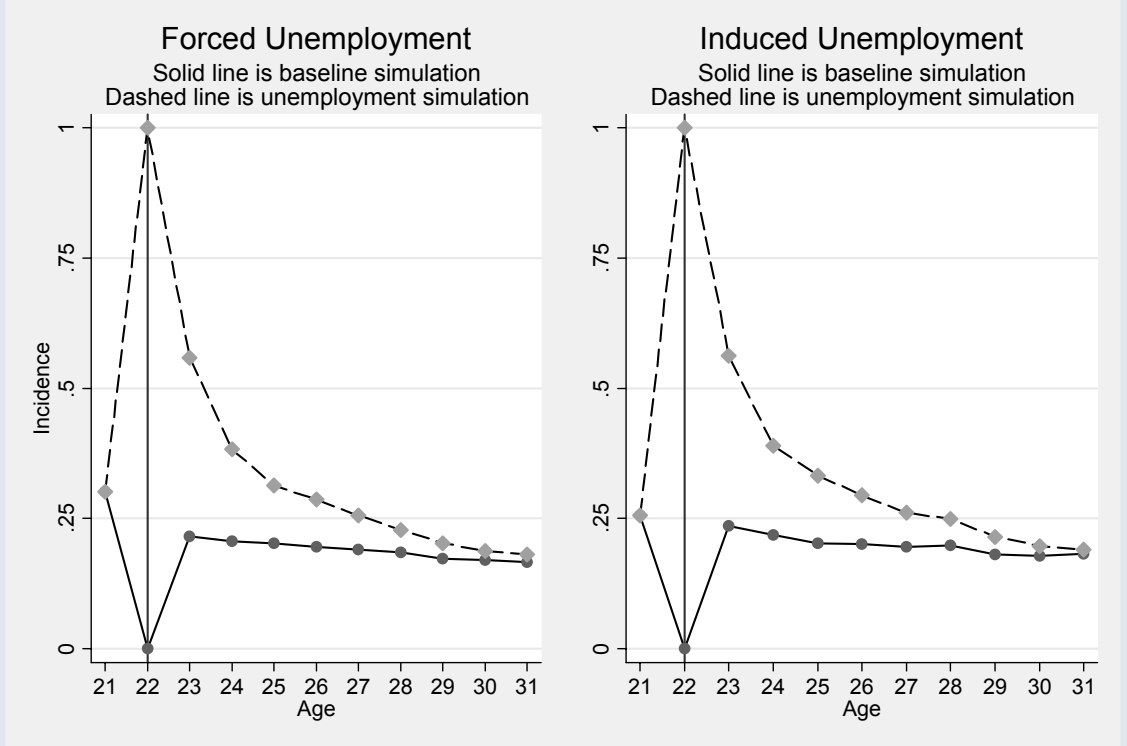
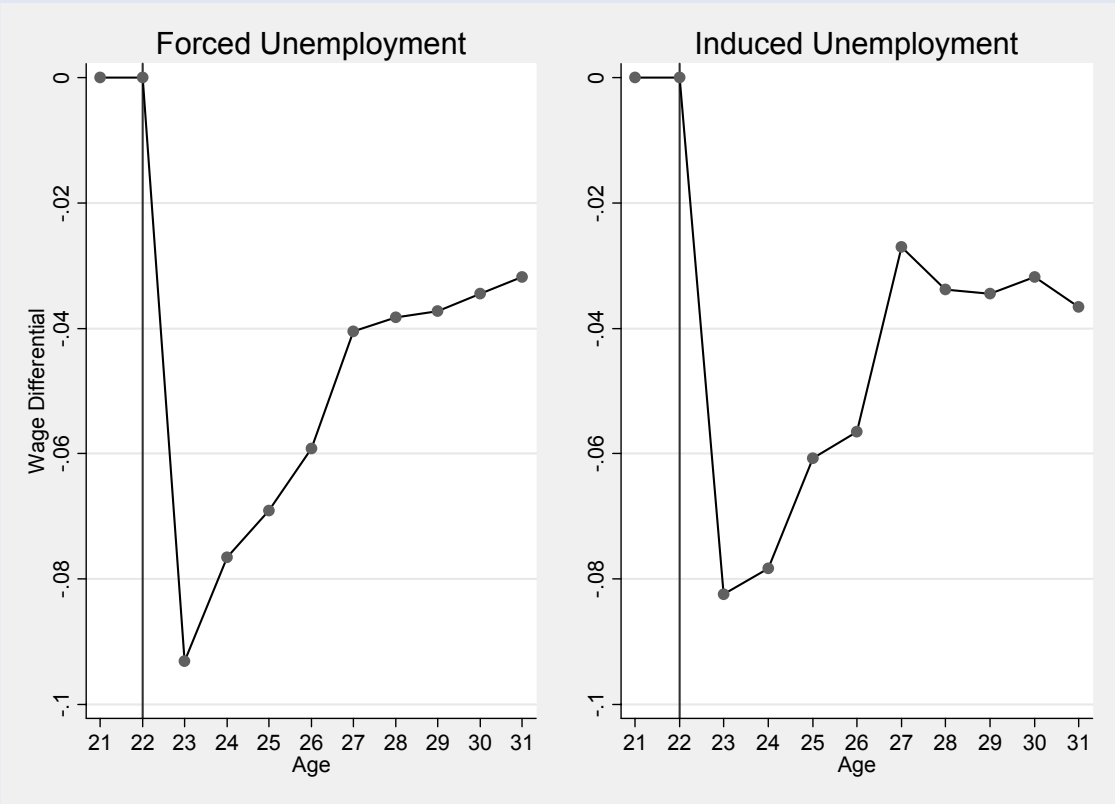
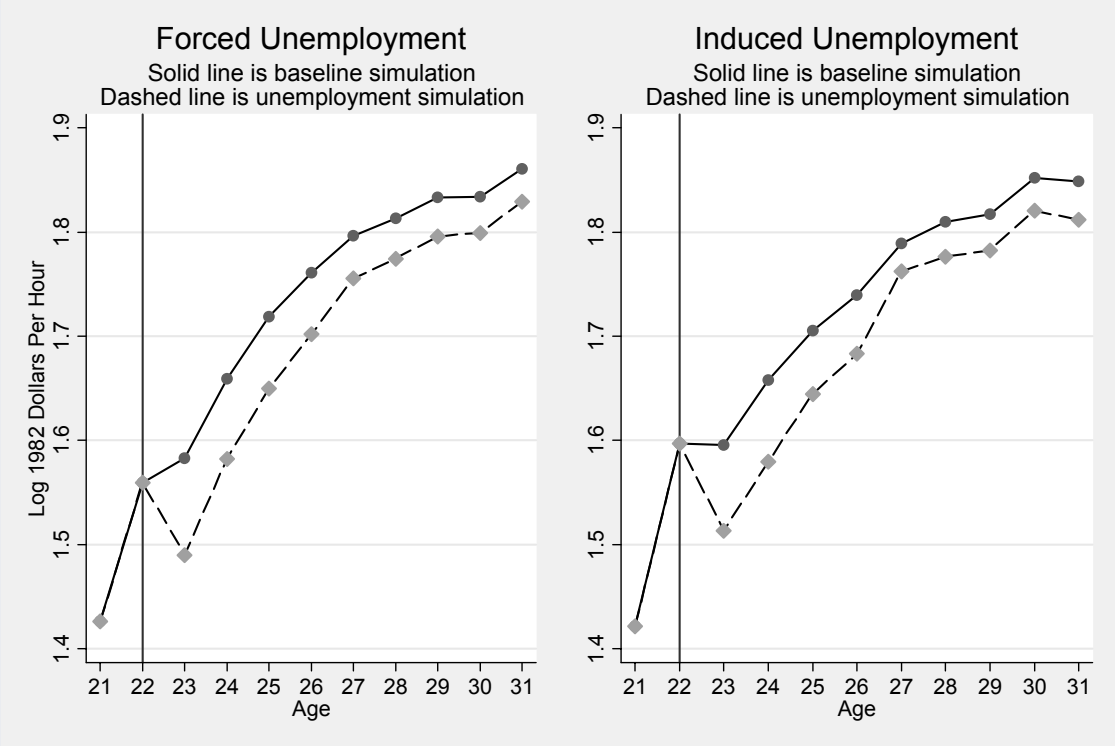


Figure 6: Unemployment Impacts on Log Wages



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. Most importantly, there is strong evidence of a catch-up response to unemployment. That is, an unemployment spell experienced today increases the likelihood that a young person trains in the near future. A dynamic model of human capital accumulation predicts this catch-up response. Both this theoretical implication as well as empirical evidence of it is new to the literature. Of course, we have made several simplifying assumptions to reach both the theoretical predictions and the empirical conclusions.

We also uncover relatively large longer-term impacts on earnings from unemployment experienced early in the employment lifecycle. A 26-week spell of unemployment experienced at age 22 results in persistently lower wages through the end of our simulations at age 31. The immediate wage impact is quite large and is consistent with a catch-up response in which workers pay for informal on-the-job training by accepting lower wages. Nevertheless, substantial wage differentials remain after many years. Based on our simulation results, when evaluated at 2,000 hours per year and in 2002 US dollars, a 26-week unemployment spell experienced at age 22 results in an earnings loss of \$1,400 to \$1,650 at age 26 and in a loss of \$1,050 to \$1,150 at age 30. These lasting impacts of unemployment experienced at younger ages suggest that youth unemployment may not be a purely transitory phenomenon.

APPENDIX 1: A CONCEPTUAL FRAMEWORK

Notation and Setup:

Define time to be discrete and finite, $t=1, 2, 3, \dots, T$.

Define P to be the probability of being unemployed in any particular time period t , where $0 \leq P < 1$.

Define s_t to be the fraction of each working period devoted to (planned) training, where $0 \leq s_t \leq 1$.

Define λ to be the fraction of the year an individual is not unemployed, where $0 \leq \lambda \leq 1$.

Define H_t to be the human capital stock (or productivity) of an individual at period t .

Define w to be the rental rate for human capital, which is constant over time.

Define β to be the rate at which individuals discount future incomes.

Define $f(s_t)$ to be the production function of new human capital. We assume that $f'(\cdot) > 0$, $f''(\cdot) < 0$, and that the production function satisfies the Inada conditions (Inada, 1964).⁵⁸ These conditions imply that the marginal product of training is large when an individual does at least a little training, and, therefore, given the possibility of training, it is always optimal to devote some fraction of time to training.

Human capital evolves as $H_{t+1} = H_t + f(s_t)$.

We assume that all training takes place on the job and that the fraction of time devoted to training is determined before an individual learns whether he is to become unemployed. If he does not experience unemployment, his potential income at time t is wH_t and his disposable income is potential income minus the opportunity cost of training, $w(1 - s_t)H_t$. On the other hand, if he becomes unemployed, then potential and disposable

⁵⁸ Given the finite time horizon, we in fact only rely on the condition that $\lim_{k \rightarrow 0} f(k) = \infty$.

incomes are given by $\lambda w H_t$ and $\lambda w(1 - s_t) H_t$, respectively. We assume the fraction of time that is spent unemployed, if unemployment is experienced, is not stochastic.

Period T

At the last time period, it is never optimal to train because there is no future return to training. In this case,

$$\text{Disposable Income} = \begin{cases} wH_T & \text{if the individual works full-time.} \\ \lambda wH_T & \text{if the individual is unemployed.} \end{cases}$$

We focus on the situation in which an individual maximizes the present discounted value of his disposable income. Therefore, the individual's expected utility as a function of the human capital stock at the start of the final period T is

$$EV_T(H_T) = (1 - P)(wH_T) + P(\lambda wH_T).$$

Period T-1:

In period T-1, an individual makes a decision about how much time to devote to training. Time spent training is not paid, but training in period T-1 increases the amount of human capital in period T. This in turn increases disposable income in the last period. According to our formulation of the model, training is possible only when employed. Therefore, at the beginning of period T-1 an individual faces the following optimization problem:

$$\begin{aligned} \max_{S_{T-1}} EV_{T-1}(H_{T-1}) = & \\ & P\{\beta^{T-1}\lambda(1-S_{T-1})wH_{T-1} + \beta^T V_T(H_{T-1} + f(\lambda S_{T-1}))\} + \\ & (1-P)\{\beta^{T-1}(1-S_{T-1})wH_{T-1} + \beta^T V_T(H_{T-1} + f(S_{T-1}))\} \end{aligned}$$

This optimization can be rewritten as:

$$\begin{aligned}
\max_{S_{T-1}} EV_{T-1}(H_{T-1}) &= \\
&= P\{\beta^{T-1}\lambda(1-S_{T-1})wH_{T-1} + \beta^T P\lambda w(H_{T-1} + f(\lambda S_{T-1})) + \beta^T(1-P)w(H_{T-1} + f(\lambda S_{T-1}))\} \\
&+ \\
&(1-P)\{\beta^{T-1}(1-S_{T-1})wH_{T-1} + \beta^T P\lambda w(H_{T-1} + f(S_{T-1})) + \beta^T(1-P)w(H_{T-1} + f(S_{T-1}))\}
\end{aligned}$$

The first order condition (FOC) for the optimal choice of the fraction of time to devote to training is given by:

$$\begin{aligned}
\frac{\partial V_{T-1}(H_{T-1})}{\partial S_{T-1}} &= -\beta^{T-1}P\lambda wH_{T-1} + \beta^T P^2\lambda^2 w f'(\lambda S_{T-1}) + \beta^T P(1-P)\lambda w f'(\lambda S_{T-1}) \\
&- \beta^{T-1}(1-P)wH_{T-1} + \beta^T P(1-P)\lambda w f'(S_{T-1}) + \beta^T(1-P)^2 w f'(S_{T-1}) \\
&= 0
\end{aligned}$$

The second order condition (SOC) for a maximum is satisfied because of the concavity of the human capital production function:

$$\begin{aligned}
\frac{\partial^2 V_{T-1}}{\partial S_{T-1}^2} &= \beta^T P^2\lambda^3 w f''(\lambda S_{T-1}) + \beta^T P(1-P)\lambda^2 w f''(\lambda S_{T-1}) + \\
&\beta^T P(1-P)\lambda w f''(S_{T-1}) + \beta^T(1-P)^2 w f''(S_{T-1}) < 0
\end{aligned}$$

These conditions ensure that there exists a unique level of training that maximizes an individual's objective function at time period T-1. After re-arrangement, the decision-rule for optimal training at T-1, given the amount of capital accumulated prior to this period, is:

$$\beta [P\lambda w + (1-P)w] [f'(\lambda S_{T-1})P\lambda + f'(S_{T-1})(1-P)] = [P\lambda w + (1-P)w] H_{T-1}$$

or

$$wH_{T-1} = \beta w [f'(\lambda S_{T-1})P\lambda + f'(S_{T-1})(1-P)]$$

The economic interpretation of this condition is that the expected income loss from additional training today should be equal to the expected present discounted value of the gain from the addition human capital available in the next time period.

Let $S_{T-1}^*(H_{T-1})$ be the optimal choice of training as a function of the level of the human capital stock at the beginning of period T-1. By the Implicit Function Theorem (IFT):

$$\frac{dS_{T-1}^*}{dH_{T-1}} = - \frac{\frac{\partial^2 V_{T-1}}{\partial S_{T-1}^* \partial H_{T-1}}}{\frac{\partial^2 V_{T-1}}{\partial S_{T-1}^{*2}}} < 0$$

because

$$\frac{\partial^2 V_{T-1}}{\partial S_{T-1}^* \partial H_{T-1}} = -\beta^{T-1} P\lambda w - \beta^{T-1}(1-P)w < 0$$

and

$$\frac{\partial^2 V_{T-1}}{\partial S_{T-1}^{*2}} < 0 \quad \text{from the second order condition.}$$

Therefore, those entering period T-1 with lower human capital stocks will train more than those entering the period with higher human capital stocks. In anticipation of the main theoretical result, suppose there were two identical individuals at the start of period T-2, and one experienced unemployment while the other did not. Upon entering period T-1, the individual who experienced unemployment in T-2 would choose to train more during period T-1 than the individual who did not experience unemployment.

It is important to note that we have a single value function at the start of this time period, which can be evaluated at different levels of the human capital stock. It is useful to rewrite the value function in a general form and prove its concavity in H_{T-1} .

$$V_{T-1}(S^*_{T-1}(H_{T-1}), H_{T-1}) =$$

$$\begin{aligned} & P \{ \beta^{T-1} \lambda (1-S_{T-1}) w H_{T-1} + \beta^T P \lambda w [H_{T-1} + f(\lambda S_{T-1})] + \beta^T (1-P) w [H_{T-1} + f(\lambda S_{T-1})] \} + \\ & (1-P) \{ \beta^{T-1} (1-S_{T-1}) w H_{T-1} + \beta^T P \lambda w [H_{T-1} + f(S_{T-1})] + \beta^T (1-P) w [H_{T-1} + f(S_{T-1})] \} \end{aligned}$$

By the Envelope Theorem the first total derivative of this value function is:

$$\frac{dV_{T-1}(S^*_{T-1}(H_{T-1}), H_{T-1})}{dH_{T-1}} = \frac{\partial V_{T-1}}{\partial S^*_{T-1}} \frac{dS^*_{T-1}}{dH_{T-1}} + \frac{\partial V_{T-1}}{\partial H_{T-1}} = \frac{\partial V_{T-1}}{\partial H_{T-1}}$$

since $\frac{\partial V_{T-1}}{\partial S^*_{T-1}} = 0$ by the FOCs for a maximum.

Then

$$\frac{\partial V_{T-1}}{\partial H_{T-1}} = \beta^{T-1} P \lambda w (1-S^*_{T-1}) + \beta^T P^2 \lambda w + \beta^T P (1-P) w + \beta^{T-1} (1-P) w (1-S^*_{T-1}) + \beta^T P (1-P) \lambda w +$$

$$\beta^T (1-P)^2 w = \text{positive constant.}$$

By the Envelope Theorem the second total derivative is:

$$\frac{d^2 V_{T-1}(S^*_{T-1}(H_{T-1}), H_{T-1})}{dH_{T-1}^2} = \frac{\partial^2 V_{T-1}}{\partial S^*_{T-1}^2} \left(\frac{dS^*_{T-1}}{dH_{T-1}} \right)^2 + \frac{\partial V_{T-1}}{\partial S^*_{T-1}} \frac{d^2 S^*_{T-1}}{dH_{T-1}^2} + \frac{\partial^2 V_{T-1}}{\partial H_{T-1}^2} = \frac{\partial^2 V_{T-1}}{\partial S^*_{T-1}^2} \left(\frac{dS^*_{T-1}}{dH_{T-1}} \right)^2 < 0$$

because $\frac{\partial V_{T-1}}{\partial S^*_{T-1}} = 0$ by FOC,

$$\frac{\partial^2 V_{T-1}}{\partial H_{T-1}^2} = 0 \quad \text{because } \frac{\partial V_{T-1}}{\partial H_{T-1}} = \text{positive constant, and}$$

$$\frac{\partial^2 V_{T-1}}{\partial S^*_{T-1}^2} < 0 \quad \text{by SOC of optimization problem at period T-1.}$$

The concavity of the value function in time period T-1 is sufficient to ensure that the

FOCs at time T-2 define behaviors necessary to maximize the objective function at T-2.

Period T-2:

The individual's optimization problem in T-2:

$$\max_{S_{T-2}} EV_{T-2}(H_{T-2}) = P \{ \beta^{T-2} \lambda (1-S_{T-2}) w H_{T-2} + \beta^{T-1} V_{T-1}(H_{T-2} + f(\lambda S_{T-2})) \} \\ + (1-P) \{ \beta^{T-2} (1-S_{T-2}) w H_{T-2} + \beta^{T-1} V_{T-1}(H_{T-2} + f(S_{T-2})) \},$$

where

$$V_{T-1}(H_{T-2} + f(\lambda S_{T-2})) = \\ = P \left\{ \begin{array}{l} \beta^{T-1} \lambda (1-S_{T-1}) w [H_{T-2} + f(\lambda S_{T-2})] + \\ + \beta^T P \lambda w [H_{T-2} + f(\lambda S_{T-2}) + f(\lambda S_{T-1})] + \beta^T (1-P) w [H_{T-2} + f(\lambda S_{T-2}) + f(\lambda S_{T-1})] \end{array} \right\} \\ + (1-P) \left\{ \begin{array}{l} \beta^{T-1} (1-S_{T-1}) w [H_{T-2} + f(\lambda S_{T-2})] + \\ + \beta^T P \lambda w [H_{T-2} + f(\lambda S_{T-2}) + f(S_{T-1})] + \beta^T (1-P) w [H_{T-2} + f(\lambda S_{T-2}) + f(S_{T-1})] \end{array} \right\}$$

and

$$V_{T-1}(H_{T-2} + f(S_{T-2})) = \\ = P \left\{ \begin{array}{l} \beta^{T-1} \lambda (1-S_{T-1}) w [H_{T-2} + f(S_{T-2})] + \\ + \beta^T P \lambda w [H_{T-2} + f(S_{T-2}) + f(\lambda S_{T-1})] + \beta^T (1-P) w [H_{T-2} + f(S_{T-2}) + f(\lambda S_{T-1})] \end{array} \right\} \\ + (1-P) \left\{ \begin{array}{l} \beta^{T-1} (1-S_{T-1}) w [H_{T-2} + f(S_{T-2})] + \\ + \beta^T P \lambda w [H_{T-2} + f(S_{T-2}) + f(S_{T-1})] + \beta^T (1-P) w [H_{T-2} + f(S_{T-2}) + f(S_{T-1})] \end{array} \right\}$$

The value function in T-2 is concave when both $V_{T-1}(H_{T-2} + f(\lambda S_{T-2}))$ and $V_{T-1}(H_{T-2} + f(S_{T-2}))$ are concave in human capital stock, a result which was proved above for arbitrary levels of the human capital stock at the start of T-1.

Conclusions for T, T-1, and T-2:

1. $V'_T(\cdot) =$ positive constant and $V''_T(\cdot) = 0$ because the value function in the last period T is linear in human capital/income.

2. $V'_{T-1}(\cdot) > 0$ and $V''_{T-1}(\cdot) < 0$ because the value function of period T-1 is concave in the human capital stock (or income).
3. $V'_{T-2}(\cdot) > 0$ and $V''_{T-2}(\cdot) < 0$ because the value function of period T-2 is concave in human capital as it is a linear combination of a linear utility function and a concave value function in period T-1.

Periods $t < T$:

The individual's optimization problem in each earlier period t is given by:

$$\max_{S_t} EV_t(H_t) = P\{\beta^t \lambda (1 - S_t) w H_t + \beta^{t+1} V_{t+1}(H_t + f(\lambda S_t))\} + (1-P)\{\beta^t (1-S_t) w H_t + \beta^{t+1} V_{t+1}(H_t + f(S_t))\}$$

FOC:

$$\frac{\partial V_t(H_t)}{\partial S_t} = -P\beta^t \lambda w H_t + P\beta^{t+1} V'_{t+1}(H_t + f(\lambda S_t)) f'(\lambda S_t) \lambda - (1-P)\beta^t w H_t + (1-P)\beta^{t+1} V'_{t+1}(H_t + f(S_t)) f'(S_t) = 0;$$

After rearrangement, the FOC for optimal training in an arbitrary period t is:

$$\beta[V'_{t+1}(H_t + f(\lambda S_t)) f'(\lambda S_t) P \lambda + V'_{t+1}(H_t + f(S_t)) f'(S_t) (1-P)] = [P \lambda w + (1-P)w] H_t$$

Now we prove that the value function of an arbitrary period $t < T$ is concave in human capital stock (or income). To do this, we show that concavity of the value function in the next period guarantees concavity in any arbitrary period $t < T$.

By the Envelope Theorem, the first total derivative of the value function in period t is:

$$\frac{dV_t(S_t^*(H_t), H_t)}{dH_t} = \frac{\partial V_t(S_t^*(H_t), H_t)}{\partial S_t^*} \frac{dS_t^*}{dH_t} + \frac{\partial V_t(S_t^*(H_t), H_t)}{\partial H_t} = \frac{\partial V_t(S_t^*(H_t), H_t)}{\partial H_t}$$

Now,

$$\frac{\partial V_t(S_t^*(H_t), H_t)}{\partial H_t} = P[\beta^t \lambda(1 - S_t^*)w + \beta^{t+1} V'_{t+1}(H_t + f(\lambda S_t^*))] \\ + (1 - P)[\beta^t (1 - S_t^*)w + \beta^{t+1} V'_{t+1}(H_t + f(S_t^*))]$$

Since $V'_{t+1}(\cdot) > 0$ is true for time period T-3, it holds by induction for all earlier time periods and the value function is everywhere an increasing function of the human capital stock.

By the Envelope Theorem, the second total derivative is:

$$\frac{d^2 V_t(S_t^*(H_t), H_t)}{dH_t^2} = \frac{\partial^2 V_t}{\partial S_t^{*2}} \left(\frac{dS_t^*}{dH_t} \right)^2 + \frac{\partial V_t}{\partial S_t^*} \frac{d^2 S_t^*}{dH_t^2} + \frac{\partial^2 V_t}{\partial H_t^2} = \frac{\partial^2 V_t}{\partial S_t^{*2}} \left(\frac{dS_t^*}{dH_t} \right)^2 + \frac{\partial^2 V_t}{\partial H_t^2} < 0$$

where

$$\frac{\partial V_t}{\partial S_t^*} = 0 \quad (\text{by FOC});$$

$$\frac{\partial^2 V_t}{\partial H_t^2} = P\beta^{t+1}V''_{t+1}(H_t + f(\lambda S_t^*)) + (1 - P)\beta^{t+1}V''_{t+1}(H_t + f(S_t^*)) < 0$$

provided that the value function of the next period is concave in the stock of human capital. Again, this condition holds for T-3 and, by induction, for all earlier time periods.

The period t second order condition for the maximal choice of training intensity is given by:

$$\frac{\partial^2 V_t(H_t)}{\partial S_t^2} = P\beta^{t+1}V''_{t+1}(H_t + f(\lambda S_t))(f'(\lambda S_t)\lambda)^2 + P\beta^{t+1}V'_{t+1}(H_t + f(\lambda S_t))f''(\lambda S_t)\lambda^2 + \\ + (1 - P)\beta^{t+1}V''_{t+1}(H_t + f(S_t))(f'(S_t))^2 + (1 - P)\beta^{t+1}V'_{t+1}(H_t + f(S_t))f''(S_t)$$

The concavity of the value function of human capital in the next period t+1, the positive first derivative of this value function, and the concavity of the human capital

production function guarantee the concavity of the value function at an arbitrary period. This concavity, in turn, ensures that the first order conditions describe the behaviors necessary to maximize the expected present discounted value of disposable earnings at each point in time.

Next, we establish that a larger stock of human capital results in lower investment in additional human capital at each point in time. Since

$$\begin{aligned} \frac{\partial^2 V_t}{\partial S_t \partial H_t} &= -P\beta^t \lambda W + P\beta^{t+1} V''_{t+1}(H_t + f(\lambda S_t)) f'(\lambda S_t) \lambda \\ &\quad - (1-P)\beta^t W + (1-P)\beta^{t+1} V''_{t+1}(H_t + f(S_t)) f'(S_t) < 0 \end{aligned}$$

because of the concavity of the value function in t+1 and human capital production function. Therefore, by the Implicit Function Theorem:

$$\frac{dS_t^*}{dH_t} = - \frac{\frac{\partial^2 V_t}{\partial S_t^* \partial H_t}}{\frac{\partial^2 V_t}{\partial S_t^{*2}}} = - \frac{(-)}{(-)} < 0 \text{ for any arbitrary period } t < T.$$

The result derived for period T-1 with an explicit formulation of the utility and value functions holds for an arbitrary period as well. Therefore, an individual's optimal behavior is to invest less in training at higher levels of human capital holding age, t, constant. Since an “exogenous” unemployment shock reduces the human capital stock at the start of the next time period, those who experienced unemployment will choose to undertake more training in the next time period. This establishes Proposition 1 in the main text.

To establish Proposition 2 in the text, suppose that, at the start of period t+1, two otherwise identical individuals have human capital stocks that differ by an arbitrary amount Δ . This difference in human capital stocks could have arisen because these two

individuals had different unemployment experiences during period t. At the start of t+1, their potential earnings would differ by $w\Delta$. By Proposition 1, the individual with the lower human capital stock in t will choose to invest more in additional human capital at t+1. Let s_{t+1}^N and s_{t+1}^U be these two optimal decisions, where $s_{t+1}^N < s_{t+1}^U$ and the superscripts N and U stand, respectively, for not having been unemployed at t and having been unemployed at time period t. At the start of period t+2, if neither individual experienced unemployment during t+1, then the potential earnings would differ by $w(\Delta + [f(s_{t+1}^N) - f(s_{t+1}^U)]) < w\Delta$ because higher levels of training increase the stock of human capital. If both individuals had experienced unemployment during t+1, then potential earnings at the start of t+2 would differ by $w(\Delta + [f(\lambda s_{t+1}^N) - f(\lambda s_{t+1}^U)]) < w\Delta$, which also is a convergence of the potential human capital stocks. So, provided that unemployment experiences do not increase the propensity to experience future unemployment too severely (the model assumes a zero effect), there will be a convergence in expected potential earnings from t+1 to t+2. By induction, there will be continued convergence in expected earnings for t+3 and for later periods.

The first part of Proposition 3 in the text follows directly because the fraction of time spent earning income (i.e., not spent training) is higher for those who did not experience unemployment at time t. Therefore, the observed disposable earnings differential at t+1 is larger than that that implied if there were no training differential in response to experiencing unemployment at t. In particular,

$$\begin{aligned} (1-s_{t+1}^N)w(H_t + \Delta) - (1-s_{t+1}^U)w(H_t) &= (1-s_{t+1}^U)w\Delta + (s_{t+1}^N - s_{t+1}^U)w(H_t) \\ &> (1-s_{t+1}^U)w\Delta \end{aligned}$$

The second part of Proposition 3 in the text follows from two observations. First, for a given human capital differential between two individuals, there will be a larger training differential at $t+1$ than at $t+2$ because the future benefit of additional human capital declines as t approaches T , holding constant one of the individual's human capital stock. The second observation follows from the concavity of the human capital production function. Consider holding constant the human capital at $t+2$ for the individual with the higher level of human capital at the start of period $t+1$ by examining a particular type of (un)employment experience during $t+1$. Following from the optimal catch-up response in Proposition 1, at higher levels of the other individual's human capital stock for the same type of $t+1$ (un)employment experience, the differentials in the training responses at $t+2$ will be smaller than otherwise in the absence of the immediate catch-up response. Because of the model's assumption that future unemployment propensities do not depend on previous unemployment events, this implies that we can use equal "weights" for the two individuals when integrating over possible subsequent unemployment experiences.

These two observations, in conjunction, imply that the subsequent average training intensities for the two types of individuals, defined by one type experiencing unemployment at period t , will become more similar over time. Therefore, the convergence of their disposable earnings over time will reflect not only the convergence in their human capital stocks but also the convergence in the optimal share of time that is spent training. The observed convergence in their disposable earnings after time $t+1$, therefore, would happen at a faster rate than would be implied by solely the convergence in their human capital stocks.

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. The duration of unemployment spells, however, 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 search theory would contribute to this simple framework in particular. 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 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. We note that 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 NLSY79 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: -220859.39

Number of parameters: 444

	COEFF.	STD.ERR	T-RATIO
Any Schooling (as):			
1 cons_sch	-5.40282	2.30871	-2.34019
2 year	0.05649	0.01169	4.83332
3 afqt	0.00741	0.00056	13.15392
4 readmat	-0.03012	0.03315	-0.90864
5 libcard	0.06536	0.02585	2.52829
6 livpar	0.06613	0.02518	2.62634
7 prot	-0.02088	0.02485	-0.84026
8 black	0.16552	0.03096	5.34641
9 hisp	0.04341	0.03396	1.27802
10 nc	0.07289	0.04575	1.59320
11 so	-0.00419	0.06025	-0.06959
12 we	0.04072	0.05643	0.72156
13 urb	0.03687	0.03246	1.13591
14 ur	0.00670	0.00433	1.54613
15 mw	0.79964	0.48936	1.63403
16 mwwage	-0.15555	0.02050	-7.58685
17 mwhgc	0.24087	0.02147	11.22086
18 ugtuit	-0.12351	0.25891	-0.47706
19 expsec	-0.26184	0.20309	-1.28928
20 expps	-0.21402	0.11324	-1.88995
21 age	0.04831	0.11669	0.41398
22 age2	0.00673	0.00163	4.13370
23 exp	-0.17608	0.01167	-15.08939
24 exp2	0.00670	0.00057	11.69062
25 hgc	-0.42516	0.06735	-6.31241
26 dum12y	-0.57403	0.04710	-12.18772
27 coldeg	-1.07555	0.05241	-20.52079
28 lag1sc	1.58061	0.03599	43.91313
29 lag1wu	-0.00688	0.00143	-4.80965
30 lag2wu	-0.00688	0.00151	-4.54923
31 lag3wu	-0.00456	0.00171	-2.66375
32 lag4wu	-0.00432	0.00180	-2.39687
33 lag5wu	0.00064	0.00178	0.36010
34 cumtr	0.02549	0.01142	2.23258
35 year79	-0.31345	0.10275	-3.05065
36 year8082	-0.08663	0.06421	-1.34918
37 year9294	-0.11862	0.06743	-1.75917
38 age1415	0.94031	0.24527	3.83375
39 age16	1.15128	0.19533	5.89391
40 age17	0.53692	0.15164	3.54075

41	age1819	-0.11913	0.09632	-1.23677
42	age2021	-0.36704	0.06483	-5.66170
43	rhod11	-0.12899	0.08088	-1.59496
44	rhod12	-0.16098	0.06922	-2.32545

Any Training (tr):

45	cons_tra	-7.62289	1.86784	-4.08113
46	year	0.01437	0.01215	1.18265
47	afqt	0.00109	0.00051	2.13251
48	readmat	0.01565	0.03109	0.50341
49	libcard	0.04166	0.02390	1.74324
50	livpar	-0.01075	0.02421	-0.44401
51	prot	0.01949	0.02231	0.87363
52	black	-0.00854	0.03073	-0.27794
53	hisp	0.02800	0.03277	0.85448
54	nc	0.13633	0.03974	3.43093
55	so	0.04304	0.05299	0.81225
56	we	0.08520	0.05038	1.69113
57	urb	-0.01042	0.02599	-0.40090
58	ur	-0.00846	0.00372	-2.27217
59	mw	0.76114	0.37831	2.01196
60	mwage	-0.00273	0.01451	-0.18787
61	mwhgc	-0.05418	0.01885	-2.87400
62	ugtuit	-0.32935	0.22278	-1.47837
63	expsec	0.35550	0.16719	2.12634
64	expps	-0.26458	0.09504	-2.78380
65	age	0.18231	0.07622	2.39182
66	age2	-0.00391	0.00085	-4.59464
67	exp	0.02128	0.01014	2.09937
68	exp2	-0.00004	0.00044	-0.09536
69	hgc	0.20305	0.05946	3.41472
70	dum12y	0.11290	0.03762	3.00108
71	coldeg	0.15048	0.04559	3.30105
72	lag1wu	0.00351	0.00134	2.61187
73	lag2wu	0.00111	0.00154	0.72009
74	lag3wu	-0.00188	0.00159	-1.18583
75	lag4wu	0.00061	0.00158	0.38600
76	lag5wu	-0.00054	0.00165	-0.32558
77	cumtr	0.25118	0.00930	27.02045
78	year79	-0.27332	0.09459	-2.88957
79	year8082	0.16708	0.05659	2.95256
80	year9294	-0.10617	0.04705	-2.25641
81	oldcoh	-0.01503	0.03663	-0.41017
82	lag1ch	0.03625	0.05080	0.71350
83	lag2ch	0.01289	0.05598	0.23032
84	lag3ch	-0.11927	0.06042	-1.97416
85	lag4ch	-0.00804	0.06231	-0.12911

86	lag5ch	-0.12287	0.06438	-1.90856
87	rhod21	0.16462	0.07470	2.20368
88	rhod22	0.08093	0.05749	1.40782

Any Work (work) :

89	cons_wo	22.32405	5.19979	4.29326
90	year	-0.12317	0.03333	-3.69558
91	afqt	0.00389	0.00155	2.51672
92	readmat	-0.10216	0.06703	-1.52404
93	libcard	-0.09337	0.05690	-1.64089
94	livpar	0.06955	0.05639	1.23347
95	prot	-0.02522	0.05907	-0.42704
96	black	-0.42809	0.07549	-5.67083
97	hisp	-0.20362	0.08292	-2.45555
98	nc	0.34945	0.10242	3.41181
99	so	0.44976	0.13748	3.27137
100	we	0.27055	0.12232	2.21181
101	urb	-0.03057	0.07020	-0.43552
102	ur	-0.04419	0.00861	-5.13382
103	mw	-3.77947	1.07507	-3.51554
104	mwage	0.11122	0.04210	2.64217
105	mwhgc	0.10043	0.04463	2.25040
106	ugtuit	0.51153	0.57046	0.89670
107	expsec	1.11080	0.41570	2.67213
108	expss	-0.02553	0.28613	-0.08921
109	age	-0.06406	0.20003	-0.32028
110	age2	-0.00832	0.00206	-4.03865
111	exp	0.54387	0.02508	21.68812
112	exp2	-0.01910	0.00172	-11.09092
113	hgc	-0.20883	0.14067	-1.48456
114	dum12y	0.03572	0.08737	0.40881
115	coldeg	0.58514	0.22084	2.64967
116	lag1wu	-0.00144	0.00233	-0.62084
117	lag2wu	0.00259	0.00292	0.88722
118	lag3wu	0.00877	0.00317	2.76588
119	lag4wu	0.00004	0.00310	0.01310
120	lag5wu	0.00379	0.00269	1.41008
121	cumtr	0.15554	0.03191	4.87432
122	year79	-0.24914	0.27897	-0.89308
123	year8082	0.14971	0.14845	1.00847
124	year9294	0.20260	0.12490	1.62207
125	oldcoh	0.04065	0.10252	0.39653
126	lag1ch	-0.37553	0.07427	-5.05657
127	lag2ch	-0.07009	0.08997	-0.77907
128	lag3ch	-0.16504	0.09275	-1.77949
129	lag4ch	-0.01650	0.09935	-0.16612
130	lag5ch	-0.00535	0.10855	-0.04926

131	rhod31	-3.78445	0.23214	-16.30238
132	rhod32	-0.24393	0.12996	-1.87694

Any Unemployment (un) :

133	cons_un	-0.74671	4.69515	-0.15904
134	year	0.06530	0.02525	2.58576
135	afqt	-0.00604	0.00101	-5.98804
136	readmat	-0.04357	0.05226	-0.83374
137	libcard	-0.00557	0.04256	-0.13093
138	livpar	-0.04730	0.04267	-1.10830
139	prot	0.05083	0.04439	1.14523
140	black	0.18790	0.05589	3.36207
141	hisp	-0.00868	0.06349	-0.13677
142	nc	0.29733	0.08151	3.64801
143	so	0.27573	0.10801	2.55272
144	we	0.32793	0.10133	3.23614
145	urb	0.08488	0.05182	1.63807
146	ur	0.06484	0.00735	8.81730
147	mw	0.35621	1.06182	0.33547
148	mwage	-0.02910	0.04007	-0.72628
149	mwhgc	0.04306	0.04101	1.04981
150	ugtuit	0.08569	0.42106	0.20352
151	expsec	1.28847	0.34161	3.77172
152	exppts	0.38318	0.18632	2.05657
153	age	-0.38773	0.19468	-1.99156
154	age2	0.00726	0.00212	3.42409
155	exp	0.00083	0.02038	0.04049
156	exp2	-0.00013	0.00115	-0.11505
157	hgc	-0.20773	0.12884	-1.61228
158	dum12y	-0.09233	0.07082	-1.30378
159	coldeg	0.01134	0.11492	0.09868
160	lag1wu	0.09265	0.00386	23.98149
161	lag2wu	0.00411	0.00281	1.46375
162	lag3wu	0.00688	0.00274	2.51465
163	lag4wu	0.00851	0.00279	3.05033
164	lag5wu	0.00302	0.00252	1.19717
165	cumtr	-0.05241	0.01995	-2.62756
166	year79	0.12579	0.31275	0.40221
167	year8082	0.46921	0.14090	3.33015
168	year9294	-0.17808	0.09167	-1.94250
169	oldcoh	0.10904	0.07092	1.53750
170	lag1ch	0.30694	0.08554	3.58822
171	lag2ch	0.22186	0.08693	2.55207
172	lag3ch	0.12513	0.08415	1.48708
173	lag4ch	0.22416	0.09049	2.47731
174	lag5ch	0.00448	0.08995	0.04984
175	rhod41	1.87575	0.14864	12.61938

176 rhod42	-1.36867	0.10659	-12.84061
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Any Job Change (ch) :

177 cons_ch	4.39813	5.19413	0.84675
178 year	-0.00547	0.03051	-0.17931
179 afqt	-0.00460	0.00128	-3.58572
180 readmat	-0.03884	0.06086	-0.63824
181 libcard	0.02831	0.05195	0.54486
182 livpar	-0.06131	0.05110	-1.19976
183 prot	0.05564	0.05487	1.01414
184 black	0.19311	0.06956	2.77607
185 hisp	0.04618	0.07570	0.61012
186 nc	0.08828	0.10065	0.87706
187 so	0.03647	0.13019	0.28009
188 we	0.13910	0.11870	1.17189
189 urb	0.06088	0.06629	0.91851
190 ur	0.04999	0.00893	5.59698
191 mw	-0.15158	1.06520	-0.14231
192 mwage	-0.00485	0.03991	-0.12158
193 mwhgc	0.03470	0.04340	0.79968
194 ugtuit	-0.36683	0.54402	-0.67430
195 expsec	0.44405	0.41192	1.07800
196 expps	-0.28266	0.22398	-1.26197
197 age	-0.33359	0.20315	-1.64209
198 age2	0.00643	0.00223	2.89025
199 exp	0.00292	0.02412	0.12115
200 exp2	-0.00092	0.00124	-0.74296
201 hgc	-0.16177	0.13824	-1.17021
202 dum12y	-0.09284	0.08463	-1.09706
203 coldeg	0.05012	0.14111	0.35518
204 lag1wu	0.01654	0.00236	7.01810
205 lag2wu	0.00645	0.00245	2.63323
206 lag3wu	-0.00361	0.00247	-1.46429
207 lag4wu	0.00527	0.00267	1.97501
208 lag5wu	0.00010	0.00248	0.04087
209 cumtr	-0.01271	0.02598	-0.48897
210 year79	-1.87776	0.28855	-6.50768
211 year8082	0.04009	0.13133	0.30531
212 year9294	-0.12556	0.10816	-1.16090
213 oldcoh	-0.06027	0.09013	-0.66868
214 lag1ch	0.17112	0.07020	2.43763
215 lag2ch	0.10180	0.08085	1.25909
216 lag3ch	0.25839	0.07755	3.33208
217 lag4ch	0.24215	0.08722	2.77629
218 lag5ch	0.17742	0.09300	1.90765
219 rhod51	1.77302	0.18589	9.53822
220 rhod52	-0.98839	0.12069	-8.18933

Annual Hours Work (h, Conditional on Working) :

221	cons_hw	3732.28816	959.17900	3.89113
222	year	-17.08248	7.64238	-2.23523
223	afqt	0.91746	0.31697	2.89449
224	readmat	-17.59887	17.79130	-0.98918
225	libcard	-9.01697	14.17603	-0.63607
226	livpar	49.54895	15.13751	3.27326
227	prot	-1.21263	13.91489	-0.08715
228	black	-94.30124	18.05057	-5.22428
229	hisp	-31.05630	19.69059	-1.57722
230	nc	-32.60257	22.34989	-1.45873
231	so	18.17003	27.16728	0.66882
232	we	-10.92480	25.86992	-0.42230
233	urb	-51.91571	13.25442	-3.91686
234	ur	-17.19556	1.63393	-10.52406
235	mw	-163.06607	192.18122	-0.84850
236	mwage	-1.58275	7.32497	-0.21608
237	mwhgc	13.85266	7.48268	1.85130
238	ugtuit	322.02056	102.98940	3.12673
239	expsec	-59.09172	78.00897	-0.75750
240	expps	-39.11304	45.31896	-0.86306
241	age	54.30585	35.77315	1.51806
242	age2	-1.81219	0.37444	-4.83976
243	exp	112.38616	4.71022	23.86007
244	exp2	-2.60099	0.17962	-14.48028
245	hgc	11.62469	23.61971	0.49216
246	dum12y	-12.82351	20.41242	-0.62822
247	coldeg	56.21566	32.23167	1.74411
248	lag1wu	-6.13522	0.55146	-11.12538
249	lag2wu	1.48764	0.56054	2.65397
250	lag3wu	1.30891	0.55155	2.37315
251	lag4wu	1.39288	0.55675	2.50183
252	lag5wu	1.24083	0.53497	2.31943
253	cumtr	25.07666	4.79220	5.23280
254	year79	-80.94356	51.77019	-1.56352
255	year8082	-110.73201	24.69076	-4.48475
256	year9294	54.12616	19.64162	2.75569
257	oldcoh	44.50441	23.64567	1.88214
258	lag1ch	-115.63616	16.58982	-6.97031
259	lag2ch	-34.60553	16.23511	-2.13152
260	lag3ch	-26.36610	18.11034	-1.45586
261	lag4ch	12.13116	19.14107	0.63378
262	lag5ch	35.69885	21.25885	1.67925
263	sdhw	464.13570	2.79081	166.30857
264	rhoc11	-1558.49060	32.12707	-48.51019
265	rhoc12	150.36015	32.08095	4.68690

Annual Weeks of Unemployment (wun, Conditional on Unemployment) :

266	cons_wu	-1.21723	37.19787	-0.03272
267	year	-0.01714	0.21620	-0.07927
268	afqt	-0.02301	0.00927	-2.48110
269	readmat	-0.18629	0.39441	-0.47232
270	libcard	-0.02405	0.36048	-0.06672
271	livpar	-0.71227	0.33642	-2.11722
272	prot	0.51331	0.37418	1.37183
273	black	1.22613	0.46920	2.61321
274	hisp	0.82405	0.52764	1.56176
275	nc	0.79769	0.69494	1.14785
276	so	-1.02733	0.92372	-1.11216
277	we	-1.23083	0.87079	-1.41346
278	urb	-0.05863	0.44295	-0.13236
279	ur	0.39704	0.05794	6.85263
280	mw	1.46456	7.39617	0.19802
281	mwage	-0.07298	0.30176	-0.24184
282	mwhgc	0.08580	0.30575	0.28061
283	ugtuit	-6.08689	4.00414	-1.52015
284	expsec	-1.87526	2.93697	-0.63850
285	exppts	1.00824	1.69214	0.59584
286	age	0.12530	1.59188	0.07871
287	age2	0.00457	0.01806	0.25292
288	exp	0.23105	0.17888	1.29165
289	exp2	-0.00871	0.01266	-0.68788
290	hgc	-0.49446	1.00435	-0.49232
291	dum12y	0.47143	0.56712	0.83127
292	coldeg	0.70045	1.14054	0.61414
293	lag1wu	0.14474	0.01425	10.15383
294	lag2wu	0.02528	0.01519	1.66455
295	lag3wu	0.03026	0.01570	1.92667
296	lag4wu	0.00138	0.01576	0.08732
297	lag5wu	0.02328	0.01595	1.45945
298	cumtr	-0.34769	0.18970	-1.83286
299	year79	-0.49721	1.78280	-0.27890
300	year8082	1.93042	0.80413	2.40063
301	year9294	0.14282	0.81495	0.17525
302	oldcoh	-1.01979	0.60431	-1.68753
303	lag1ch	-0.19298	0.44556	-0.43312
304	lag2ch	-0.61154	0.50298	-1.21583
305	lag3ch	-0.63270	0.58094	-1.08910
306	lag4ch	0.25363	0.62387	0.40655
307	lag5ch	0.50435	0.64186	0.78576
308	sdwun	9.03644	0.13109	68.93370
309	rhoc21	12.51703	1.35019	9.27057

310 rhoc22	-3.14764	0.90937	-3.46135
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Log of Hourly Average Earnings (w) :

311 cons_lnw	-0.79345	0.70452	-1.12624
312 year	-0.01642	0.00547	-3.00415
313 afqt	0.00359	0.00022	16.03136
314 readmat	0.03431	0.01343	2.55570
315 libcard	0.02460	0.01048	2.34703
316 livpar	-0.02949	0.01067	-2.76306
317 prot	-0.04015	0.01080	-3.71902
318 black	-0.07863	0.01386	-5.67332
319 hisp	-0.00597	0.01487	-0.40132
320 nc	-0.14034	0.01366	-10.27481
321 so	-0.12452	0.01249	-9.96872
322 we	-0.06747	0.01377	-4.89873
323 urb	0.08424	0.01000	8.42671
324 ur	-0.00811	0.00130	-6.24792
325 mw	0.07405	0.14320	0.51712
326 mwwage	0.00351	0.00553	0.63577
327 mwhgc	-0.00968	0.00640	-1.51177
328 age	0.13150	0.02625	5.00916
329 age2	-0.00267	0.00028	-9.43860
330 exp	0.06732	0.00409	16.46816
331 exp2	-0.00160	0.00018	-9.06741
332 hgc	0.07907	0.02086	3.78987
333 dum12y	-0.04068	0.01550	-2.62389
334 coldeg	0.09227	0.02476	3.72709
335 lag1wu	-0.00177	0.00040	-4.45569
336 lag2wu	-0.00126	0.00038	-3.32614
337 lag3wu	-0.00115	0.00040	-2.88001
338 lag4wu	-0.00081	0.00042	-1.90704
339 lag5wu	0.00024	0.00042	0.57447
340 cumtr	0.03255	0.00358	9.08066
341 year79	0.13989	0.04227	3.30958
342 year8082	0.04067	0.02026	2.00760
343 year9294	-0.00968	0.01594	-0.60745
344 oldcoh	-0.01013	0.01783	-0.56847
345 lag1ch	-0.03192	0.01211	-2.63596
346 lag2ch	-0.00084	0.01253	-0.06680
347 lag3ch	-0.00270	0.01371	-0.19669
348 lag4ch	-0.00832	0.01371	-0.60640
349 lag5ch	0.01062	0.01428	0.74410
350 sdlnw	0.33642	0.00175	192.79140
351 rhoc31	0.73388	0.02455	29.89510
352 rhoc32	1.50124	0.02059	72.90562

Initial Schooling Level in 1979 (is):

353	cons_ini	-5.70145	3.87557	-1.47113
354	mohgc	0.01863	0.00690	2.69980
355	fahgc	0.01844	0.00574	3.21460
356	sibnum	-0.02429	0.00653	-3.72103
357	rbne	0.08320	0.08732	0.95281
358	rbnc	0.29234	0.09655	3.02799
359	rbso	0.02224	0.07750	0.28698
360	rbwe	0.22578	0.09657	2.33795
361	r14ne	1.02708	0.09308	11.03479
362	r14nc	0.78330	0.09515	8.23262
363	r14so	1.03586	0.08045	12.87626
364	r14we	1.10845	0.09235	12.00222
365	afqt	0.01262	0.00071	17.72058
366	readmat	0.19703	0.04181	4.71209
367	libcard	0.14383	0.04112	3.49746
368	livpar	0.05846	0.03765	1.55274
369	prot	0.06035	0.04388	1.37546
370	black	0.26490	0.04969	5.33104
371	hisp	0.11269	0.06146	1.83346
372	ugtuit	1.49251	0.63685	2.34358
373	expsec	-0.47857	0.32260	-1.48349
374	expps	-0.01924	0.18976	-0.10141
375	age	1.01264	0.43514	2.32714
376	age2	-0.01145	0.01230	-0.93044
377	age1415	-0.66638	0.18732	-3.55745
378	age16	-0.37201	0.11488	-3.23832
379	age17	-0.10472	0.07952	-1.31691
380	sdhgcini	0.92389	0.00732	126.24723
381	rhoc41	0.11976	0.13810	0.86726
382	rhoc42	0.32200	0.11723	2.74673

Heterogeneity Information:

POINT PROB. WEIGHT MASS POINT

FIRST PERMANENT HETEROGENEITY

1	0.02925	0.00000
2	0.08027	0.37403
3	0.32656	0.60835
4	0.44150	0.77702
5	0.12242	1.00000

SECOND PERMANENT HETEROGENEITY

1	0.12959	0.00000
2	0.35603	0.58521
3	0.48150	0.31993
4	0.03288	1.00000

NONLINEAR TRANSITORY HETEROGENEITY

Any Schooling

1	0.17477	0.00000
2	0.03244	0.02102
3	0.01183	-0.12577
4	0.42026	0.22717
5	0.02763	-0.07135
6	0.33308	0.69062

Any Training

1	0.17477	0.00000
2	0.03244	-0.00446
3	0.01183	0.07182
4	0.42026	0.04399
5	0.02763	0.05970
6	0.33308	-0.05100

Any Work

1	0.17477	0.00000
2	0.03244	2.53530
3	0.01183	-3.18005
4	0.42026	-0.12075
5	0.02763	4.94166
6	0.33308	0.16036

Any Unemployment

1	0.17477	0.00000
2	0.03244	-0.04904
3	0.01183	-0.75519
4	0.42026	-4.95586
5	0.02763	-1.23314
6	0.33308	-1.22591

Any Job Change

1	0.17477	0.00000
2	0.03244	0.29726

3	0.01183	0.19501
4	0.42026	-2.23391
5	0.02763	-0.84130
6	0.33308	-99.00000

Hours worked

1	0.17477	0.00000
2	0.03244	-952.28885
3	0.01183	255.23279
4	0.42026	398.01243
5	0.02763	-76.58800
6	0.33308	96.74391

Weeks Unemployed

1	0.17477	0.00000
2	0.03244	15.27832
3	0.01183	27.98220
4	0.42026	21.25957
5	0.02763	0.00354
6	0.33308	-4.32722

Log Wage

1	0.17477	0.00000
2	0.03244	1.25946
3	0.01183	-3.60136
4	0.42026	0.04553
5	0.02763	-1.58095
6	0.33308	0.10578

Initial Schooling Level (no transitory heterogeneity)

1	0.17477	0.00000
2	0.03244	0.00000
3	0.01183	0.00000
4	0.42026	0.00000
5	0.02763	0.00000
6	0.33308	0.00000

ST. DEV. OF FIRST PERMANENT HETEROGENEITY: 0.19800532191946

ST. DEV. OF SECOND PERMANENT HETEROGENEITY:0.21874620581648

ST. DEV. OF NONLINEAR TRANSITORY HETEROGENEITY:

Equation:	1	St. Dev. :	0.42531946262434
Equation:	2	St. Dev. :	4.2893100665523D-02
Equation:	3	St. Dev. :	1.0086913177151
Equation:	4	St. Dev. :	3.2971649614189
Equation:	5	St. Dev. :	57.154377787081
Equation:	6	St. Dev. :	316.29440007216
Equation:	7	St. Dev. :	14.595081582500
Equation:	8	St. Dev. :	0.52774440325561
Equation:	9	St. Dev. :	0.

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