# THE LONG-TERM EFFECTS OF YOUTH UNEMPLOYMENT

Thomas A. Mroz[¤]
Timothy H. Savage[*]
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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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[¤] Department of Economics, The University of North Carolina at Chapel Hill and The Carolina Population Center. Email: tom_mroz@unc.edu.
[*] Charles River Associates. Email: tsavage@crai.com.

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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 an eight percent lower wage rate, 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, 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.

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[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

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[4] See Freeman and Medoff (1982), Freeman and Wise (1982), and more recently Topel and Ward(1992).
[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. 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. Burgess, Propper, Rees, and Shearer (2003), using British data, find that the impacts of early career unemployment on later employment outcomes varies according to an individual's skill level, with the lesser skilled being more prone to suffer adverse consequences later in life.

A number of studies have used information on displaced workers to examine the consequences of layoffs on subsequent wage rates and earnings. Nearly all of these studies find substantial effects for older individuals, whereas the longer-term adverse effects tend to be more moderate for younger individuals.[14] Topel (1990) in particular found more complete convergence in the wages of younger displaced individuals when compared to their non-displaced counterparts.

In a study of the impacts of displacement on young people, Kletzer and Fairlie (2003) use NLSY79 data and find that the wage gap between displaced and non-

[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.
[13] The US sample is from the Current Population Survey. The Canadian sample is based on Canadian census data.
[14] See, for example, Jacobson, LaLonde, and Sullivan (1993).

displaced men grows through at least five years after displacement. Their results differ from the results that we report here due largely to the fact that the comparison group they use, as is done in many other displaced-worker studies, consists of individuals who never have experienced a spell of unemployment. Our economic model and empirical analysis, however, examine what would happen if one were able to prevent a single spell of unemployment. As Stevens (1997) demonstrates, much of the estimated persistence in low earnings after displacement can be attributed to the fact that the displaced worker group can experience multiple spells of unemployment. For policy purposes, it may be more reasonable to ask what would happen if one could prevent a single spell of unemployment for a young person rather than asking what would happen if one could forever banish unemployment.

In summary, much of the current literature on the long-term effects of youth unemployment contains potential 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 potential 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 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.

## 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.[15] 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.[16] 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: $E_t^* = wH_t$.[17] It is always possible to obtain these earnings, except when experiencing involuntarily unemployment. Disposable income (or net earnings) is the difference between potential

[15] 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.
[16] Because training is costly and there is no future gain, it is optimal not to train in the last period.
[17] 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 $f(\lambda s_t)$.[18] Unemployment, therefore, perturbs an

[18] 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 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.[19]

***Proposition 1: The "Catch-up" Response***

*After experiencing an involuntary unemployment spell in any period before 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.[20] 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

[19] See Appendix 1 for proof of these propositions.

[20] 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.[21] 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.

[21] This model does not address job search or time voluntary 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.[22] Hourly earnings may also be affected by prior unemployment.[23] 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.[24] 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

[22] 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.
[23] 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.
[24] 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 $\varepsilon_{it}$ 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 $\rho$ is a matrix of factor loads and $\mu_i$ 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 $\varepsilon_{it}$ is that all correlation across equations in different time periods enters solely through the linear factors $\mu_i$ . Within time periods, the covariance pattern is unrestricted due to the freely-estimated relationships among the elements of $\eta_{it}$, though we do impose that the joint distribution does not vary through time. The factors $\mu_i$ capture unobserved determinants that do not vary as young people age such as, perhaps, ability.[25] The factor $\eta_{it}$ captures time-specific unobserved determinants that may vary across time such as preferences for work.[26] 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.

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

where $\mathrm{tr}_{\mathrm{it}} = 1$ 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.[27] 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

[25] The error structure for initial schooling is modeled only with the permanent heterogeneity factors.
[26] This specification we use is linear in two permanent heterogeneity factors and is nonlinear in the transitory heterogeneity factor.
[27] These variables are listed in Tables 1 and 2 in the data section and in Appendix 2.

five years.[28] 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 $\tau = 1,\ldots,5$ .

As an example of a continuous outcome, consider annual hours worked.[29]

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

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, $\mu_i$ and $\eta_{it}$. 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:

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[28] 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.

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\begin{aligned}
&L_{it}(\Theta \mid \mu_i,\eta_{it}) = \Pr\{as_{it}=1 \mid \mu_i,\eta_{it}\}^{as_{it}} \cdot \\
&\begin{bmatrix}
\Pr\{as_{it}=0 \mid \mu_i,\eta_{it}\} \cdot \\
\left[\Pr\{work_{it}=1 \mid \mu_i,\eta_{it}\} \cdot f_h(h_{it} \mid \mu_i,\eta_{it}) \cdot f_w(w_{it} \mid \mu_i,\eta_{it})\right]^{work_{it}} \cdot \Pr\{work_{it}=0 \mid \mu_i,\eta_{it}\}^{(1-work_{it})} \cdot \\
\left[\Pr\{un_{it}=1 \mid \mu_i,\eta_{it}\} \cdot f_{wun}(wun_{it} \mid \mu_i,\eta_{it})\right]^{un_{it}} \cdot \Pr\{un_{it}=0 \mid \mu_i,\eta_{it}\}^{(1-un_{it})} \cdot \\
\Pr\{ch_{it}=1 \mid \mu_i,\eta_{it}\}^{ch_{it}} \cdot \Pr\{ch_{it}=0 \mid \mu_i,\eta_{it}\}^{(1-ch_{it})}
\end{bmatrix}^{(1-as_{it})} . \\
&\Pr\{tr_{it}=1 \mid \mu_i,\eta_{it}\}^{tr_{it}} \cdot \Pr\{tr_{it}=0 \mid \mu_i,\eta_{it}\}^{(1-tr_{it})}
\end{aligned}
\qquad \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 $\mu_i$ and $\eta_{it}$ with mass points $\mu_{1j}$, for j = 1,…,J, $\mu_{2k}$, for k = 1,…,K, and $\eta_m$ (vector) for m = 1,…,M, the unconditional contribution to the likelihood function of individual i is :

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

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. These variables are outcomes as well as determinants of later outcomes.

[29] 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.

Therefore, it is important to demonstrate that there is sufficient information to obtain identification of the effect of lagged outcomes, prior unemployment in particular, on current labor market events.

Because we treat the youths' places of residence as exogenous, this analysis contains numerous non-deterministically varying, time-dependent exogenous variables. These include local unemployment rates and the real level of minimum wages, an urban residence dummy, region dummy variables, state-level college undergraduate tuition levels, and separately real per-pupil state expenditures on secondary and post-secondary education (see Table 2). It is important to ask whether these variables are sufficient to achieve identification of the approximation to the structural model.

As discussed in Bhargava (1991) and Mroz and Surette (1998), panel-data relationships like those examined here implicitly provide many additional identification conditions than one might infer by simply counting the number of contemporaneous exogenous variables (e.g., instruments) excluded from a structural equation of interest. There are two primary reasons for this.

First, consider the case of linear dynamic models examined by Bhargava (1991), in which one is willing to impose stability on the structural parameters over time. In the empirical model, we also impose this restriction. Bhargava derives the reduced form equations for a system of dynamic equations and demonstrates that *every lag* of each instrumental variable could have a separate impact on the "contemporaneous" value of an endogenous explanatory variable. The time dimension for the exogenous time-varying instruments, therefore, creates a multiplicity of "instruments" associated with each "exclusion restriction," resulting in significantly more degrees of freedom to control for endogenous determinants. His analysis demonstrates that over-identification can be obtained under quite weak conditions in linear dynamic models.

A second source of identification arises in the context of dynamic nonlinear models. Mroz and Surette (1998) discuss this in greater detail. Their discussion exploits the fact that variations in the time ordering of the exogenous variables provide even higher degrees of over-identification than would be obtained by a simple reference to Bhargava's (1991) observation discussed above. It is especially appropriate for economic relationships like school attendance and work decisions, in which there can be considerable fixed costs of changing status over time.

The basic idea underlying their argument of additional identification is that, in dynamic nonlinear models of the type used here, the impact of any lagged exogenous variable on a current endogenous explanatory variable depends crucially on the precise forms of the prior time series of all exogenous variables. Implicitly, the impact of any single lagged exogenous variable is modified by prior lagged values of all other exogenous variables. For example, the impact of low college tuition in 1984 on school attendance for a 21 year old in 1984 would depend explicitly on school attendance at age 20; the magnitude of the 1984 tuition effect in the "reduced form equation," then, would depend on the level of tuition in 1983. Further, the magnitude of the impact of the tuition variable at age-20 on age-20 attendance depends on the lagged (age 19) attendance decision; and so this reduced form effect depends interactively on tuition levels at that as well as prior ages. As long as subsequent values of the lagged exogenous variables cannot be perfectly forecasted in time-separable non-linear models, there should be an even greater degree of identification than that discussed by Bhargava (1991).

As another example, consider the local unemployment rate. 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 outcomes. Similarly, variation in 1983 has a direct impact on 1983 outcomes. Because of the timing of decision-making, however, the 1983 rate has no direct impact on 1985 outcomes except through the accumulated stock of human capital as of 1985. As a consequence, the 1983 rate is, theoretically, an instrument for human capuital stocks observed in in 1985.

By using an explicit sequential dynamic modeling framework one can incorporate all such interactions that depend on the precise timing and sequencing of the values of the time-varying exogenous variables. The maximum likelihood approach we use here automatically incorporates these interactions among the time series properties of the sets of exogenous variables. They do so efficiently, without one having to resort to including numerous time-varying interactions of the exogenous variables in an arbitrary fashion, as would be the case with a more static instrumental variables approach.

Identification in this model is also secured through contemporaneous, theoretical exclusion restrictions and functional form. Some of the time-varying exogenous variables already mentioned, for example, can be assumed to affect indirectly 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. And, of course, it is certainly the case that our assumed functional forms for index functions do provide some additional "over-identification" above that which could be achieved in a fully nonparametric model that only incorporated the dynamic exclusion restrictions discussed above and interactions among the sequences of lagged exogenous variables.

*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 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]

[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).

*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 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.

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[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.

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 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.

[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.

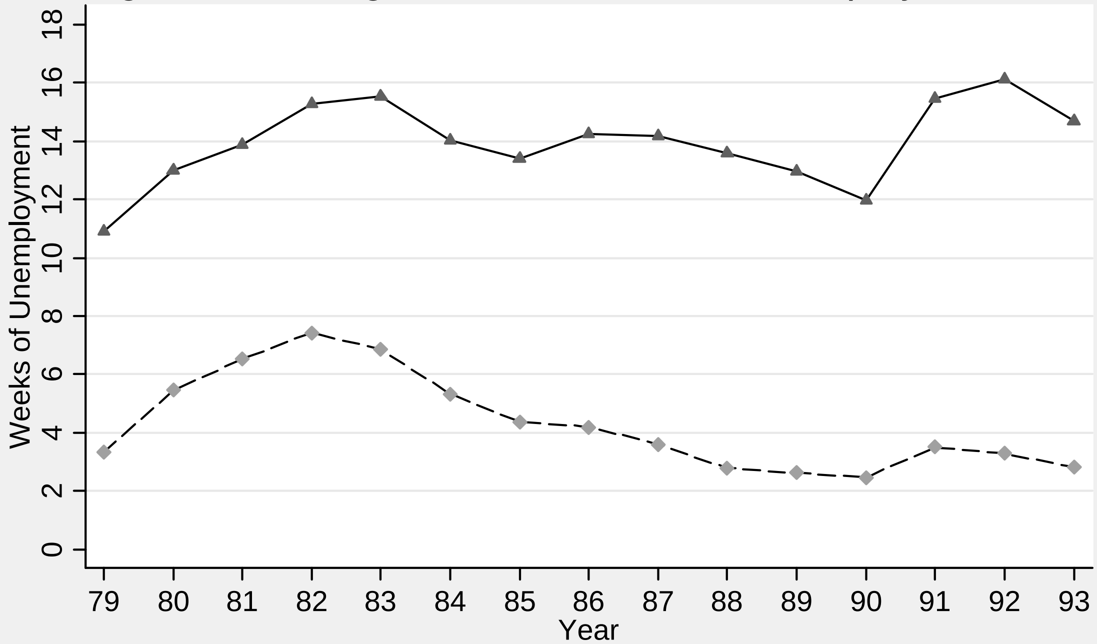
**Table 1: Summary Statistics of Time-Invariant Characteristics**
(Standard Deviations Omitted for Dummy Variables)

| **Variable Name** | **Variable Description** | **Entire (St. Dev.)** 3731 obs | **Represent. (St. Dev.)** 2286 obs | **Over-sample (St. Dev.)** 1445 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 |
| Overhisp | Over-sampled Hispanic | 0.15 | 0.00 | 0.31 |

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

| Variable Name | Variable Desciption | 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) |
| ugtuit | 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) |

Figure 1: Average Annual Weeks of Unemployment




Series with triangles is average conditional on any unemployment during the year.
Series with diamonds is average for the entire sample.
Source: NLSY79.

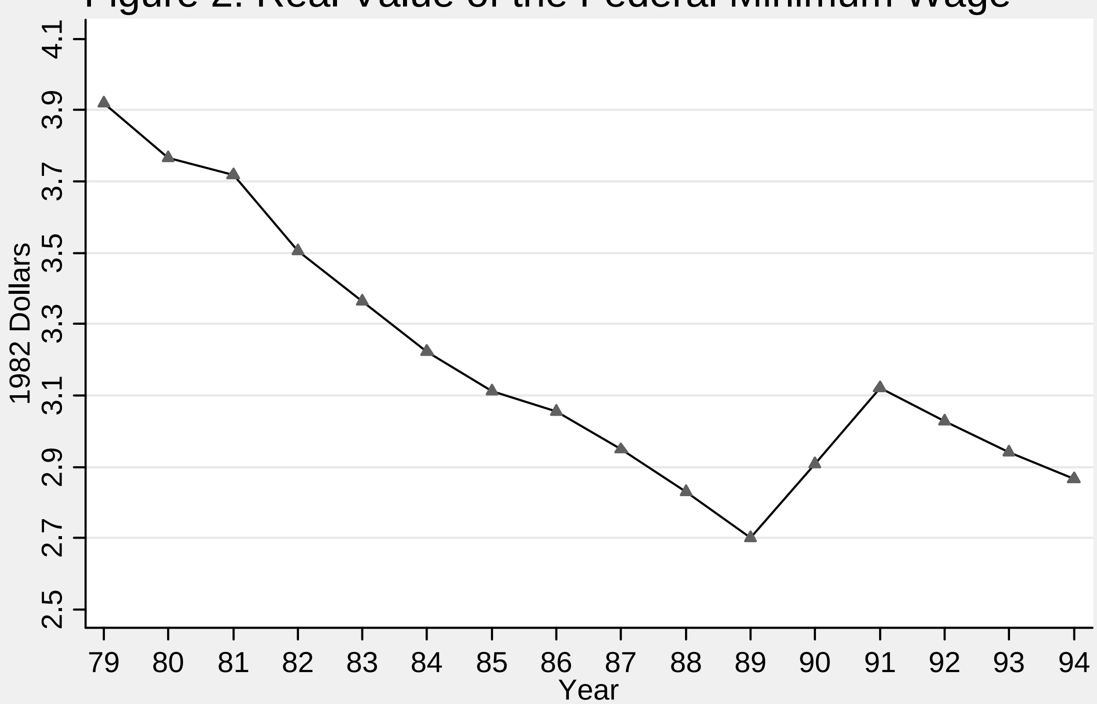
There are several sources of state-level data that are matched to the NLSY sample. The first is data taken from the Digest of Education Statistics (DES) on per-student public expenditure at public secondary education institutions. The second is DES data on per-student public expenditure at post-secondary 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.

Figure 2: Real Value of the Federal Minimum Wage




Source: US Department of Labor and Bureau of Labor Statistics.

## 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 statistical 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]

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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 fxed 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

| ***Method*** Outcome | Lag of Annual Weeks of Unemployment | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| ***DFML*** | | | | | |
| Any Training | **0.0035** | 0.0011 | -0.0019 | 0.0006 | -0.0005 |
| | (0.0013) | (0.0015) | ( 0.0016) | (0.0016) | (0.0017) |
| Any Work | -0.0014 | 0.0026 | **0.0087** | 0.0004 | 0.0038 |
| | (0.0023) | (0.0029) | (0.0032) | (0.0031) | (0.0027) |
| Annual Hours Worked | **-6.1351** | **1.4876** | **1.3089** | **1.3928** | **1.2408** |
| | (0.5515) | (0.5605) | (0.5516) | (0.5568) | (0.5350) |
| ***Fixed Effects*** | | | | | |
| Annual Hours Worked | **-8.0821** | 1.0700 | 0.5976 | **1.1307** | 0.5965 |
| | (0.5673) | (0.5488) | (0.5315) | (0.5229) | (0.5264) |
| ***OLS**** | | | | | |
| Annual Hours Worked | **-11.8621** | 0.8996 | 0.6007 | **1.7038** | **1.3521** |
| | (0.6697) | (0.6571) | (0.6149) | (0.5746) | (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 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. This effect is not directly captured in our theoretical model, but it is consistent with a spell of unemployment inducing a wealth effect on future hours of work.

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

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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.

two more conventional specifications.[44] For the DFML specification, the effect of one 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,

[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 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.

uncovered a significant response of job training to having changed a job in either of the two prior years.

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 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.

**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) |

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 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

[47] This measure is 0.1447*26 = 3.7622.

heterogeneity might be necessary. It is important to note that this is the only important 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 most previous studies have shown.

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[48] For a discussion of these issues, see Topel and Ward (1992) and 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

| *Method* | Lag of Annual Weeks of Unemployment | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| *DFML* | **-0.0018** | **-0.0013** | **-0.0011** | -0.0008 | 0.0002 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| *FE* | **-0.0019** | **-0.0019** | **-0.0010** | **-0.0012** | -0.0000 |
| | (0.0006) | (0.0006) | (0.0005) | (0.0005) | (0.0005) |
| *OLS** | **-0.0023** | **-0.0019** | **-0.0014** | -0.0006 | 0.0001 |
| | (0.0008) | (0.0008) | (0.0007) | (0.0006) | (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 in wages due to experiencing a 26 weeks of unemployment is equivalent to the wage loss from 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*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.

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 of unemployment 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,

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

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]

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

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

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 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

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.

[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.

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 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.[56] 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 to train for those who experienced unemployment at age 22. 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

[56] Note that these effects differ in this model primarily because some functional forms are nonlinear.

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.[57] Immediately after age 23, however, the wage differential begins to shrink. The simple theoretical model also predicted this

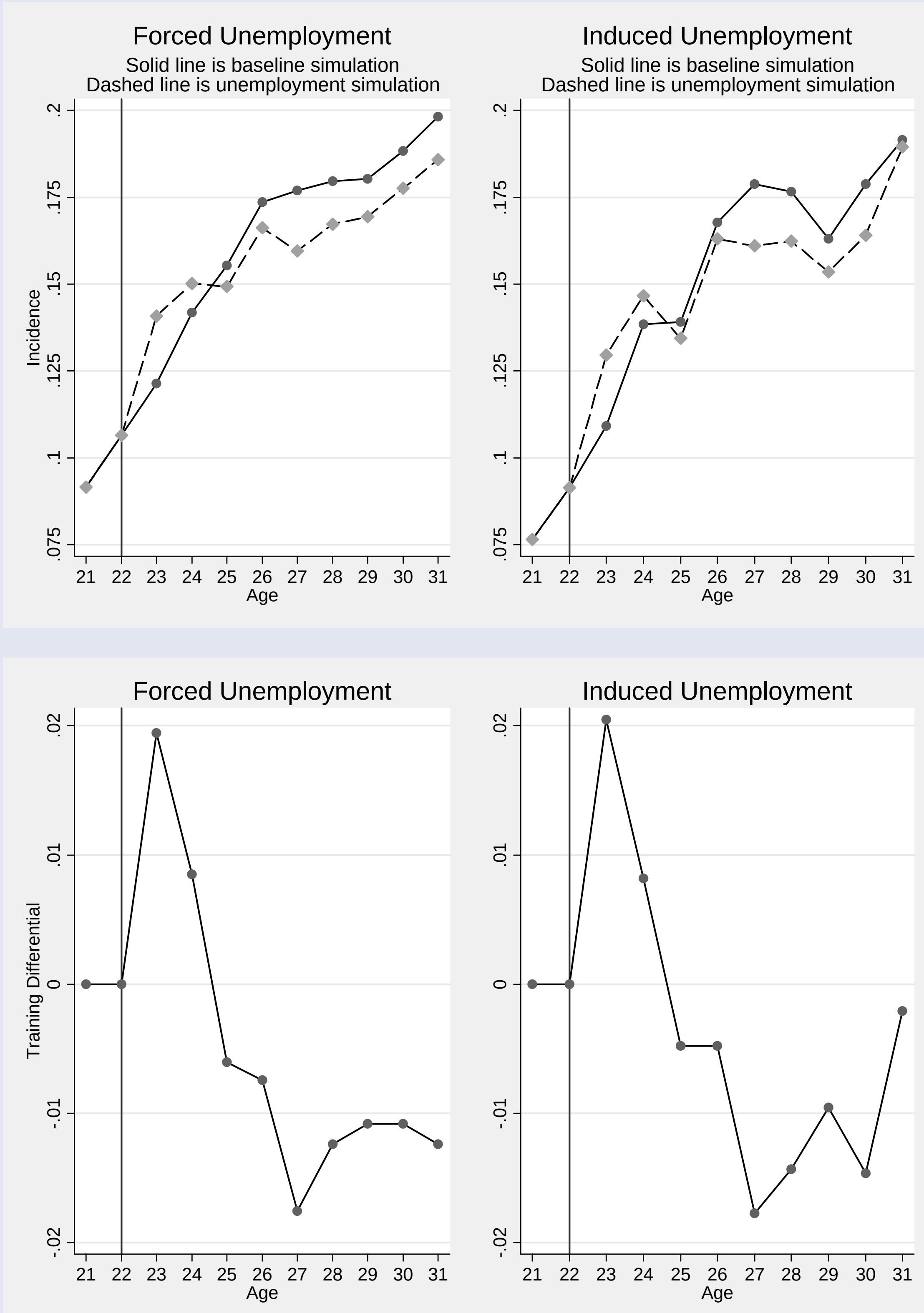
[57] Informal training of this type might not be captured by our more formal measure of vocational training.

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.

The simulation results presented here are generally consistent with the predictions of the theoretical model.[58] 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.

[58] 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. They arise through the cumulative impacts on the human capital stocks.

## Figure 3: Unemployment Impacts on Training



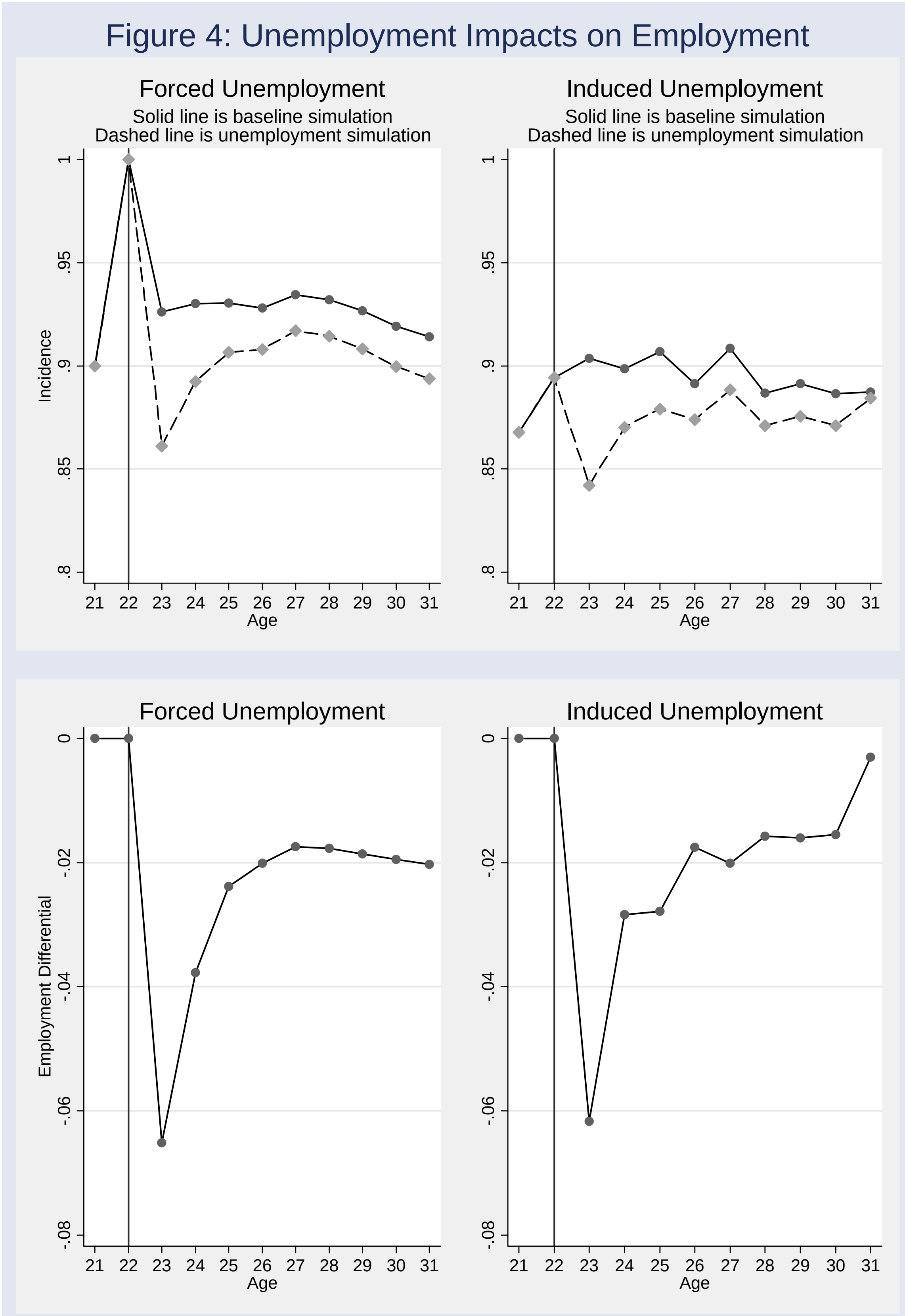


Figure 4: Unemployment Impacts on Employment
Forced Unemployment
Solid line is baseline simulation
Dashed line is unemployment simulation
Induced Unemployment
Solid line is baseline simulation
Dashed line is unemployment simulation
Incidence
.8
.85
.9
.95
1
21 22 23 24 25 26 27 28 29 30 31
Age
Forced Unemployment
Induced Unemployment
Employment Differential
0
-.02
-.04
-.06
-.08

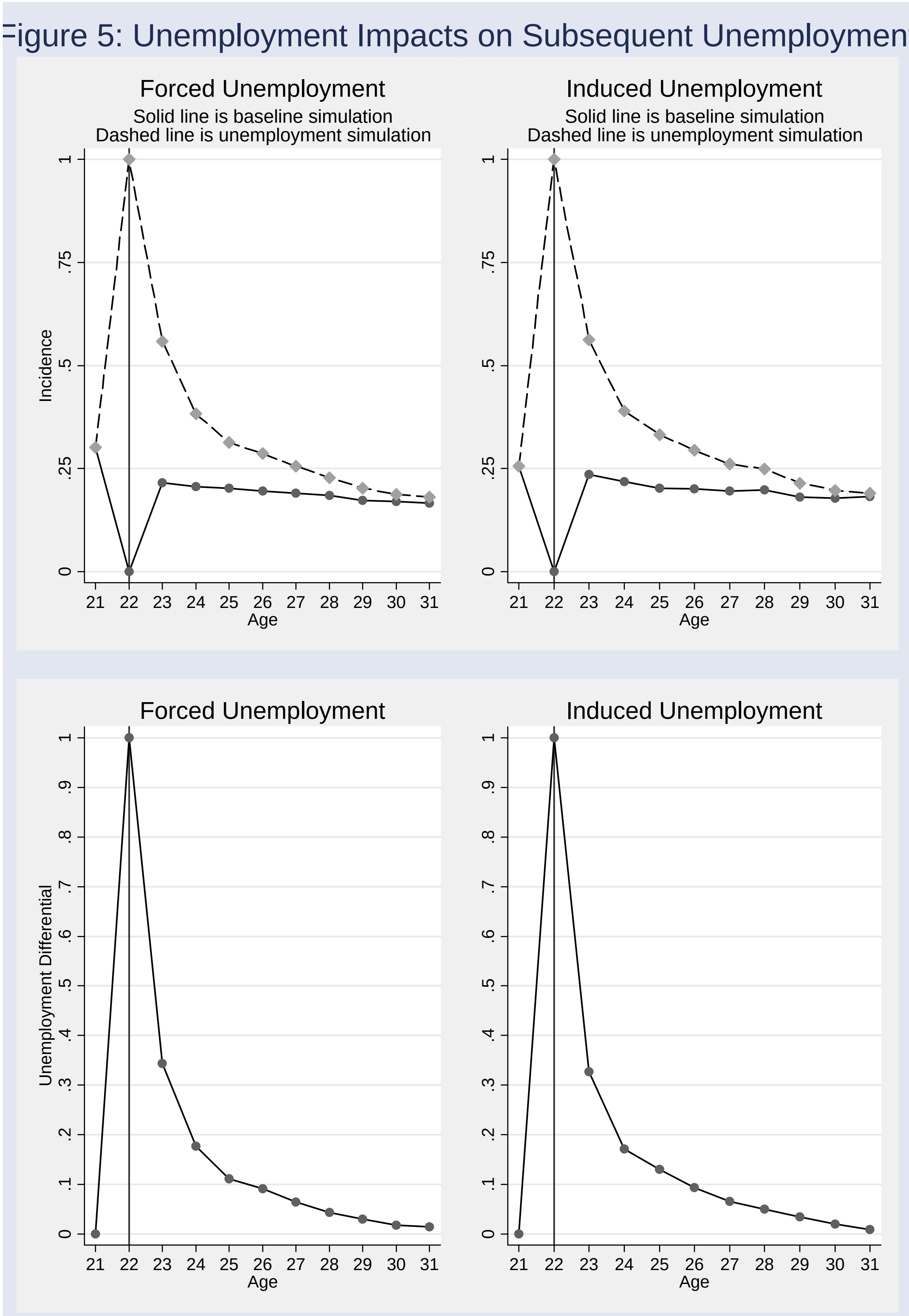


Figure 5: Unemployment Impacts on Subsequent Unemployment
Forced Unemployment
Solid line is baseline simulation
Dashed line is unemployment simulation
Induced Unemployment
Solid line is baseline simulation
Dashed line is unemployment simulation
Incidence
0
.25
.5
.75
1
21
22
23
24
25
26
27
28
29
30
31
Age
Forced Unemployment
Induced Unemployment
Unemployment Differential
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
Age

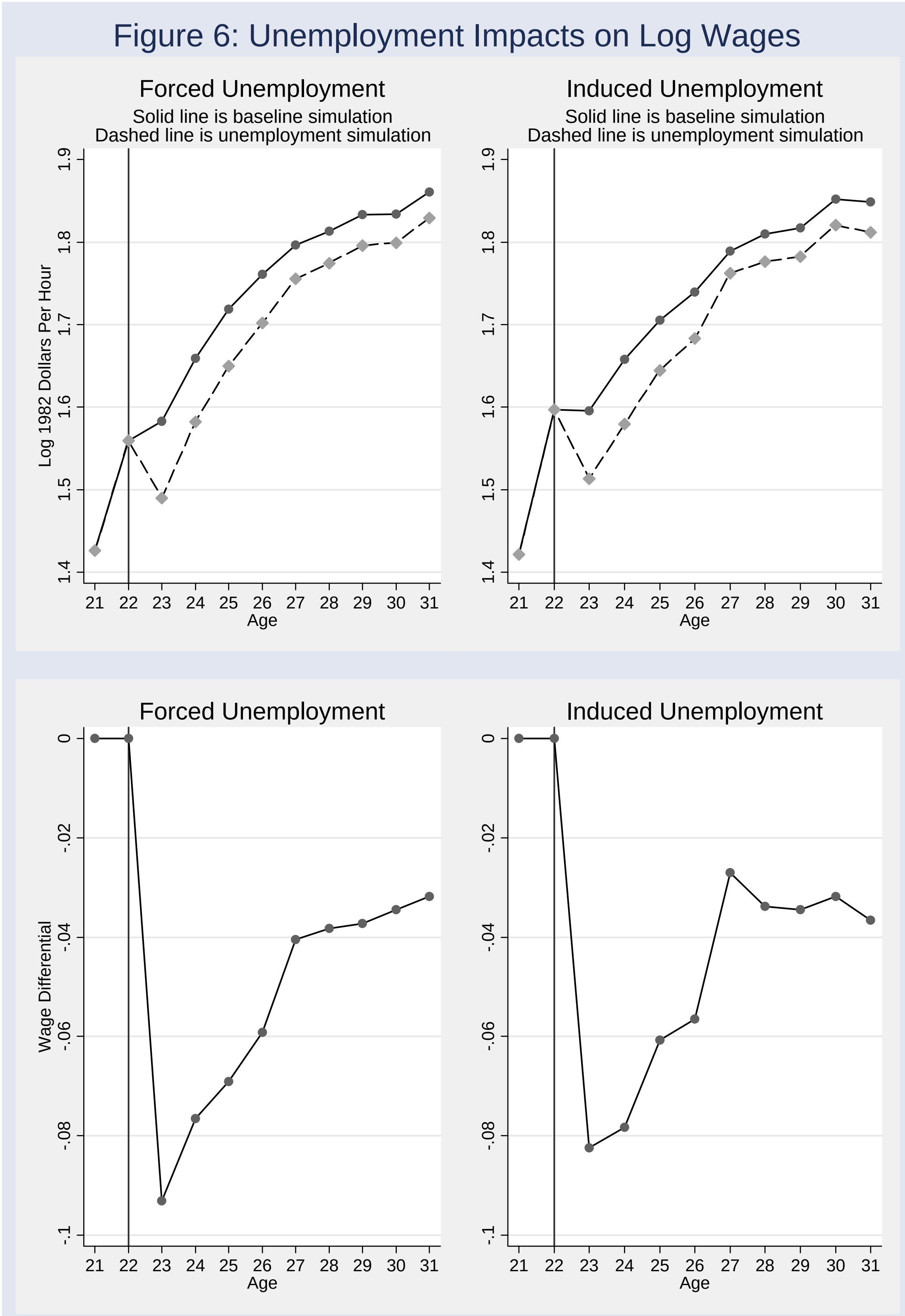


Figure 6: Unemployment Impacts on Log Wages
Forced Unemployment
Solid line is baseline simulation
Dashed line is unemployment simulation
Induced Unemployment
Solid line is baseline simulation
Dashed line is unemployment simulation
Log 1982 Dollars Per Hour
1.4
1.5
1.6
1.7
1.8
1.9
Age
21 22 23 24 25 26 27 28 29 30 31
Forced Unemployment
Induced Unemployment
Wage Differential
0
-.02
-.04
-.06
-.08
-.1
Age
21 22 23 24 25 26 27 28 29 30 31

## 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

**<u>Notation and Setup</u>:**

Define time to be discrete and finite, t=1, 2, 3, …, 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 $\lambda$ 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 $\beta$ 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 $f'(.) > 0$, $f''(.) < 0$, and that the production function satisfies the Inada conditions (Inada, 1964).[59] 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

[59] Given the finite time horizon, we in fact only rely on the condition that $\lim_{k\to 0} f'(k) = \infty$.

incomes are given by $\lambda wH_t$ 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:

$$\max_{S_{T-1}} EV_{T-1} (H_{T-1}) =$$

$$P\{\beta^{T-1}\lambda (1-S_{T-1}) wH_{T-1} + \beta^T V_T (H_{T-1} + f (\lambda S_{T-1}))\} +$$

$$(1-P)\{\beta^{T-1} (1-S_{T-1}) wH_{T-1} + \beta^T V_T(H_{T-1} + f (S_{T-1}))\}$$

This optimization can be rewritten as:

$$\max_{S_{T-1}} EV_{T-1}(H_{T-1}) =$$

$$= P\{\beta^{T-1}\lambda(1-S_{T-1})wH_{T-1} + \beta^{T}P\lambda w(H_{T-1} + f(\lambda S_{T-1})) + \beta^{T}(1-P)w(H_{T-1} + f(\lambda S_{T-1}))\}$$

$+$

$$(1-P)\{\beta^{T-1}(1-S_{T-1})wH_{T-1} + \beta^{T}P\lambda w(H_{T-1} + f(S_{T-1})) + \beta^{T}(1-P)w(H_{T-1} + f(S_{T-1}))\}$$

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

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

$$- \beta^{T-1}(1-P)wH_{T-1} + \beta^{T}P(1-P)\lambda w f'(S_{T-1}) + \beta^{T}(1-P)^{2}w f'(S_{T-1})$$

$$= 0$$

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

$$\frac{\partial^{2}V_{T-1}}{\partial S_{T-1}^{2}} = \beta^{T}P^{2}\lambda^{3}wf''(\lambda S_{T-1}) + \beta^{T}P(1-P)\lambda^{2}wf''(\lambda S_{T-1}) +$$

$$\beta^{T}P(1-P)\lambda wf''(S_{T-1}) + \beta^{T}(1-P)^{2}wf''(S_{T-1}) < 0$$

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):

$$\frac{dS^{*}_{T-1}}{dH_{T-1}} = -\frac{\partial^2 V_{T-1} \big/ \partial S^{*}_{T-1}\partial H_{T-1}}{\partial^2 V_{T-1} \big/ \partial {S^{*}_{T-1}}^2} < 0$$

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

$$\frac{\partial^2 V_{T-1}}{\partial {S^{*}_{T-1}}^2} < 0$$ 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 $H_{T-1}$.

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

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

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

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

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

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

By the Envelope Theorem the second total derivative is:

$$\frac{d^2V_{T-1}(S^*_{T-1}(H_{T-1}), H_{T-1})}{dH_{T-1}^{2}} = \frac{\partial^2 V_{T-1}}{\partial S^{*2}_{T-1}}\left(\frac{dS^*_{T-1}}{dH_{T\_1}}\right)^2 + \frac{\partial V_{T-1}}{\partial S^*_{T-1}}\frac{d^2 S^*_{T-1}}{dH_{T-1}^{2}} + \frac{\partial^2 V_{T-1}}{\partial H_{T-1}} = \frac{\partial^2 V_{T-1}}{\partial S^{*2}_{T-1}}\left(\frac{dS^*_{T-1}}{dH_{T-1}}\right)^2 < 0$$

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

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

$\frac{\partial^2 V_{T-1}}{\partial S^{*2}_{T-1}} < 0 \qquad$ by SOCs 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:

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

$$+ (1-P)\,\{\beta^{T-2}(1-S_{T-2})wH_{T-2} + \beta^{T-1}V_{T-1}(H_{T-2} + f(S_{T-2}))\},$$

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

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

**<u>Periods t < T:</u>**

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

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

FOC:

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

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,

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

Since $V'_{t+1}(.) > 0$ 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:

$$\frac{d^2V_t(S^*{}_t(H_t),H_t)}{dH_t{}^2} = \frac{\partial^2 V_t}{\partial S^*{}_t{}^2}\left(\frac{dS^*_t}{dH_t}\right)^2 + \frac{\partial V_t}{\partial S^*{}_t}\frac{d^2\ S^*_t}{dH_t^2} + \frac{\partial^2 V_t}{\partial H_t} = \frac{\partial^2 V_t}{\partial S^*{}_t{}^2}\left(\frac{dS^*_{tt}}{dH_t}\right)^2 + \frac{\partial^2 V_t}{\partial H_t} < 0$$

where

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

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

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:

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

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

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

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

$$\frac{dS^*_t}{dH_t} = -\frac{\partial^2 V_t \big/ \partial S^*_t \partial H_t}{\partial^2 V_t \big/ \partial S^{*2}_t} = -\frac{(-)}{(-)} < 0 \text{ for any arbitrary period t < T.}$$

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 $w\left(\Delta + \left[f(s_{t+1}^{N}) - f(s_{t+1}^{U})\right]\right) < w\Delta$ 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 $w\left(\Delta + \left[f(\lambda s_{t+1}^{N}) - f(\lambda s_{t+1}^{U})\right]\right) < w\Delta$, 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 form 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 the 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 | mwage | -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 | expps | -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 | expps | 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 |

**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 | expps | 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 |

**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 | mwage | 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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