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THE EFFECTS OF UNEMPLOYMENT COMPENSATION ON THE UNEMPLOYMENT OF YOUTHS

by

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Executive Summary

Objectives

This report examines the role of unemployment insurance (UI) policies on the amount of unemployment that youths experience between jobs. Specifically, the analysis focuses on determining how the weekly benefit amounts and the weeks of eligibility offered by UI programs influence three aspects of nonemployment activities: the total length of time spent in nonemployment; the fraction of this time reported as unemployment; and the likelihood that an individual collects UI during a nonemployment episode.

En route to this primary objective, we pursue two intermediate goals concerned with developing a picture of youths' participation in the labor market and utilization of UI programs exploiting the rich source of data provided by the Youth Cohort of National Longitudinal Survey (YNLS). The first of these goals involves the computation of a comprehensive summary of the weekly work and earnings experiences of youths, and the second consists of assessing the extent to which youths are eligible for UI and the degree to which they draw on UI entitlements. The aim is to identify two sets of patterns: those describing differences across demographic characteristics; and those capturing changes over the period 1979–1984 covered by the data.

Methodology

The analysis constructs a data set that links individuals' unemployment experiences to dependable measures of their UI eligibility, benefits and use. The YNLS offers information on a random sample of youths with detailed histories of each person's labor-market statuses, along with considerable data on profiles of weekly earnings, on episodes of both employment and nonemployment, and on the division of nonemployment time between out-of-the-labor-force and unemployment classifications. In conjunction with supplementary data on State of residency and UI-program rules of that State, the analysis infers the weekly benefit amount and the weeks of UI eligibility available to each person at the time of every job separation; and it further combines this information with the characteristics associated with the resulting nonemployment episode. The constructed data set is unique in that no other source relates CPS-type measures of unemployment to the full complement of UI entitlements (i.e. to both the weekly benefit amount and to weeks of eligibility) and to UI collection.

To assess the influence of UI policies on the distribution of unemployment durations that occur upon leaving jobs, this study develops an econometric model that jointly determines the effects of UI on three aspects of behavior which in combination characterize the nonemployment activities of individuals. One component of the model describes the role of UI programs on the lengths of nonemployment spells. A second evaluates the effects of UI on the classification of these spells as unemployment. Finally, to account for distinctions between UI recipients and non-recipients, a third component of the model analyzes whether the generosity of UI programs influences the likelihood that individuals collect UI benefits. In specifying these components, this study accounts for all the dimensions of UI benefits and allows these benefits to affect unemployment in a nonuniform manner varying according duration length. Further, the analysis takes great care to avoid biases in estimating responses to UI entitlements by ensuring that variation in benefits reflect differences in the generosity of UI programs rather than movements along UI schedules.

Findings

For men, the empirical results presented in this study indicate that an individual who collects UI typically experiences a longer spell of nonemployment, at least up to the exhaustion of UI benefits, and reports a larger fraction of this spell as unemployment than a nonrecipient. In total, UI recipients report more weeks of unemployment before returing to jobs.

Regarding the influence of UI entitlements on the experiences of men, these benefits alter individuals' activities through several routes. Concerning the effect of a rise in the weekly benefit amount paid by a program, the results show slight increases in recipiency and in the fraction of a nonemployment spell listed as unemployment; but this rise in weekly benefits has essentially no effect on either the length of nonemployment spells or on the number of weeks of unemployment, irrespective of whether one considers the population at large or only the population of UI recipients.

Turning to the effects of an increase in the weeks of eligibility offered by a program, this policy shift induces only a relatively minor rise in the likelihood of recipiency, as is the case for an increase in weekly benefit amounts. However, in sharp contrast to the effects of weekly benefits, an extension of weeks of UI eligibility lengthens both nonemployment spells and the amount of unemployment that occurs between jobs both for UI recipients and for the population at large. This extension does not influence short durations of either nonemployment or unemployment, but it leads to an expansion of the longer durations with the highest durations being stretched out the most. In particular, the findings indicate that an extention of weeks of eligibility from 26 to 39 generates only about a 1 week lengthening of unemployment duration for the median individual, but unemployment lengthens by as much as 8 weeks for those persons experiencing the longer durations.

The findings summarized above for young men also apply for young women with only two exceptions. First, while female UI recipients experience more unemployment than nonrecipients at least up to the point of benefit exhaustion, there is some ambiguity as to whether a similar relationship exists for women when comparing lengths of nonemployment spells. Second, the weekly benefit amount is not a factor at all in influencing women's experiences. In contrast to men, changes in weekly benefits have no effect on the fraction of a nonemployment spell reported as unemployment, nor do they affect the likelihood that a women collects UI benefits. Whereas total UI benefits serve as the primary measure of UI entitlements determining UI recipiency status for men, the results for women indicate that only weeks of eligibility matter. Other than these two relatively minor exceptions, the influences of UI policies on women's experiences between jobs in nonemployment and in unemployment follow the same pattern as those outlined above for men, although the magnitudes of the various effects differ.

Implications

The findings of this report suggest several implications concerning the role of UI policies on the amount of unemployment. At the most basic level, the results indicate that features of UI programs that change the size of weekly benefit amounts are not likely to affect unemployment, whereas features that alter the amount of weeks of eligibility are likely to shift unemployment for those individuals who experience the longer durations. Thus, changes in the maximum level of weekly benefits paid by a program can be expected to have no effect on unemployment. In contrast, the introduction of extended benefit programs can be expected to lead to greater unemployment with a more uneven distribution of experiences across nonemployed persons.

At a more subtle level, these implications highlight the importance of eligibility qualifications in UI programs. A casual comparison of UI regimes across states reveals that those programs paying higher benefits also apply more stringent qualification requirements. Such programs in effect offer higher weekly benefit amounts to those persons who qualify and at the same time assign zero weeks to eligibility to a greater fraction of the nonemployed population. Consequently, these programs are likely to induce less unemployment according to the findings of this report because the higher weekly benefit amount paid by a program yields no change and the lowering to weeks of eligibility reduces the amount of unemployment.

1. Introduction

Over the past 20 years there has been a steady flow of empirical research on evaluating the effects of unemployment insurance (UI) programs on the unemployment activities of various demographic groups. Regardless of the group considered, assessing the full impact of these programs requires empirical knowledge of the way in which UI policies influence a variety of labor-market decisions. Most obvious, one needs to know how changes in a UI system alter the unemployment duration of recipients of UI benefits. In addition, one needs to determine whether such changes induce nonworking individuals to become UI recipients. Considering more indirect effects, an analyst also requires information concerning the potential responses of working individuals to policy changes in adjusting their employment activities to collect future UI benefits. Finally, if program changes involve alterations in financing features, one needs some determination of the likelihood that firms alter their hiring and separation behavior. Existing research examines aspects of each of these possible routes through which UI can influence unemployment, but available studies tend to consider effects in isolation due to data limitations or methodological problems. Incompatibilities across studies make it very difficult to integrate results for the purpose of developing reliable estimates of comprehensive effects of UI policies that account for combinations of the factors noted above. This paper presents an empirical analysis that provides estimates of such effects. The analysis exploits a new data source that permits one to overcome many of the shortcomings inherent in other sources, and it develops a flexible econometric framework for assessing the role of UI-system features on the nonemployment experiences of individuals accounting for both their unemployment activities and participation in UI programs.

The central empirical question investigated in this analysis concerns the influence of UI policies on the amount of unemployment that individuals experience between jobs, where the concept of unemployment of interest corresponds to a CPS type measure of the sort most commonly cited in national statistics rather than weeks of UI collection which is a popular choice for other research on this topic. To study the effects of UI entitlements on how much unemployment occurs during spells of nonemployment, one needs to examine the influence of these entitlements on both the length of nonemployment spells and the division of these spells between unemployment and out-of-the-labor force (OLF) activities. One often encounters the argument that the distinction between being unemployed and OLF is an arbitrary choice for many people when they are not working. Eligibility to receive UI benefits during this time along with the levels of these benefits are potentially important factors in explaining a person's decision to report himself or herself as unemployed instead of as OLF during an episode of nonemployment. The current body of empirical research provides only indirect evidence at best to infer the influence of UI on the distinction between unemployed and OLF; in fact, most of this work does not even recognize OLF as a possible status in the labor market.

Data limitations have been a major obstacle in analyzing the relationships linking UI and unemployment experiences, regardless of the demographic group considered. A study of the full effects of UI makes substantial demands of any sample used in the empirical work. A sample must include sufficient information to infer the potential UI benefits available to individuals over an extended time horizon, to determine the utilization of these benefits over this horizon, and to relate these items to the individuals' unemployment experiences during the relevant time frame. Further, the sample requires a random composition in order to draw inferences from its results about the effects of UI policies on segments of the U.S. population. Data sources analyzed in the existing literature do not meet these demands. Past research either uses program data, which offers accurate information on UI entitlements only for samples of UI recipients, or uses survey data, which provides a random sample with sparse information to infer individuals' UI benefits, eligibility, and utilization. Program data permit one to analyze the unemployment durations of UI recipients, but only if one is interested in that concept of unemployment measured as time spent collecting UI compensation; these data do not allow for an analysis of the effects of UI policies on CPS measures of unemployment. Further, program data do not provide a basis for evaluating the impact of policies on shifting individuals to recipiency status. Survey data, on the other hand, often lack sufficient information to include key benefit variables in specifications and to create reliable proxies for those included. The shortage of information in survey data also commonly forces the imposition of stationarity assumptions in statistical models, which results in specifications known to be grossly inconsistent with the facts.

This paper develops and analyzes a new data set based on the Youth Cohort of the National Longitudinal Survey (YNLS), which constitutes an unparalleled source for studying the influence of UI programs on youths' labor market experiences. The YNLS offers a random sample of youths with detailed histories of each person's labor market statuses over a period covering the years 1978 through mid- 1985, with considerable data available on earnings and on episodes of both employment and nonemployment. In conjunction with supplementary data on State of residency and UI program rules of that State, the YNLS provides sufficient information to construct an accurate assessment of an individual's UI eligibility, benefits and utilization. Exploiting the unique opportunity offered by the YNLS to link the unemployment histories of a random sample of individuals to dependable measures of their UI eligibility, this analysis explores the importance of UI benefits on the unemployment durations of young people.

En route to examining this topic, this paper develops a comprehensive picture of youth's involvement in UI programs and their nonemployment experiences. The analysis assesses the extent to which youths are eligible for UI and the degree to which they draw on UI entitlements. Further, it links this information to a variety of measures of time spent in nonemployment activities, including time in insured and total unemployment. In addition to offering insights into the connections between UI and unemployment, the analysis presented here furnishes a natural setting for integrating and evaluating many findings in the literature.

To develop a comprehensive picture of the influence of UI policies on the distribution of unemployment durations that occur upon leaving jobs, this paper proposes an econometric model that jointly determines the effects of UI on three aspects of behavior which in combination characterize the nonemployment activities of individuals. One component of the model describes the role of UI programs on the lengths of nonemployment spells. A second assesses the effects of UI on the classification of these spells as unemployment. Finally, to account for distinctions between UI recipients and non-recipients, a third component of the model analyzes whether the generosity of UI programs influences the likelihood that individuals collect UI benefits. In specifying these components, this study accounts for all the dimensions of UI benefits and incorporates controls for the tax-rate features faced by firms in financing programs. Further, the analysis takes great care to avoid biases in estimating responses to UI entitlements by ensuring that variation in benefits reflect differences in the generosity of UI programs rather than differences in workers' attributes which also determine benefits.

The remainder of this report consists of ten sections. Section 2 outlines the advantages of the YNLS over other sources for constructing a data set that integrates UI entitlements and unemployment for a random sample of individuals. Section 3 characterizes the earnings and employment experiences of youths using the weekly work histories provided by the YNLS. Section 4 provides a detailed account of youths' eligibility for and utilization of UI during the first half of the 1980's decade. Section 5 presents an econometric framework for analyzing the effects of UI on unemployment, and Section 6 tailors this framework to investigate the problem of whether the generosity of UI programs influences the amount of unemployment youths experience between jobs. As a first step in answering this question, Section 7 investigates the effects of UI programs on the lengths of spells in nonemployment. Section 8 proceeds to the next step and examines the relationships between UI entitlements and the fraction of nonemployment time classified as unemployment. Section 9 explores the empirical link between UI recipiency and UI benefits. Section 10 combines the findings to determine the comprehensive effects of UI policies on the duration of unemployment that occurs after job separations. Finally, Section 11 summarizes the results.

2. Linking UI Entitlements and Unemployment Experiences

Data limitations have severely curtailed our ability to formulate a comprehensive description of the links between unemployment, UI eligibility, and UI utilization. The main obstacles stem from an incapacity using current data sources to reliably match potential UI benefits and the collection of these benefits to measures of unemployment. Such a match requires sufficient information not only to distinguish between the amounts of insured and uninsured unemployment experienced by an individual over an extended time horizon, but also to infer the individual's UI entitlements over this horizon. The inadequacies of data sources to provide this level of information have forced previous research either to focus on narrow aspects of the relationship between unemployment and UI programs or to make substantial compromises in accounting for data shortcomings. These compromises often take the form of heroic assumptions that permit the creation of proxies for missing information, and they also commonly involve the introduction of restrictive statistical structures to avoid the need for detailed knowledge. Given the deficiencies of data sources used in previous work, there has been no opportunity to provide an assessment of the degree to which these compromises have clouded our understanding of the empirical relationships linking UI eligibility, UI participation and unemployment experiences. The availability of the YNLS provides an opportunity to begin such an assessment.

2.1 *Data Requirements to Impute UI Eligibility and Benefits*

A considerable amount of information is needed to determine whether an individual is eligible to receive UI compensation and the amount of benefits to which he or she is entitled. The specific rules and regulations determining eligibility, weekly benefit amounts and potential duration vary substantially across states and are characterized by complex relationships between an individual's earnings history, benefit schedules and qualification requirements. One essentially requires a complete time series of weekly earnings to obtain accurate measures of the UI benefits individuals are entitled to receive; the rules determining eligibility in almost every state depend not only on the amount of income, but also on the pattern of wages over the relevant time period.

The entitlement variables associated with UI programs consist of an assigned weekly benefit amount (WBA) and the number of weeks of eligibility during which benefits are available (WE). An individual must meet certain criteria to qualify for benefits and then satisfy a set of qualification requirements on a week by week basis. While the weekly qualification tests are not unimportant, the program features of central importance for this analysis are the set of eligibility criteria. These conditions determine whether an individual is entitled to any benefits as well as the amount of benefits available during a fifty-two week period initiated with the filing of a UI claim, termed the "benefit year."

While there is a large amount of diversity among States in the exact rules used to determine entitlements, every State applies two types of eligibility criteria. The first concerns the reason for separation from the most recent employer. All States have disqualification provisions for leaving work without good cause, discharge for misconduct and unemployment resulting from direct involvement in a labor dispute. The second eligibility criterion requires a worker to have an employment history that demonstrates a permanent attachment to the labor force. The evidence for such an attachment consists of a minimum level of earnings and/or a minimum number of weeks of work in covered employment during a recent fifty-two week period, termed the "base period."

All States use some combination of total earnings received in the base period (BPE), highest earnings in any quarter of the base period (HQE), and total weeks of work during the base period (WW) to establish an individuals eligibility to receive UI payments. Approximately half of the States require a worker to have a minimum HQE along with BPE greater than some multiple (usually 1.25 or 1.5) of HQE to become eligible for benefits. Another one-fourth of the State express their eligibility requirements in terms of a minimum level of BPE, and half of these States add a requirement of wages in more than one calendar quarter. The remainder of the States determine eligibility based upon a required number of weeks of work with wages greater than some nominal amount. Whether explicit or implicit, all but five States require wages in more than one calendar quarter for an individual to be judged eligible for UI payments.

Once deemed eligible, an individual's WBA is determined as a fraction of his or her "usual" earnings in covered employment up to some maximum level such that approximately half of the usual weekly wage is replaced by UI payments. States use three methods to calculate a person's WBA. The most common method defines usual earnings as HQE with WBA typically equal to 1/25 of HQE. A second approach defines the usual wage as average weekly earnings (AWE) over the base period (i.e., $AWE = BPE/WW$). Among the ten States using this procedure the WBA ranges from 1/2 to 2/3 of AWE. Finally, the third regime sets the WBA equal to approximately 1.5 percent of BPE, which implicitly defines BPE as the appropriate measure of usual earnings.

States apply two basic approaches for determining the number of weeks of benefits (WE) available to qualified individuals. The first approach, adopted by about ten States, provides the same number of weeks of benefits to every individual who is eligible for UI payments. All but a few of these uniform duration States provide everyone with twenty-six weeks of benefits. The second approach determines WE as a function of an individual's work experiences in the base period by one of three methods that use information on BPE, HQE and WW. The most prevalent method calculates the total amount of benefits available (TBA) to an individual over the benefit year as a fraction (usually 1/3) of BPE and then calculates WE by the ratio of TBA/WBA up to a maximum number of weeks. Another common method assigns WE as a fraction ranging from 1/2 to 4/5 of WW in the base period, again up to some maximum. The third scheme determines WE by using a schedule based on the ratio of BPE to HQE. Under this regime, an individual with a ratio above 3.5 is assigned the maximum number of weeks, people with a ratio close to 1.5 are allotted the minimum number of weeks, and individuals with a ratio between these two extremes are given an intermediate number of weeks.

2.2 *Data Sources Used in the Previous Literature*

There are principally two types of data analyzed in existing studies to examine the issues of UI eligibility and utilization. First, there are data available from State administration offices of UI programs, such as that provided by the Continuous Wage Benefit History (CWBH).[1] While these program data sets offer very reliable information on the amount and potential duration of UI compensation, the individuals making up these samples are observed

[1] Studies using such data sources include Newton and Rosen (1979), Classen (1979), and Moffitt (1985).

only as long as they are actually collecting benefits. Consequently, these data sets include information on only a very select group of the nonworking population (i.e. UI recipients).

Second, there are data from various representative surveys of individuals such as the CPS, the Panel Study of Income Dynamics (PSID), and the earlier National Longitudinal Surveys (NLS).[2] In contrast to the first type of data, these survey data contain insufficient information to impute individuals' potential UI compensation without relying on assumptions that are not credible. Previous studies (e.g. Clark and Summers (1982a), Topel (1985), and Blank and Card (1988)) have attempted to infer a person's eligibility and available benefits by treating an out-of-work individual's previous annual labor income as the appropriate measure of his or her earnings history. Further, one often cannot distinguish between insured and uninsured unemployment in these surveys and at best these sources provide data on accumulated unemployment during a year or on single episodes of unemployment over a relatively short time horizon with some spells interrupted in progress.

2.3 *Features of the YNLS*

The YNLS classifies among the second type of data listed above, but it supplies an incomparable source of information on the unemployment and employment activities of youths that enables one to overcome many of the problems encountered with the data sets used in past work. The YNLS includes a nationally representative sample of youths with comprehensive histories on each person's labor-market statuses and earnings over a period covering the years 1978 through mid-1985. In conjunction with supplementary data on State of residency and the UI benefit rules of that State, the YNLS provides sufficient employment information to infer an individual's UI eligibility and available benefits during times of unemployment. In addition, these data contain comprehensive information on the receipt of UI benefits, providing reliable calendar year information on the total number of weeks a youth received UI payments, the average weekly benefit amount over the year and the months in which benefits were received. When combined, these data permit one to construct a reasonably accurate picture integrating UI entitlements, the utilization of these entitlements, and the

[2] Studies using such data sources include Ehrenberg and Oaxaca (1976), Clark and Summers (1979, 1982a) and Katz (1986).

labor market activities of individuals.

The development of this picture initially requires the construction of complete work histories of individuals, not only dating their periods of employment, nonemployment and unemployment, but also identifying the precise time pattern of their weekly earnings. This level of detail is needed to infer UI benefits and to determine the availability of these benefits during episodes when individuals do not work. The task of describing the earnings and employment experiences of youths is the topic of Section 3, which immediately follows the current discussion.

Using this information on work histories to impute UI benefits, Section 4 examines the extent to which young workers are eligible for UI benefits along with the degree to which they draw on available compensation. Knowledge of youths' eligibility and utilization of UI is an important ingredient in assessing the role of UI programs on their labor market activities. To take advantage of the richness of the information provided by the YNLS on the collection of UI compensation, the analysis focuses on calendar years as the periods of observation.

The later sections exploit the data set characterized in Sections 3 and 4 to examine the influence of UI policy on the nonemployment experiences of youths. The particular problem of concern in this analysis is to determine whether the generosity of UI programs affects the amount of unemployment that occurs between jobs. Such an empirical analysis cannot be done without the opportunity provided by the YNLS to construct a data set that links UI entitlements, UI collection and labor market activities.

While the YNLS offers this unique opportunity, there are three shortcomings of the YNLS relevant to this analysis. First, data are not provided on the lengths of unemployment spells, but only on the number of weeks that an individual reports himself or herself as being unemployed during a contiguous sequence of weeks in which the youth does not work. This lack of information on the timing of unemployment spells rules out the possibility of applying familiar statistical models of duration analysis and has lead us to focus on predicting the effects of UI programs on the total number of weeks a youth reports himself or herself as unemployed during a nonemployment episode.

A second limitation of the YNLS arises because survey respondents were not asked detailed questions about extraneous jobs. Specifically, wage information is missing for jobs that were not the main job held at the date of the interview, were not part of a government training program, and were held for less than nine weeks or required less than twenty hours of work per week. To obtain uninterrupted time series of weekly earnings for as many people as possible, we impute a wage rate for those individuals with missing wage information even though the earnings from these small jobs account for a negligible fraction of total labor income. This imputation procedure utilizes wage data available in preceding and subsequent interviews as well as earnings on other jobs held during the current interview year. Appendix A contains a description of the procedures used to impute wages rates for those jobs with missing information.

Third, while the YNLS contains more comprehensive information on the receipt of UI benefits than are available in other data sources, these data preclude a detailed analysis of UI utilization within single nonemployment episodes. Specifically, the YNLS provides reliable calendar year information on the total number of weeks a youth received UI payments, the average weekly benefit amount over the year and the months in which benefits were received. However, this annual information is insufficient to determine what occurs within each nonemployment spell, unless an individual happens to experience only one nonemployment spell that starts and ends within the year. We can infer whether UI receipt takes place within spells, but not how much.

3. A Description of the Earnings and Employment Experiences of Youths

The imputation of UI benefits requires comprehensive earnings information on individuals during a 12-month horizon (termed a base period). Remarkably little is known about the patterns and volatility of labor market activities over such horizons. Current knowledge of these activities in the case of youths rests primarily on information from the Current Population Survey, the National Longitudinal Surveys of Young Men and of Young Women, and the National Longitudinal Survey of 1972 High School Seniors. These data essentially depict the earnings and employment activities of individuals either in the context of a short sequence of survey weeks or over a previous calendar year at a level of detail indicating the number of weeks worked, usual hours worked per week, and annual earnings. While such information conveys the broad outlines of annual experiences, it fails to capture much of the volatility that occurs within a year.

The YNLS provides a source for constructing a weekly history of both earnings and hours of work which one can use to summarize the patterns of these quantities over annual periods. The following discussion describes these work histories at decreasing levels of aggregation. In summarizing earnings experiences the analysis begins with annual measures, then considers characteristics of weekly earnings over the year, and finally examines the patterns of hourly earnings. The discussion next turns to the topic of employment experiences. This analysis begins by summarizing information about weeks worked and jobs held within a year, and it then takes up the topic of annual and weekly measures of hours worked.

3.1 *Sample Compositions and Descriptive Statistics*

The following discussion considers a variety of variables to characterize both the earnings and the employment experiences of youths within annual horizons, with the focus directed towards describing how these variables vary across and within age-education groups and over time. The 12-month horizons considered in this analysis correspond to the 6 calendar years 1979–1984. The samples used to describe each variable consist of all the observations on individuals in the YNLS for which data are available for the year considered.

The use of all available data means that different sample compositions are exploited depending on the particular variable and year analyzed. Appendix A describes these sample compositions in detail and reports the sample sizes associated with each composition for the years 1979–84 (i.e. see Section A.5 and Tables A.1). The least stringent sample selection criteria incorporate all individuals who are age 18 or more in March of the calendar year, not in the military and not in school at any time during the year, and with education of grade 8 or more. The more stringent criteria require individuals to work some time during the year and for there to be non-missing data for these individuals on a wide range of variables needed to infer earnings and employment experiences, with the most demanding data requirement involving the availability of wage rates for all jobs held during the year – recall that the YNLS does not supply wage information for intermittent jobs. In all, the analysis of this section relies on twelve distinct sample compositions to construct the various descriptions of youths' labor-market experiences.

There are two dimensions of interest for describing how the various measures of earnings and work activities vary among youths: the first involves a comparison across different education and age groups; and the second focuses on the time path of these measures. This analysis considers both of these dimensions. It does so by decomposing each measure into age-education and time effects using a simple regression framework.

In particular, let the variable y_{it} denote an observation associated with an earnings or hours-of-work measure for the i^{th} individual in year t. Consider the regression equation

$$y_{it} = \sum_{j=1}^{T} \theta_j \, d_{1j} + \sum_{k=1}^{K} \gamma_k \, d_{2k} + \text{ error,} \tag{3.1}$$

where $d_{1j} = 1$ if $t = j$ and $= 0$ otherwise, and $d_{2k} = 1$ if individual i is a member of age-education group k and $= 0$ otherwise; in other words, the d_{1j}'s are time dummies and the d_{2k}'s are age-education dummies. Impose the identification condition $\sum_{j=1}^{T} \theta_j = 0$, in which case the coefficient γ_k represents the average of y associated with age-education group k over the period 1 to $T (k = 1, \ldots, K)$, and the θ_j's represent the common deviation experienced by all groups in year $j \, (j = 1, \ldots T)$.

In the following empirical work the periods $1 \ldots T$ refer to the calendar years 1979, ..., 1984. The age-education categories considered below are: (1) ages 18–19, 20–22, 23–24, 25–27 for grades 8–11; (2) ages 18–19, 20–22, 23–24, 25–27 for grade 12; (3) ages 20–22, 23–24, 25–27 for grades 13–15; and (4) ages 23–24, 25–27 for grades 16 and above (i.e. 16+). The term grade here refers to the highest year of education completed by an individual. Tables A.1–M and A.1–W in Appendix A list respectively for men and women the sample sizes associated with these various age-education categories for each of the years and the alternative sample compositions.

3.2 *Measures of Annual Earnings*

Information from the YNLS permits the construction of two variables measuring the earnings of individuals over the period of a calendar year. These quantities are:

$$\begin{aligned} \text{ARE} &= \text{annual reported earnings;} \\ \text{ACE} &= \text{annual computed earnings.} \end{aligned}$$

The first variable corresponds to a CPS-type measure of annual earnings, which is a data item directly collected by the YNLS for each calendar year. One calculates the second variable by summing the weekly earnings received on all jobs held in those weeks making up the calendar year. The construction of ACE requires use of all the wage and employment history information provided by the YNLS, which involves a considerable amount of detail. Appendix A (Sections A.2, A.3 and A.5) describes the steps followed to create values of both ARE and ACE, along with the sample compositions associated with each variable.

Tables 3.1–M and 3.1–W present summary statistics describing the variation of these earnings measures across and within the various age-education categories and over time. The designator "M" attached to the numbering of a table indicates that the results refer to men, while the designator "W" signifies that the statistics refer to women. Each column of a table presents results for a variable listed at the top of the column. Moving down a column, three numbers appear in each box: the top number is the estimate of the coefficient γ_k from regression equation (3.1), with k identifying the age-education group listed along the corresponding row at the far left of the table and with the variable listed at the top of the column taken as the dependent variable y in the regression; and the two numbers reported below this estimate of γ_k represent the lower and the upper quartiles associated with all observations falling into the designated demographic group in all years. Thus, the top number gives the average for an age-education group, and the two lower numbers describe the dispersion within the group. The six numbers reported in the bottom rows of each column are the estimates of the θ_j's from regression (3.1), which capture the period effects occurring in each of the calendar years.

Tables 3.1–M and 3.1–W report statistics describing the variation in the annual earnings measures ARE and ACE. The second column of these tables, with the variable ARE_ listed at the top, presents results computed for the variable ARE using a sample composition which matches that used in constructing ACE. Because the calculation of ACE requires nonmissing data on a wide range of variables in the YNLS, the sample available for summarizing the properties of ACE is smaller than that available for characterizing ARE. The ACE sample excludes individuals who hold intermittent jobs at any time during the year – because wage data are unavailable for these jobs – so the earnings data for these persons do not go into the description of ACE. A comparison of the results in the first and second columns shows that the average values of ARE are higher in the sample used to construct ACE, which is consistent with the view that annual earnings are lower for individuals who hold intermittent jobs.

Three patterns emerge from the results in Tables 3.1. First, average annual earnings increase with age and education. Second, dispersion within demographic categories typically increases with age and education. Finally, average earnings generally declined over the period 1979–1984.

3.3 *Reliability of Earnings Measures*

In carrying out the empirical work on the effects of UI discussed in the later sections of this report, we infer UI entitlements of individuals using weekly data on earnings. This is the same sort of information that goes into the construction of ACE. Thus, assessing the accuracy of ACE as a measure of annual earnings provides some guidance as to the reliability of our imputations for UI benefits done below. The sample composition used below to impute UI benefits is much less restrictive than the ACE sample composition considered here because missing wage information is assigned where possible in constructing the samples containing imputed UI information to avoid deleting individuals who hold intermittent jobs in covered employment. (See Appendices A and B for further discussion of this issue.) In any case,

TABLE 3.1-M
Summary Statistics for Measures of Annual Earnings*
(1984 $)

VARIABLE		ARE ($1000)			ARE_ ($1,000)			ACE ($1,000)		
EDUC.	AGE									
8+	18-19	7.6	2.5	10.7	8.7	3.8	11.5	8.9	4.5	12.1
	20-22	10.2	4.0	14.0	11.2	5.4	14.6	11.6	5.9	15.2
	23-24	11.7	4.8	15.6	12.3	5.3	16.0	13.1	7.4	15.9
	25-27	13.4	4.2	15.8	14.3	5.0	16.7	14.8	5.8	18.1
12	18-19	10.0	5.1	13.8	10.5	5.8	14.1	11.2	6.8	14.3
	20-22	13.2	7.3	17.4	13.8	8.3	18.2	14.4	8.8	18.6
	23-24	16.5	9.7	20.8	17.1	10.3	21.1	17.7	10.8	20.8
	25-27	18.1	10.4	24.0	19.1	12.1	24.0	19.0	12.4	22.6
13+	20-22	14.4	8.5	18.3	14.7	9.4	18.8	15.1	10.1	19.3
	23-24	17.3	10.3	21.9	18.7	12.0	23.0	18.9	12.0	23.5
	25-27	18.7	10.8	23.5	19.2	10.6	23.2	19.0	11.0	24.4
16+	23-24	19.4	11.8	25.0	20.6	14.1	26.0	21.1	13.6	26.1
	25-27	23.8	14.6	30.3	25.4	16.0	31.2	25.7	16.5	30.5
Year Effects										
79	80		2.0	0.5		2.3	0.9		3.2	1.0
81	82		0.2	-0.7		0.1	-0.7		-0.1	-0.9
83	84		-1.2	-0.8		-1.6	-1.0		-1.9	-1.3

* For education-age groups, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

TABLE 3.1-W
Summary Statistics for Measures of Annual Earnings*
(1984 $)

VARIABLE		ARE ($1000)			ARE_ ($1,000)			ACE ($1,000)	
EDUC.	AGE		3.9			4.5			4.7	
8+	18-19	1.0		5.7	1.1		7.1	1.2		7.4
			5.0			5.4			5.9	
	20-22	1.3		7.8	1.4		8.3	1.8		9.0
			6.3			6.8			6.9	
	23-24	1.6		9.6	2.0		9.9	2.3		10.0
			5.6			5.8			6.2	
	25-27	1.3		9.3	1.4		9.7	1.5		9.5
			6.9			7.4			7.8	
12	18-19	2.9		10.0	3.7		10.3	3.8		10.7
			8.1			8.8			9.0	
	20-22	3.6		11.4	4.8		11.8	5.0		12.1
			8.7			9.2			9.5	
	23-24	3.6		12.1	4.3		12.5	4.8		12.7
			9.5			10.0			10.2	
	25-27	4.0		13.5	5.0		13.7	4.8		13.8
			9.7			10.3			10.7	
13+	20-22	5.4		12.9	6.6		13.6	6.8		14.0
			10.8			11.0			11.6	
	23-24	6.2		15.0	6.7		15.0	6.3		15.2
			11.4			11.8			12.1	
	25-27	6.9		15.0	7.4		15.5	6.9		15.9
			13.6			14.4			14.5	
16+	23-24	9.2		17.0	9.6		17.9	9.6		18.1
			14.9			15.4			15.2	
	25-27	9.3		19.2	9.7		20.0	8.9		20.2
Year Effects										
79	80	0.4		0.2	0.7		0.4	0.8		0.6
81	82	0.0		-0.4	-0.1		-0.6	-0.0		-0.6
83	84	-0.3		-0.0	-0.3		-0.1	-0.5		-0.3

* For education-age groups, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

while the sample composition exploited in the current analysis of ACE differs somewhat from that used in the subsequent study of UI benefits, evaluating the degree of measurement error contaminating ACE for the samples considered here provides a valuable source of evidence for judging the reasonableness of our subsequent imputations of UI entitlements.

A comparison of the variables ARE and ACE offers a simple approach for assessing the relative accuracies for these quantities as measures of annual earnings. Inspection of columns 2 and 3 of Tables 3.1 reveals a great deal of agreement in the averages and the dispersions implied by these two variables for similar sample compositions.

A more sophisticated approach for detecting the extent of measurement error in the variables ARE and ACE involves the implementation of a multiple indicator model. Suppose that both ARE and ACE are imperfect indicators of "true annual earnings", denoted by the variable TE. Following a classical errors-in-the-variable framework, assume that the two observed earnings quantities ARE and ACE relate to the unobserved quantity TE via the relationships:

$$\begin{aligned} \ell n\,\mathrm{ARE} &= b + lnTE + \epsilon_r \\ \ell n\,\mathrm{ACE} &= -b + lnTE + \epsilon_c, \end{aligned} \tag{3.2}$$

where the coefficient b is an intercept, and ϵ_r and ϵ_c are mutually independent measurement error terms which are distributed independently of the natural log of true earnings and which possess zero means and variances equal to σ_r^2 and σ_c^2 respectively. Accordingly, the total variances of the two observed earnings variables decompose as: $\sigma^2_{\mathrm{ARE}} = \sigma^2_{TE} + \sigma^2_r$ and $\sigma^2_{\mathrm{ACE}} = \sigma^2_{TE} + \sigma^2_c$, where the symbols σ^2_{ARE}, σ^2_{ACE}, and σ^2_{TE} denote the variances of the quantities ℓn ARE, ℓn ACE, and $\ell n\, TE$ respectively. The parameters σ_r^2 and σ_c^2 determine the dispersion of measurement error in the two annual earnings variables, with a larger σ_r^2 (σ_c^2) signifying more noise in ARE (ACE). The expected values of the various earnings quantities relate to one another according to the relation $E(\ell nTE) = [E(\ell n\,\mathrm{ARE}) + E(\ell n\,\mathrm{ACE})]/2$.

Use of a single cross-section of data on ARE and ACE – i.e. given a sample of observations on ARE_i and ACE_i for individuals $i = 1, \ldots, N$ for a specific calendar year – provides sufficient information to estimate the parameters σ_r^2, σ_c^2, σ^2_{TE}, b and $E(\ell nTE)$. In particular, one can estimate the first and second moments of ℓn ARE and ℓn ACE from the cross-section data and then develop estimates of structural parameters exploiting the relationships:

$$(3.3)\qquad \begin{aligned} \sigma_r^2 &= \sigma_{\text{ARE}}^2 - \text{cov}\ (\ell n\, \text{ARE},\ \ell n\, \text{ACE}) \\ \sigma_c^2 &= \sigma_{\text{ACE}}^2 - \text{cov}\ (\ell n\, \text{ARE},\ \ell n\, \text{ACE}) \\ \sigma_{TE}^2 &= \text{cov}\ (\ell n\, \text{ARE},\ \ell n\, \text{ACE}) \\ b &= [E(\ell n\, \text{ARE}) - E(\ell n\, \text{ACE})]/2 \\ E(\ell n TE) &= [E(\ell n\, \text{ARE}) + E(\ell n\, \text{ACE})]/2. \end{aligned}$$

MaCurdy (1985) describes the details of the estimation procedure applied in this analysis both to calculate parameter estimates and to compute the standard errors associated with these estimates.

Tables 3.2–M and 3.2–W report estimated values for the variances of measurement error obtained for six cross-sections corresponding to the calendar years 1979–1984, along with a set of pooled estimates that combines the data for all years. The designation "M" in the table title signifies results for men, and "W" indicates estimates for women. Each cross-section sample composition includes individuals for which both ARE and ACE are nonmissing and nonzero. Rows 1 and 2 present estimates and standard errors for the parameters σ_r^2 and σ_c^2, and rows 3 and 4 show the fraction of total variance attributable to measurement error for the two earnings variables.

These empirical findings generally support two conclusions. First, the extent of measurement error is less of a problem for ACE than it is for ARE; σ_c^2 accounts for a smaller proportion of σ_{ACE}^2 than σ_r^2 contributes to σ_{ARE}^2. Second, the amount of measurement error contaminating ACE is tiny except in the year 1979, when it is still small. Such evidence lends some confidence to the view that computed weekly earnings data provides an accurate picture of individuals' earnings experiences over the period of a year.

Cameron and MaCurdy (1988) provide a more sophisticated discussion of these findings, along with richer statistical specifications to detect the magnitude and the properties of measurement error in the two annual earnings variables ARE and ACE. This more exhaustive empirical study exploits the panel feature of the YNLS to relax several of the restrictions of model (3.2) and to examine the autocorrelation characteristics of measurement error as well. In addition, this analysis considers a variety of sample composition issues. While this

TABLE 3.2-M

Measurement Error Variance Estimates For Log Annual Earnings[a]

(standard errors in parentheses)

Parameter	1979	1980	1981	1982	1983	1984	Pooled
σ_r^2	.138	.274	.206	.136	.187	.198	.189
	(.037)	(.109)	(.039)	(.030)	(.034)	(.025)	(.018)
σ_c^2	.129	.022	.006	.054	.053	.016	.038
	(.053)	(.023)	(.024)	(.031)	(.027)	(.026)	(.012)
$\sigma_r^2/\sigma_{ARE}^2$	.274	.413	.232	.159	.215	.249	.234
$\sigma_c^2/\sigma_{ACE}^2$	.260	.054	.008	.070	.072	.026	.059

[a] Estimates based on Sample L described in Appendix A.

TABLE 3.2-W
Measurement Error Variance Estimates For Log Annual Earnings[a]

Parameter	1979	1980	1981	1982	1983	1984	Pooled
σ_r^2	.204	.134	.114	.167	.249	.150	.171
	(.046)	(.041)	(.025)	(.028)	(.035)	(.033)	(.014)
σ_c^2	.025	.147	.058	.047	-.008	.056	.048
	(.039)	(.077)	(.026)	(.025)	(.021)	(.042)	(.016)
$\sigma_r^2/\sigma_{ARE}^2$	.243	.182	.115	.138	.213	.140	.162
$\sigma_c^2/\sigma_{ACE}^2$	.038	.196	.062	.043	-.008	.057	.052

[a]Estimates based on sample L described in Appendix A.

other analysis indicates a number of qualifications that need to be kept in mind in evaluating the validity of the two main conclusions noted above, the main thrust of these conclusions survives.

3.4 *Characteristics of Weekly and Hourly Earnings*

The availability of weekly histories on earnings and hours of work supplied by the YNLS provides the opportunity to examine the pattern of a variety of dimensions characterizing youths' labor market experiences within annual periods, both across demographic groups and over time. The current sub-section exploits this information to explore the variation in various wage measures less aggregated than total annual earnings, while the following discussion investigates aspects of employment experiences.

Beginning with the topic of weekly earnings, there are three measures of average weekly wages that one can associate with an individual during a calendar year using data from the YNLS. For each week during a year, one can infer the variables:

$$\begin{aligned} WE_\ell &= \text{ weekly earnings from all jobs in week } \ell; \text{ and} \\ WH_\ell &= \text{ weekly hours from all jobs in week } \ell, \end{aligned}$$

with $\ell = 1, \ldots, 52$ signifying the length of a calendar year.[3] Upon calculating the quantity

$$AWW = \text{ annual weeks worked,}$$

one can compute the following three variables for each individual:

$$\begin{aligned} ARE/AWW &= \text{ weekly reported earnings;} \\ ACE/AWW &= \text{ weekly computed earnings; and} \\ AVE(WE) &= \sum_{\ell=1}^{52} WE_\ell/AWW. \end{aligned}$$

The first two quantities merely represent familiar measures obtained by dividing annual earnings by weeks worked. The latter quantity denotes a simple average of an individual's weekly earnings over a year.

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[3] In constructing the annual measure ACE, we use the actual calendar year which involves slightly more than 52 weeks. See Appendix A for further discussion.

Table 3.3–M for men and Table 3.3–W for women present summary statistics describing the variation in the three measures of average weekly earnings across persons of various age-education categories over the calendar years 1979–1984. These tables, and the remaining ones presented in this sub-section, have exactly the same structure as Tables 3.1. The top of each column lists the variable to which the numbers refer, and the three estimated values in each box represent the coefficient estimate θ_j of regression model (3.1) (the top number) along with the 25th and 75th percentiles associated with observations in the relevant demographic category (the lower two numbers). The six numbers reported at the bottom of each column are the estimated year effects γ_k associated with regression model (3.1).

Comparing summary statistics for the alternative measures of average weekly earnings listed in the first three columns of Tables 3.3 reveals general agreement among the results associated with these measures. For the older and more educated groups, the findings are quite similar. For the younger and less educated categories, there is tendency for the hourly reported earnings to indicate slightly lower weekly wages than the other two measures. In light of the results presented in Tables 3.1, this lower tendency no doubt partially reflects differences in the sample compositions used to compile the statistics in the various columns. These findings are consistent with the view that the younger and less educated individuals with intermittent jobs – whose earnings observations are not included in the statistics describing the measures ACE/AWW and $AVE(WE)$ – tend to have lower weekly earnings than their counterparts. The estimates for year effects reported in the bottom rows of the table indicate that weekly earnings declined over the period 1979–1984.

In addition to these various averages, Tables 3.3 also present results to capture the extent to which a person's own weekly wage varies within a calendar year. Define Max(WE) and Min(WE) as the maximum value and the minimum value, respectively, of WE_ℓ over weeks $\ell = 1, \ldots, 52$ for which both WE_ℓ and WH_ℓ have nonzero and nonmissing values. Form the quantities:

$$RR(WE) = \ell n\ (\text{Max}(WE)/\text{Min}(WE)) = \text{Max}(\ell nWE) - \text{Min}(\ell nWE);\ \text{and}$$

$$AR(WE) = \text{Max}(WE) - \text{Min}(WE).$$

The measure RR captures the notion of a "relative range" (or percentage difference) for the variable WE over the year, and AR represents an "absolute range" for WE. As in the case

TABLE 3.3-M
Summary Statistics for Measures of Weekly Earnings *
(1984 $)

VARIABLE Educ	Age	ARE/AWW $ mean	ARE/AWW 25%	ARE/AWW 75%	ACE/AWW $ mean	ACE/AWW 25%	ACE/AWW 75%	AVE(WE) $ mean	AVE(WE) 25%	AVE(WE) 75%	RR(WE) mean	RR(WE) 25%	RR(WE) 75%	AR(WE) $ mean	AR(WE) 25%	AR(WE) 75%
8+	18-19	210	110	264	229	160	280	229	154	274	0.37	0.00	0.49	75	0	104
	20-22	246	140	303	270	178	320	263	174	314	0.31	0.00	0.43	79	0	100
	23-24	274	146	331	292	182	342	298	181	348	0.29	0.02	0.40	87	3	89
	25-27	333	158	372	343	189	379	325	186	375	0.29	0.00	0.51	105	0	120
12	18-19	226	139	285	247	170	299	249	167	300	0.41	0.02	0.56	88	4	127
	20-22	290	178	361	307	204	373	298	197	364	0.31	0.03	0.42	84	8	108
	23-24	350	218	418	368	243	426	359	231	417	0.26	0.02	0.31	92	7	97
	25-27	384	239	461	397	258	448	392	251	442	0.21	0.02	0.29	84	5	102
13+	20-22	310	198	373	316	228	379	311	221	377	0.34	0.06	0.48	93	17	125
	23-24	360	226	436	380	243	461	364	233	442	0.30	0.06	0.39	103	15	117
	25-27	389	223	469	387	227	480	390	229	496	0.25	0.04	0.29	96	10	106
16+	23-24	392	261	484	419	288	503	403	269	497	0.32	0.07	0.43	100	20	135
	25-27	473	292	591	505	333	584	493	319	578	0.27	0.03	0.29	118	10	116

Year/Effects		ARE/AWW		ACE/AWW		AVE(WE)		RR(WE)		AR(WE)	
79	80	37	12	58	18	48	19	-0.00	-0.04	19	-2
81	82	2	-8	-1	-12	0	12	0.02	-0.02	4	-11
83	84	-21	-21	-22	-35	-28	-27	0.00	0.04	-10	-1

* For education-age groups, upper entry is the mean and lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

TABLE 3.3-W
Summary Statistics for Measures of Weekly Earnings[a]
(1984 $)

VARIABLE		ARE/AWW $			ACE/AWW $			AVE(WE) $			RR(WE)			AR(WE) $		
Educ	Age															
8	18-19	127	72	171	147	101	184	146	104	185	0.27	0.00	0.35	38	0	50
	20-22	148	78	189	166	111	202	167	109	201	0.25	0.00	0.31	37	0	48
	23-24	169	82	207	183	107	217	178	96	217	0.27	0.00	0.34	47	0	52
	25-27	162	93	209	183	95	228	185	98	235	0.34	0.00	0.47	49	0	74
12	18-19	163	101	208	179	130	220	173	126	214	0.35	0.02	0.45	53	3	70
	20-22	188	116	240	200	146	244	195	141	241	0.27	0.00	0.32	47	1	59
	23-24	202	113	251	212	144	258	208	134	254	0.26	0.00	0.30	44	0	54
	25-27	217	115	276	224	140	274	219	129	272	0.22	0.00	0.33	39	0	53
13+	20-22	209	140	268	225	167	272	220	162	269	0.30	0.04	0.36	55	9	69
	23-24	236	161	301	246	174	297	245	166	293	0.25	0.02	0.27	54	5	62
	25-27	257	169	324	265	182	326	277	182	323	0.26	0.04	0.38	59	7	79
16+	23-24	287	209	350	301	227	367	295	219	349	0.32	0.05	0.43	79	11	107
	25-27	323	234	394	321	213	403	318	213	395	0.30	0.05	0.30	62	12	77
Year Effects																
79	80		13.3	5.5		17.2	10.6		18	12		-0.02	-0.02		1	0
81	82		2.6	-6.8		1.3	-8.7		1	-8		-0.00	-0.00		1	-3
83	84		-8.5	-6.0		-10.4	-10.0		-11	-11		0.02	0.04		-0	2

[a] For education-age groups, upper entry is the mean and lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

of the averages discussed above, one can calculate a value for RR and AR for each individual in each calendar year and use these data as dependent variables in regression model (3.1).

The fourth and the fifth columns of Tables 3.3–M and 3.3–W report the findings associated with these variables. According to these results, individuals experience large variation in weekly earnings within calendar years. Percentage changes (i.e. RR) average about 30 percent, with a quarter of individuals experiencing around 40 percent or more. Estimates for absolute ranges (i.e. AR) indicate average changes of about $100 (in 1984 dollars) in weekly wages, with a quarter of individuals experiencing changes of about $10 to $20 above the averages.

One can construct a set of measures for hourly earnings that are completely analogous to those formulated above for weekly earnings. Given the quantities

$$AH = \sum_{\ell=1}^{52} WH_\ell = \text{ annual hours at all jobs}$$

and

$$AH\_ = \text{ annual hours at all jobs for which wage data are nonmissing,}$$

the three measures of a person's average hourly wages earned over a year are:

$$ARE/AH = \text{ hourly reported earnings;}$$

$$ACE/AH\_ = \text{ hourly computed earnings; and}$$

$$AVE\,(WE/WH) = \left[\sum_{\ell=1}^{52} WE_\ell/WH_\ell\right] /AWW = \text{ the average of hourly earnings for those weeks in which a person works,}$$

where in the calculation of this average, $WE_\ell/WH_\ell = 0$ when either $WE_\ell = 0$ or $WH_\ell = 0$. Also similar to the range variables introduced above, one can calculate:

$$RR\,(WE/WH) = \ell n\ (\text{Max}(WE/WH)) - \ell n(\text{Min}(WE/WH)); \text{ and}$$

$$AR\,(WE/WH) = \text{Max}(WE/WH) - \text{Min}(WE/WH).$$

Respectively, these variables capture the relative and the absolute ranges of an individual's hourly wages earned within the year.

Tables 3.4–M and 3.4–W present summary statistics for the five variables formed above to characterize the hourly earnings of youths. The first three columns report findings for

Table 3.4-M
Summary Statistics for Measures of Hourly Earnings*
(1984 $)

EDUC	AGE	ARE/AH (cents) Mean	ARE/AH 25%	ARE/AH 75%	ACE/AH_ (cents) Mean	ACE/AH 25%	ACE/AH 75%	AVE(WE/WH) (cents) Mean	AVE 25%	AVE 75%	RR(WE/WH) Mean	RR 25%	RR 75%	AR(WE/WH) (cents) Mean	AR 25%	AR 75%
8+	18-19	520	289	626	552	403	618	558	403	615	0.29	0.00	0.38	154	0	194
	20-22	612	343	721	628	430	715	632	431	721	0.25	0.00	0.34	151	0	190
	23-24	654	342	790	695	433	799	699	434	806	0.27	0.02	0.35	178	10	194
	25-27	721	383	792	719	435	764	724	436	785	0.25	0.00	0.31	201	0	215
12	18-19	556	354	673	595	426	714	598	425	716	0.29	0.03	0.39	160	8	215
	20-22	692	427	859	700	473	853	702	474	82	0.24	0.03	0.33	163	15	208
	23-24	803	494	964	812	535	942	816	535	951	0.22	0.02	0.27	169	16	193
	25-27	877	555	1093	895	592	1043	904	591	1048	0.19	0.02	0.24	164	12	184
13+	20-22	728	440	863	721	511	840	720	510	829	0.28	0.07	0.37	188	43	229
	23-24	827	527	1002	838	557	1025	841	556	1026	0.27	0.05	0.36	223	27	257
	25-27	917	506	1078	928	553	1082	929	554	1084	0.22	0.02	0.25	207	19	208
16+	23-24	902	601	1134	902	601	1108	929	610	1118	0.29	0.06	0.31	228	40	285
	25-27	1098	682	1334	1135	729	1349	1122	729	1361	0.25	0.05	0.31	255	54	291

Year Effects		ARE/AH		ACE/AH_		AVE(WE/WH)		RR(WE/WH)		AR(WE/WH)	
79	80	93	28	101	51	106	49	0.02	-0.01	49	6
81	82	7	-21	7	-21	4	-21	0.01	-0.01	6	-23
83	84	-42	-65	-66	-72	-66	-72	-0.02	0.2	-26	-12

* For education-age groups, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

Table 3.4-W
Summary Statistics for Measures of Hourly Earnings*
(1984 $)

EDUC	AGE	ARE/AH (cents) mean	ARE/AH 25%	ARE/AH 75%	ACE/AH_ (cents) mean	ACE/AH_ 25%	ACE/AH_ 75%	AVE(WE/WH) (cents) mean	AVE(WE/WH) 25%	AVE(WE/WH) 75%	RR(WE/WH) mean	RR(WE/WH) 25%	RR(WE/WH) 75%	AR(WE/WH) (cents) mean	AR(WE/WH) 25%	AR(WE/WH) 75%
8+	18-19	387	232	477	421	356	501	423	357	501	0.18	0.00	0.22	69	0	95
	20-22	428	245	480	466	358	533	470	357	534	0.16	0.00	0.21	77	0	96
	23-24	465	267	538	485	356	548	487	352	549	0.19	0.00	0.23	91	0	106
	25-27	497	258	541	533	363	584	532	364	585	0.17	0.00	0.31	88	0	149
12	18-19	450	309	544	471	384	551	473	385	549	0.24	0.01	0.28	109	5	139
	20-22	511	343	613	526	397	613	530	400	617	0.21	0.00	0.26	105	0	130
	23-24	566	356	673	566	398	662	568	400	660	0.20	0.00	0.24	104	0	123
	25-27	592	346	702	595	412	691	598	412	688	0.15	0.00	0.22	88	0	115
13+	20-22	544	397	668	575	438	655	576	439	659	0.22	0.03	0.28	116	15	148
	23-24	639	419	778	640	457	770	641	456	770	0.21	0.02	0.26	118	12	150
	25-27	693	420	832	715	480	878	719	478	875	0.19	0.05	0.26	120	25	150
16+	23-24	747	521	887	751	551	911	755	550	915	0.28	0.04	0.36	192	24	242
	25-27	868	565	1015	826	522	967	829	517	974	0.26	0.03	0.24	147	23	180

Year Effects

		ARE/AH		ACE/AH_		AVE(WE/WH)		RR(WE/WH)		AR(WE/WH)	
79	80	48.3	15.8	42.2	29.6	44	30	-0.01	-0.01	5	-1
81	82	-5.0	-2.0	.6	-16.1	1	-16	-0.01	-0.01	4	-5
83	84	-24.2	-32.9	-25.1	-31.2	-26	-32	0.00	0.03	-4	2

* For education-age groups, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

averages, and the fourth and the fifth columns list results for the two range measures. These statistics outline essentially the same picture as that portrayed by the result for weekly earnings presented in Tables 3.3. This is true for the pattern of both the average and the ranges of hourly earnings across age-education groups, as well as the profiles over time.

3.5 *Characteristics of Employment Activities*

There are a wide variety of variables that one can infer from the weekly work histories of the YNLS to describe the employment activities of youths during calendar years. The above discussion of earnings already introduced several of these variables, and this analysis formulates a few additional quantities to provide a richer characterization of work experience.

Tables 3.5–M and 3.5–W report summary statistics for quantities capturing the fraction of a year that individuals work and the number of jobs that they hold during the year. The first column presents results for the quantity

$$DAEMP = \text{dummy variable for whether an individual is employed at any time during the year } (DAEMP = 1 \text{ signifies employment})\,.$$

This variable, of course, characterizes annual employment rates. The second column of Tables 3.5 reports statistics for the number of weeks worked per year, (AWW), and the third column lists estimates for the variable

$$AEMPS = \text{ number of employers over the year.}$$

$AEMPS$ does not capture the extent to which individuals hold multiple jobs at the same time because a person can work for different employers at distinct times during the year. To provide measures of the extent of simultaneous job holding, the fourth, fifth and sixth columns of these tables present statistics for the variables:

$$ADMJ = \text{ dummy variables signifying whether an individual holds multiple jobs in any week during the year } (ADMJ = 1 \text{ indicates simultaneous jobs});$$

$$AWMJ = \text{ number of weeks associated with multiple jobs; and}$$

$$AWMJ/AWW = \text{ fraction of total weeks worked in which multiple jobs were held.}$$

TABLE 3.5-M
Summary Statistics for Weeks Worked and Jobs Per Year[a]

EDUC.	AGE	DAEMP	AWW mean	AWW 25%	AWW 75%	AEMPS mean	AEMPS 25%	AEMPS 75%	ADMJ	AWMJ mean	AWMJ 25%	AWMJ 75%	AWJ/AWW mean	AWJ/AWW 25%	AWJ/AWW 75%
8+	18-19	89.0	36	22	51	1.9	1.0	2.0	8.9	13	4	19	34	12	58
	20-22	91.1	39	29	52	1.6	1.0	2.0	8.1	13	4	19	30	10	44
	23-24	91.9	42	34	52	1.6	1.0	2.0	9.3	17	5	33	37	11	75
	25-27	91.3	40	32	52	1.6	1.0	2.0	5.9	29	10	42	58	40	79
12	18-19	96.4	43	38	52	1.7	1.0	2.0	14.9	22	7	40	43	13	77
	20-22	97.7	45	43	52	1.6	1.0	2.0	13.3	22	7	40	43	14	77
	23-24	97.7	46	45	52	1.5	1.0	2.0	13.8	24	8	41	47	19	79
	25-27	97.0	47	47	52	1.4	1.0	2.0	11.7	27	13	45	55	24	88
13+	20-22	99.0	46	46	52	1.7	1.0	2.0	15.4	19	6	33	37	12	61
	23-24	99.9	48	49	52	1.7	1.0	2.0	15.5	22	5	49	44	13	92
	25-27	99.9	47	46	52	1.5	1.0	2.0	14.0	20	6	38	42	18	73
16+	23-24	97.8	49	50	52	1.6	1.0	2.0	16.6	24	9	44	47	17	84
	25-27	98.7	50	52	52	1.4	1.0	2.0	17.5	23	9	42	44	18	80

Year	Effects	DAEMP	DAEMP	AWW	AWW	AEMPS	AEMPS	ADMJ	ADMJ	AWMJ	AWMJ	AWJ/AWW	AWJ/AWW
79	80	3.1	0.4	2	0	0.1	-0.1	-0.2	-3.1	-4	0	-8	-0
81	82	0.1	-1.5	-0	-1	-0.0	-0.1	-0.1	-0.0	-1	2	-2	3
83	84	-2.1	0.1	-1	0	-0.0	0.1	1.4	2.9	2	1	5	2

a For education-age group, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

TABLE 3.5-W
Summary Statistics for Weeks Worked and Jobs Per Year*

VARIABLE		DAEMP	AWW			AEMPS			ADMJ	AWMJ			AWJ/AWW		
EDUC.	AGE														
8+	18-19	64.6	28	13	45	1.7	1.0	2.0	7.6	12	4	15	30	12	43
	20-22	62.4	31	15	50	1.5	1.0	2.0	7.5	13	4	19	29	8	44
	23-24	54.9	34	18	52	1.5	1.0	2.0	10.2	16	6	23	39	13	63
	25-27	52.4	31	15	50	1.3	1.0	1.0	3.9	14	3	30	29	5	59
12	18-19	90.3	41	33	52	1.7	1.0	2.0	13.4	15	5	21	31	11	46
	20-22	84.2	41	33	52	1.5	1.0	2.0	11.5	19	6	28	40	13	65
	23-24	80.5	41	34	52	1.4	1.0	2.0	10.9	19	7	30	41	19	65
	25-27	77.2	42	35	52	1.3	1.0	2.0	8.6	24	11	42	50	24	83
13+	20-22	91.9	45	42	52	1.6	1.0	2.0	18.2	19	7	27	41	13	61
	23-24	91.5	44	42	52	1.4	1.0	2.0	12.9	25	9	46	48	17	94
	25-27	88.1	44	42	52	1.4	1.0	2.0	13.4	19	8	29	40	18	59
16+	23-24	98.0	47	45	52	1.6	1.0	2.0	17.5	17	6	26	33	12	50
	25-27	92.6	46	43	52	1.4	1.0	2.0	19.6	23	9	42	45	19	78

Year	Effects	DAEMP		AWW		AEMPS		ADMJ		AWMJ		AWJ/AWW	
79	80	0.2	0.0	0	0	0.0	0.1	-1.8	-1.0	-2	-0	-5	-1
81	82	0.6	-1.1	-0	-1	-0.0	-0.1	-0.1	-0.0	-0	1	-1	3
83	84	-0.9	1.2	-0	1	0.0	0.0	1.9	1.0	2	-0	5	-1

* For education-age group, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

The results for the variable $ADMJ$ reported in Tables 3.5 are computed using all available data and individuals, whereas the results for the variables $AWMJ$ and AWJ/AWW refer to samples incorporating only those persons for which $ADMJ = 1$.

The findings in Tables 3.5 generally convey a picture of extensive annual employment participation and only a modest amount of simultaneous job holding. As one would predict, labor-market involvement is greater for men than for women; and it generally rises with age and education in the case of men, but follows a nonmonotonic relationship in the case of women.

Tables 3.6–M and 3.6–W describe the variation in annual and weekly hours of work across the various age-education categories and over time. The previous discussion defines all the variables appearing in these tables. Comparing the findings in the first and second columns reveals that wage data are missing for only 6% of annual hours (i.e. the average of *AH_* is roughly 0.94 times that of *AH*). However, as noted in Section A.5 of Appendix A, these missing wages affect over a quarter of the sample in any one year. In all of the subsequent work described in this report, missing wages are imputed, where possible, using the procedures outlined in Appendix A.

A more comprehensive examination of the full complement of results in these tables reveals a fairly wide dispersion in annual hours across the population, but a relatively narrow dispersion in average hours per week. The variables $AVE(WH)$, $RR(WH)$ and $AR(WH)$ are calculated only over those weeks in which an individual works. The measures of relative and absolute ranges suggest a large amount of person-specific variation in the number of hours that he or she works per week during times of employment in a year.

TABLE 3.6-M
Summary Statistics for Annual and Weekly Hours of Work*

VARIABLE		AH			AH_			AVE(WH)			AR(WH)			RR(WH)		
EDUC.	AGE															
8+	18-19		1515			1379			42			0.35			13	
		829		2088	638		2011	38		46	0.00		0.48	0		20
	20-21		1707			1603			42			0.24			10	
		1086		2124	955		2088	40		47	0.00		0.32	0		13
	23-24		1843			1746			43			0.24			9	
		1304		2294	1094		2180	40		48	0.00		0.32	0		12
	25-27		1843			1727			46			0.27			11	
		1174		2404	1025		2234	40		52	0.00		0.42	0		20
12	18-19		1812			1702			41			0.33			12	
		1400		2167	1270		2096	39		45	0.00		0.43	0		13
	20-22		1947			1849			43			0.26			10	
		1607		2282	1516		2188	40		46	0.00		0.32	0		13
	23-24		2078			1963			44			0.20			9	
		1771		2413	1626		2329	40		49	0.00		0.22	0		10
	25-27		2090			1989			44			0.15			7	
		1899		2374	1793		2312	40		48	0.00		0.21	0		10
13+	20-22		2033			1920			44			0.27			11	
		1723		2365	1523		2329	40		48	0.00		0.41	0		16
	23-24		2204			2028			45			0.25			11	
		1943		2476	1778		2312	40		49	0.00		0.32	0		15
	25-27		2083			1981			44			0.22			9	
		1843		2407	1679		2309	40		48	0.00		0.33	0		15
16+	23-24		2204			2117			45			0.23			9	
		1980		2545	1871		2482	40		50	0.00		0.26	0		10
Year	Effects															
79	80	88		6	61		18	1		-0	-0.02		-0.04	-0		-2
81	82	-29		-51	-13		-42	-0		-0	-0.02		-0.04	-0		-2
83	84	-62		47	-55		31	-0		1	0.03		0.05	1		2

* For education-age group, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

TABLE 3.6-W
Summary Statistics for Annual and Weekly Hours of Work*

VARIABLE: EDUC.	AGE	AH (mean)	AH (25%)	AH (75%)	AH_ (mean)	AH_ (25%)	AH_ (75%)	AVE(WH) (mean)	AVE(WH) (25%)	AVE(WH) (75%)	RR(WH) (mean)	RR(WH) (25%)	RR(WH) (75%)	AR(WH) (mean)	AR(WH) (25%)	AR(WH) (75%)
8+	18-19	1015	382	1608	913	277	1486	35	29	40	0.31	0.00	0.47	10	0	16
	20-21	1152	472	1834	1066	363	1768	35	30	40	0.28	0.00	0.36	8	0	13
	23-24	1269	560	2080	1187	380	2012	36	28	40	0.26	0.00	0.35	8	0	11
	25-27	1065	400	1755	987	288	1594	33	22	40	0.26	0.00	0.26	7	0	10
12	18-19	1500	945	2088	1423	804	2073	36	33	40	0.33	0.00	0.47	10	0	15
	20-22	1564	1044	2088	1495	922	2088	37	35	40	0.24	0.00	0.29	8	0	10
	23-24	1560	1043	2088	1487	919	2088	36	32	40	0.25	0.00	0.29	7	0	10
	25-27	1558	1000	2088	1465	840	2080	36	33	40	0.24	0.00	0.28	6	0	10
13+	20-22	1759	1432	2096	1646	1269	2088	39	36	41	0.28	0.00	0.30	9	0	11
	23-24	1743	1422	2088	1660	1288	2088	38	35	40	0.22	0.00	0.22	7	0	9
	25-27	1717	1253	2088	1619	1224	2083	38	35	41	0.25	0.00	0.34	7	0	14
16+	23-24	1894	1577	2182	1811	1480	2088	40	38	44	0.30	0.00	0.41	10	0	15
	25-27	1840	1436	2302	1745	1203	2088	39	37	45	0.19	0.00	0.27	6	0	10

Year Effects		AH		AH_		AVE(WH)		RR(WH)		AR(WH)	
79	80	13.4	13.6	9.1	7.8	0	-0	-0.04	0.01	-1	-0
81	82	1.1	-46.9	10.1	-39.1	0	-1	-0.00	-0.01	-0	-0
83	84	18.3	37.1	-29.5	41.6	-0	0	0.03	0.01	1	1

* For education-age group, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

4. UI Eligibility and Use Among Young Workers

A major source of controversy in the literature about the influence of UI policies on the amount of unemployment experienced by youths in the U.S. turns on the issue of the extent to which youths participate in the UI system. Whereas many empirical studies suggest that both the level of weekly UI benefits and the duration of these benefits exert a significant effect on the extent of unemployment,[4] other studies argue that UI programs play only a minor role in youth unemployment because most young people are ineligible for compensation from these programs.[5]

This section presents an array of measures designed to describe UI coverage and UI utilization among young workers during the years 1979–84. The analysis relies on the work history data described in the previous section to impute UI eligibility and benefits and combines the information with data provided by the YNLS on UI collection over the year to calculate the measures developed below. The discussion constructs measures considering several period lengths as the relevant time frame and viewing both nonemployment and unemployment as the pertinent base for calculating eligibility and usage of UI.

4.1 *Measures of Eligibility*

Considering a period covering one year, there are several ways of measuring the eligibility of an individual for UI compensation. In particular, one can designate a person as eligible for UI if he or she is not working sometime during the year and this individual is qualified to collect UI benefits. Such a classification scheme suggests the measure

$$E/N = \frac{\#\ \text{eligible}}{\#\ \text{nonemployed}} \tag{4.1}$$

where the quantity "# eligible" designates the number of individuals who are deemed qualified for UI compensation at sometime during the year, and the quantity "# nonemployed" represents the number of individuals who are not employed during some part of the year. (Of course, # eligible is necessarily a subset of # nonemployed; so E/N ranges between zero and one.)

[4] Examples of such studies include Feldstein (1978), Hammermesh (1977), Topel and Welch (1980), Ehrenberg and Oaxaca (1976), Newton and Rosen (1979), Moffitt and Nicholson (1982), and Clark and Summers (1982a).

[5] See, for example, Feldstein and Ellwood (1982) and Clark and Summers (1979).

Suppose that one wishes to calibrate this measure to weight individuals according to the fraction of nonemployment time during the year that they were qualified for UI compensation. A second measure incorporating such a calibration is

$$
(4.2) \qquad \begin{aligned} we/wn &= \frac{\#\text{ weeks eligible}}{\#\text{ weeks nonemployed}} \\ WE/WN &= Ave\,\{we/wn\} \end{aligned}
$$

where the quantity "# weeks eligible" gives the number of weeks during a year in which a person is eligible for UI benefits, the quantity "# weeks nonemployed" designates the number of weeks that this person spent not working during the year, and the notation $Ave\,\{\cdot\}$ denotes the average of the variable in brackets computed over individuals making up a sample.

Instead of considering nonemployment as the relevant frame of reference as is presumed by the above measures, suppose that one views unemployment status as the proper reference perspective for assessing the extent of eligibility. Modifying the measure E/N to reflect this adjustment yields a third measure given by

$$
(4.3) \qquad E/U = \frac{\#\text{ eligible}}{\#\text{ unemployed}}
$$

where the quantity "# unemployed" represents the number of individuals who are classified as unemployed at sometime during the year. (Note that "# eligible" need not be a subset of "# unemployed", so E/U can in principle go above one in value.) Similarly, an analogous modification of WE/WN yields a fourth measure given by

$$
(4.4) \qquad \begin{aligned} we/wu &= \frac{\#\text{ weeks eligible}}{\#\text{ weeks unemployed}} \\ WE/WU &= Ave\,\{we/wu\} \end{aligned}
$$

where the quantity "# weeks unemployed" denotes the number of weeks that an individual reports as being unemployed during the year.

The variables WE/WN and WE/WU correspond to average point-in-time measures of eligibility, while the variables E/N and E/U reflect notions of eligibility over a period lasting a year. Assuming a random sample of individuals and a stationary environment, (4.2) and (4.4) give proxies for the kind of eligibility measures derived from CPS-type information concerning weekly status: WE/WN corresponds to the ratio of the number of persons eligible for UI in a survey week over the number not working; and WE/WU measures the ratio of the number of eligible persons in a survey week over the number reported as unemployed. The variables E/N and E/U have analogous interpretations if one adjusts the period of observation from a survey week to a survey year.

4.2 *Measures of Utilization*

Considering a period covering one year, there are several quantities describing the extent to which individuals eligible for UI compensation draw on their available benefits. A direct translation of the concept introduced above yields the following two measures:

$$R/E = \frac{\#\text{ recipients}}{\#\text{ eligible}} \tag{4.5}$$

and

$$\begin{aligned} wr/we &= \frac{\#\text{ weeks receipt}}{\#\text{ weeks eligible}} \\ WR/WE &= Ave\,\{wr/we\} \end{aligned} \tag{4.6}$$

where the quantity "# recipients" designates the number of individuals who collect UI benefits during the year, and the quantity "# weeks receipt" represents the number of weeks during the year in which UI recipients draw benefits. (Both R/E and WR/WE must lie between zero and one because a person cannot collect benefits unless he or she is eligible for compensation). Whereas the variable R/E corresponds to an annual utilization measure of UI programs, the variable WR/WE reflects a point-in-time measure of use.

The most popular statistic cited to describe the degree of UI utilization is the ratio of insured unemployment over total unemployment, which implicitly takes all those who are unemployed as the relevant frame of reference for calculating usage. A measure based on this statistic is

$$\begin{aligned} wr/wu &= \frac{\#\text{ weeks receipt}}{\#\text{ weeks unemployed}} \\ WR/WU &= Ave\,\{wr/wu\}. \end{aligned} \tag{4.7}$$

This quantity represents an annualized average of a point-in-time measure of usage.

A measure comparable to WR/WU takes time spent nonemployed rather than time spent unemployed as the appropriate reference for guaging the extent of UI utilization. This quantity is

$$wr/wr = \frac{\text{\# weeks receipt}}{\text{\# weeks nonemployed}} \tag{4.8}$$
$$WR/WN = Ave\,\{wr/wu\},$$

which provides another measure of an annualized average of point-in-time usage.

A fifth concept of utilization summarizes the fraction of the dollar amounts of UI entitlements that are actually collected during the year by eligible individuals. A measure capturing this concept is given by

$$ar/ae = \frac{\text{\$ amount received}}{\text{\$ amount eligible}} \tag{4.9}$$
$$AR/AE = Ave\,\{ar/ae\}$$

where the quantity "$ amount received" denotes the number of dollars an individual collects in UI benefits during the year, and the quantity "$ amount eligible" designates the maximum dollar amount of UI compensation that the individual could have collected had he or she drawn benefits during all weeks of eligibility in the year.

4.3 *A Data Set Integrating UI Eligibility and Utilization*

To calculate the various measures discussed above, the following analysis uses a sample created by more stringent selection criteria than are invoked to carry out the empirical study of Section 3. The sample considered here consists of 3028 individuals drawn from the nationally-representative component of 6,111 youths in the YNLS who met the following five conditions: (1) interviewed in each of the first 7 years; (2) worked at least once since January 1979; (3) have valid beginning and ending dates for time periods spent employed, between jobs and in the military; (4) left school and did not return prior to the 1985 interview date; and (5) have a reasonably accurate and complete time series of weekly earnings beginning with January 1978 or the last date of school attendance. As noted previously, the YNLS does not provide wage data for secondary jobs of short duration or which involve only part-time hours of work. For jobs falling into this category determined to be in covered employment, the analysis assigns wages using a procedure described in Appendix A to avoid having to delete observations from the sample. The resulting data set includes 1409 men and 1619 women who experience 4031 and 4250 episodes of nonemployment respectively over the period 1979–85. Section 6.1 presents summary statistics describing this data set in detail.

For each calendar year, the YNLS provides not only comprehensive information on work histories as described in Section 3, but also reliable data on the total number of weeks that a youth receives UI payments during the year along with the average weekly benefit amount over this period. Combining an individual's weekly earnings history in covered employment with data on his or her State of residency and the UI benefit rules of that State in the relevant year, one can infer this person's UI eligibility and available benefits during times of nonemployment and unemployment. These constructed data provide the sample used below to calculate measures of UI eligibility. Integrating these data and the information on time and amounts of UI collection during the calendar year create the sample exploited below to carry out the analysis on UI utilization.

Appendix B outlines our procedure for inferring each individual's UI entitlements during periods of nonemployment. As discussed in this appendix, our imputation of available UI benefits yields remarkable accurate predictions of the average weekly benefit amounts that are self-reported by UI recipients in the YNLS. The differences in our imputed values and the values reported in the YNLS averages about \$2, with lower and upper quartiles of −\$11 and \$20. Our assessment of UI eligibility and of total benefits available from UI compensation also appear to match well with data provided in the YNLS on the total number of weeks a youth receives UI payments over the year and the months in which benefits were collected.

For determining UI eligibility, the YNLS offers two options for defining job separations due to quits as a disqualification for benefits. Major reasons for disqualification from UI benefit receipt are voluntary separations without good cause, discharge for mis-conduct, refusal of suitable work and unemployment resulting from direct involvement in an organized labor stoppage. Unfortunately, the current literature has interpreted the provision for voluntarily leaving work without good cause to mean that all "quitters" are ineligible to receive UI benefits. While such provisions are often ambiguously phrased, the majority of states do not disqualify individuals who quit for reasons related to the employment relationship. A large number of states allow an individual to collect benefits if he or she quit to accept "better" work or join the armed forces. Thus, in practice this provision usually disqualifies only those individuals who quit for personal reasons.[6] To examine the sensitivity of results to alternative interpretations of voluntary separation provisions in deciding an individual's eligibility for UI, the following analysis considers two definitions of eligibility: a narrow concept that presumes all persons who quit their previous job are ineligible for compensation, and a broader definition that disqualifies individuals only if they quit for personal reasons.

4.4 *Patterns of UI Eligibility*

There are two dimensions of interest for calculating the various measures of UI eligibility and of UI use: the first involves a comparison across different education and age groups; and the second focuses on the time path of these measures. This analysis considers both of these dimensions. It does so by decomposing each measure into age-education and time effects using regression framework (3.1) introduced in Section 3.1, with the dependent variable y_{it} denoting an observation associated with an eligibility or utilization measure for the i^{th} individual in year t.[7] As previously, the coefficient γ_k represents the average of y associated with age-education group k over the period 1 to T, and the θ_j's represent the common deviation experienced by all groups in year $j\,(j = 1, \ldots, T)$. The age-education categories considered below are the same as those analyzed in Section 3, as are the calendar years.

Tables 4.1 and 4.2 present values for the four measures of UI eligibility, with the averages calculated using estimates of the regression coefficients of equation (3.1). The tables designated by "M" provide results for men, while those marked by "W" report findings for women. Tables 4.1–M and 4.1–W present estimates of the coefficients γ_k, which characterize averages for the various age-education groups. Tables 4.2–M and 4.2–W list estimates of the coefficients $\theta_j + \gamma_k$ for $j = 1979, \ldots, 1984$ with k designating 25 year-old high school graduates, which describes changes over time using the 25–27 age category of high school

[6] A casual survey of the data on benefit determination cases suggests that only 15–20 percent of new insured unemployment spells come to a determination over separation from work issues and only 30–40 percent of the cases that come to determination are denied because of voluntary separation from work.

[7] For the measures E/N, E/U and R/E, y_{it} is an indicator variable that takes the value of one when individual i is a member of the groups making up the numerator and the denominator and takes the value of zero if this individual is a member of only the denominator group. In the case of the other measures, such as WE/WN, $y_{it} = we/wn$ where the variable we/wn is the observation for individual i in year t.

TABLE 4.1-M

Measures of Unemployment Insurance Eligibility by Age-Education Categories

Catagory		Broad Definition of Eligiblity Measure				Narrow Definition of Eligibility Measure			
Education	Age	E/N	WE/WN	E/U	WE/WU	E/N	WE/WN	E/U	WE/WU
8-11	18-19	0.413	0.325	0.446	0.642	0.256	0.175	0.307	0.335
	20-22	0.532	0.421	0.594	0.743	0.394	0.284	0.447	0.449
	23-24	0.656	0.526	0.732	0.753	0.547	0.405	0.625	0.577
	25-27	0.533	0.427	0.602	0.651	0.397	0.279	0.489	0.433
12	18-19	0.486	0.419	0.601	0.910	0.287	0.219	0.399	0.416
	20-22	0.596	0.495	0.694	0.787	0.475	0.369	0.600	0.608
	23-24	0.659	0.553	0.785	0.819	0.541	0.436	0.663	0.631
	25-27	0.689	0.583	0.785	0.832	0.547	0.440	0.671	0.632
13-15	20-22	0.480	0.413	0.581	1.213	0.301	0.243	0.411	0.622
	23-24	0.520	0.468	0.663	1.229	0.313	0.256	0.433	0.635
	25-27	0.607	0.559	0.748	0.880	0.416	0.338	0.585	0.532
16	23-24	0.492	0.472	0.750	1.242	0.325	0.281	0.490	0.559
	25-27	0.685	0.609	0.870	0.881	0.343	0.287	0.350	0.299

TABLE 4.1-W

Measures of Unemployment Insurance Eligibility by Age-Education Categories

Catagory		Broad Definition of Eligiblity Measure				Narrow Definition of Eligibility Measure			
Education	Age	E/N	WE/WN	E/U	WE/WU	E/N	WE/WN	E/U	WE/WU
8-11	18-19	0.243	0.179	0.303	0.835	0.118	0.076	0.157	0.321
	20-22	0.311	0.205	0.449	0.823	0.158	0.105	0.253	0.376
	23-24	0.283	0.223	0.379	0.777	0.147	0.113	0.236	0.380
	25-27	0.291	0.199	0.323	0.633	0.130	0.089	0.207	0.278
12	18-19	0.397	0.329	0.457	0.904	0.195	0.149	0.263	0.410
	20-22	0.360	0.275	0.484	1.184	0.193	0.137	0.285	0.439
	23-24	0.311	0.231	0.481	0.887	0.154	0.114	0.289	0.431
	25-27	0.344	0.243	0.560	1.102	0.197	0.132	0.387	0.694
13-15	20-22	0.319	0.274	0.421	1.132	0.120	0.103	0.196	0.259
	23-24	0.364	0.299	0.492	0.894	0.126	0.103	0.206	0.253
	25-27	0.292	0.218	0.465	0.763	0.112	0.082	0.215	0.310
16	23-24	0.435	0.340	0.514	0.724	0.218	0.165	0.213	0.365
	25-27	0.459	0.407	0.655	2.655	0.361	0.321	0.511	2.236

TABLE 4.2-M

Measures of Unemployment Insurance Eligibility by Year

(Measured as deviations from the mean for a 25 year old with 12 years of education)

Year	Broad Definition of Eligiblity				Narrow Definition of Eligibility			
	Measure				Measure			
	E/N	WE/WN	E/U	WE/WU	E/N	WE/WN	E/U	WE/WU
1979	0.803	0.722	0.919	0.956	0.603	0.500	0.776	0.696
1980	0.829	0.724	0.947	1.082	0.645	0.518	0.790	0.744
1981	0.807	0.682	0.904	1.096	0.591	0.477	0.702	0.695
1982	0.751	0.637	0.835	0.866	0.597	0.478	0.709	0.659
1983	0.569	0.430	0.652	0.599	0.487	0.376	0.590	0.572
1984	0.375	0.302	0.453	0.394	0.359	0.292	0.459	0.425
Average	0.689	0.583	0.785	0.832	0.547	0.440	0.671	0.632

TABLE 4.2-W

Measures of Unemployment Insurance Eligibility by Year

(Measured as deviations from the mean for a 25 year old with 12 years of education)

Year	Broad Definition of Eligiblity				Narrow Definition of Eligibility			
	Measure				Measure			
	E/N	WE/WN	E/U	WE/WU	E/N	WE/WN	E/U	WE/WU
1979	0.361	0.291	0.558	1.657	0.151	0.110	0.320	0.952
1980	0.401	0.287	0.674	1.263	0.212	0.142	0.427	0.681
1981	0.451	0.318	0.698	1.247	0.221	0.148	0.418	0.715
1982	0.430	0.316	0.666	1.283	0.253	0.175	0.459	0.712
1983	0.260	0.150	0.437	0.736	0.193	0.121	0.375	0.587
1984	0.160	0.097	0.326	0.425	0.152	0.094	0.324	0.517
Average	0.344	0.243	0.560	1.102	0.197	0.132	0.387	0.694

graduates as a reference group. Each table reports two sets of results to examine the implications of adopting the two different definitions of eligibility described above. The first set of four columns list estimates assuming the broader definition, which interprets all nonemployed individuals who did not quit their jobs for personal reasons and who meet earnings qualifications as eligible for UI benefits. The second set of four columns presents results presuming applicability of the narrower definition of eligibility, which assumes that all quitters (for personal reasons or not) are ineligible.

According to these findings, the definition of eligibility matters with respect to one's assessment of the extent to which youths are eligible for UI benefits. The broader definition, which does not exclude all quitters, typically implies 50 to 100 percent greater eligibility over the narrow definition. There is no systematic relationship between annual and comparable point-in-time measures of eligibility.

Certain patterns emerge regardless of the definition or measure used to quantify eligibility. In the case of men, eligibility increases with both age and education. The same is true for women with respect to education, but not with regard to age. As expected, eligibility is more extensive for men than for women. For men, the results for time effects indicate that eligibility generally declined over the period 1979–1984, dramatically so for the broad definition of eligibility. The time trends are either less prominent or nonexistent for women.

4.5 *Patterns of UI Use*

Tables 4.3 and 4.4 report analogous estimates for the five measures of UI utilization. Tables 4.3–M and 4.3–W present values associated with age-education categories. Tables 4.4–M and 4.4–W list estimates for the time effects, with 25 year-old high school graduates serving as the reference group. Once again each table provides two sets of results according to the definitions used to determine eligibility. The measures considered in the first two columns of each table are not dependent on the definition of eligibility.

The first column of each table presents findings for that measure of utilization corresponding to the fraction of insured unemployment. Inspection of these results reveals that this rate rises with age in the case of men, but does not necessarily increase as men acquire more education. This same pattern holds in the case of women except for the lowest educa-

TABLE 4.3-M

Measures of Unemployment Insurance Utilization by Age-Education Categories

Catagory		Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
				Measure			Measure		
Education	Age	WR/WU	WR/WN	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
8-11	18-19	0.076	0.050	0.181	0.137	0.129	0.276	0.216	0.204
	20-22	0.202	0.119	0.246	0.193	0.188	0.294	0.239	0.233
	23-24	0.353	0.255	0.430	0.348	0.339	0.481	0.397	0.389
	25-27	0.311	0.202	0.553	0.452	0.447	0.579	0.483	0.478
12	18-19	0.281	0.132	0.306	0.228	0.220	0.467	0.374	0.361
	20-22	0.359	0.230	0.477	0.388	0.363	0.541	0.448	0.423
	23-24	0.456	0.322	0.594	0.482	0.470	0.652	0.547	0.534
	25-27	0.874	0.379	0.654	0.561	0.536	0.726	0.635	0.607
13-15	20-22	0.146	0.090	0.198	0.165	0.144	0.294	0.250	0.218
	23-24	0.249	0.165	0.319	0.280	0.262	0.454	0.431	0.402
	25-27	0.288	0.195	0.323	0.267	0.241	0.459	0.408	0.374
16	23-24	0.169	0.090	0.182	0.187	0.190	0.262	0.271	0.274
	25-27	0.694	0.247	0.346	0.359	0.352	0.408	0.428	0.433

graduates as a reference group. Each table reports two sets of results to examine the implications of adopting the two different definitions of eligibility described above. The first set of four columns list estimates assuming the broader definition, which interprets all nonemployed individuals who did not quit their jobs for personal reasons and who meet earnings qualifications as eligible for UI benefits. The second set of four columns presents results presuming applicability of the narrower definition of eligibility, which assumes that all quitters (for personal reasons or not) are ineligible.

According to these findings, the definition of eligibility matters with respect to one's assessment of the extent to which youths are eligible for UI benefits. The broader definition, which does not exclude all quitters, typically implies 50 to 100 percent greater eligibility over the narrow definition. There is no systematic relationship between annual and comparable point-in-time measures of eligibility.

Certain patterns emerge regardless of the definition or measure used to quantify eligibility. In the case of men, eligibility increases with both age and education. The same is true for women with respect to education, but not with regard to age. As expected, eligibility is more extensive for men than for women. For men, the results for time effects indicate that eligibility generally declined over the period 1979–1984, dramatically so for the broad definition of eligibility. The time trends are either less prominent or nonexistent for women.

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Tables 4.3 and 4.4 report analogous estimates for the five measures of UI utilization. Tables 4.3–M and 4.3–W present values associated with age-education categories. Tables 4.4–M and 4.4–W list estimates for the time effects, with 25 year-old high school graduates serving as the reference group. Once again each table provides two sets of results according to the definitions used to determine eligibility. The measures considered in the first two columns of each table are not dependent on the definition of eligibility.

The first column of each table presents findings for that measure of utilization corresponding to the fraction of insured unemployment. Inspection of these results reveals that this rate rises with age in the case of men, but does not necessarily increase as men acquire more education. This same pattern holds in the case of women except for the lowest educa-

TABLE 4.3-M

Measures of Unemployment Insurance Utilization by Age-Education Categories

Catagory		Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
				Measure			Measure		
Education	Age	WR/WU	WR/WN	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
8-11	18-19	0.076	0.050	0.181	0.137	0.129	0.276	0.216	0.204
	20-22	0.202	0.119	0.246	0.193	0.188	0.294	0.239	0.233
	23-24	0.353	0.255	0.430	0.348	0.339	0.481	0.397	0.389
	25-27	0.311	0.202	0.553	0.452	0.447	0.579	0.483	0.478
12	18-19	0.281	0.132	0.306	0.228	0.220	0.467	0.374	0.361
	20-22	0.359	0.230	0.477	0.388	0.363	0.541	0.448	0.423
	23-24	0.456	0.322	0.594	0.482	0.470	0.652	0.547	0.534
	25-27	0.874	0.379	0.654	0.561	0.536	0.726	0.635	0.607
13-15	20-22	0.146	0.090	0.198	0.165	0.144	0.294	0.250	0.218
	23-24	0.249	0.165	0.319	0.280	0.262	0.454	0.431	0.402
	25-27	0.288	0.195	0.323	0.267	0.241	0.459	0.408	0.374
16	23-24	0.169	0.090	0.182	0.187	0.190	0.262	0.271	0.274
	25-27	0.694	0.247	0.346	0.359	0.352	0.408	0.428	0.433

TABLE 4.3-W

Measures of Unemployment Insurance Utilization by Age-Education Categories

Catagory		Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
				Measure			Measure		
Education	Age	WR/WU	WR/WN	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
8-11	18-19	0.103	0.043	0.247	0.177	0.175	0.399	0.307	0.298
	20-22	0.233	0.055	0.239	0.184	0.184	0.386	0.301	0.302
	23-24	0.209	0.079	0.421	0.370	0.347	0.642	0.593	0.558
	25-27	0.104	0.023	0.095	0.010	0.008	0.225	0.099	0.089
12	18-19	0.163	0.073	0.249	0.182	0.166	0.400	0.302	0.275
	20-22	0.334	0.106	0.328	0.262	0.243	0.527	0.440	0.412
	23-24	0.364	0.103	0.403	0.324	0.308	0.603	0.501	0.491
	25-27	0.750	0.114	0.476	0.361	0.346	0.686	0.531	0.510
13-15	20-22	0.077	0.030	0.149	0.118	0.103	0.264	0.228	0.220
	23-24	0.317	0.066	0.197	0.162	0.149	0.481	0.402	0.375
	25-27	0.463	0.063	0.113	0.100	0.090	0.356	0.316	0.293
16	23-24	0.208	0.055	0.098	0.064	0.068	0.044	0.050	0.055
	25-27	0.257	0.065	0.137	0.060	0.074	0.192	0.116	0.137

TABLE 4.4-M

Measures of Unemployment Insurance Utilization by Year

(Measured as deviations from the mean for a 25 year old with 12 years of education)

Year	Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
			Measure			Measure		
	WR/WN	WR/WU	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
1979	0.366	0.855	0.595	0.509	0.492	0.677	0.597	0.579
1980	0.448	0.974	0.686	0.598	0.572	0.777	0.695	0.666
1981	0.376	0.875	0.609	0.525	0.500	0.677	0.600	0.572
1982	0.412	0.891	0.694	0.600	0.577	0.787	0.690	0.663
1983	0.366	0.835	0.675	0.591	0.562	0.738	0.649	0.615
1984	0.306	0.805	0.665	0.544	0.513	0.706	0.580	0.547
Average	0.379	0.874	0.654	0.561	0.536	0.727	0.635	0.607

TABLE 4.4-W

Measures of Unemployment Insurance Utilization by Year

(Measured as deviations from the mean for a 25 year old with 12 years of education)

Year	Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
			Measure			Measure		
	WR/WN	WR/WU	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
1979	0.094	0.711	0.372	0.268	0.266	0.633	0.488	0.483
1980	0.117	0.775	0.438	0.326	0.315	0.659	0.501	0.492
1981	0.109	0.744	0.432	0.316	0.302	0.683	0.512	0.492
1982	0.126	0.766	0.473	0.349	0.332	0.742	0.564	0.536
1983	0.124	0.806	0.526	0.428	0.399	0.698	0.581	0.546
1984	0.113	0.698	0.615	0.478	0.461	0.701	0.532	0.511
Average	0.114	0.750	0.476	0.361	0.346	0.686	0.531	0.510

tion group where there is no apparent relationship between the insured rate and age. Not surprisingly, women have lower rates than men.

Examining the other measures of utilization does not change the story for men in terms of the influence of demographic variables on UI use, but it does cloud the picture for women. For these other quantities, the positive relationship between age and utilization is now the exception rather than the rule.

According to the findings in Tables 4.4–M and 4.4–W, the nature of the time trends characterizing utilization depend on the measure choosen as a guide. For men, the fraction of insured unemployment follows a downward path starting in 1980, but the other measures accounting for eligibility based on either definition show essentially no trend. For women, on the other hand, there is no apparant time pattern conveyed by either the fraction of insured unemployment or the other measures of UI utilization based on the narrow definition of eligibility. However, the quantities based on the broad definition indicate a strong upward trend in UI utilization among women over the period covered.

4.6 *Comparison with Findings in the Literature*

Several recent studies provide a valuable context for interpreting and evaluating the results presented above. The studies of Burtless (1983), Burtless and Saks (1984), Corson and Nicholson (1988) and Blank and Card (1988) examine trends in insured, eligible and total unemployment covering the 1980's. While data limitations did not permit examination of all of the measures of eligibility and utilization analyzed here, these studies document a number of important patterns that serve as useful guides for identifying whether the experiences of youths are representative of the average unemployed worker.

The most frequently cited measure used to examine the utilization of the UI system is the proportion of the unemployed receiving regular UI benefits.[8] An examination of this measure over the last 50 years shows a general downward trend beginning in the early 1960's with a sharp downturn beginning in 1981. For example, during the 1940's and 1950's the

[8] This measure does not count individuals receiving extended benefits or workers covered under special UI programs as UI recipients. The special programs are the Unemployment Compensation for Federal Employees (UCFE), Unemployment Compensation for Ex-servicemember (UCX) and the Railroad Unemployment Insurance program. While individuals who file claims under the UCFE or UCX program must satisfy the same set of qualification requirements as other claimants, they are not eligible for regular UI.

ratio was approximately 0.50, it declined to 0.44 in the 1960's, fell to 0.40 over the 1970's, and during the 1980's it ranged from 0.44 in 1980 to 0.30 in 1984. While one can attribute the gradual decline throughout the 60's and 70's to variations in the demographic and industrial composition of the unemployed, the recent drop in the fraction of insured unemployment is somewhat unexplained. All the studies just cited associate at least half of the decline in the 1980's to unobserved changes either in the propensity of individuals to collect entitlements or in State administrative practices.

Another measure of UI utilization examined by Corson and Nicholson (1988) and Blank and Card (1988) is the ratio of the average weekly number of UI recipients under all programs to the total number of unemployed. This quantity displays a similar time pattern to the more restrictive measure above, except a slightly steeper decline is observed in the 1980's. Specifically, this ratio dropped from a value of 0.51 in 1980 to 0.34 in 1984 (Corson and Nicholson (1988) p. 9). Almost all of this drop-off appears to arise from changes in Federal policies relating to extended benefit programs and the reduction in the receipt of regular UI benefits.[9]

Blank and Card (1988) further examine the relationships between eligible unemployment and total or insured unemployment. One measure that Blank and Card investigate is the proportion of the unemployed eligible to receive UI benefits under all programs. Using earnings information from a previous year available in the March CPS to infer an unemployed individual's eligibility to receive UI, they find that the fraction of eligible unemployment remains roughly constant over the 1980's ranging from 0.50 in 1980 to 0.40 in 1984. Concerning the relationship between insured and eligible unemployment, Blank and Card explore the pattern of the take-up rate defined as the ratio of insured to eligible unemployment. Combining CPS data with administrative data on the number of UI recipients, they conclude that there was a significant decrease in the take-up rate over the 1980's.[10]

[9] In 1981 the U.S. Congress tightened the eligibility standards for extended benefits, eliminated the national insured unemployment rate trigger for extended benefits and increased the State trigger rate by 1 percent. In addition, the Federal Supplemental Benefit program that was enacted in response to the recession in 1982 was not as generous as the Federal Supplemental Compensation program enacted during the 1974–75 recession.

[10] Conversely, a sample of unemployment spells from the Panel Study of Income Dynamics analyzed by Blank and Card show increasing take-up rates from 1980 through 1982.

With regard to relating our findings on the patterns of UI utilization to those in the literature, there is considerable agreement. Comparing the aggregate trends presented in Corson and Nicholson (1988) and Blank and Card (1988) with our results reported in Tables 4.4 indicates that the experiences of young workers in the 1980's are fairly representative of the population at large. This is especially true for the measures based on administrative data. For example, comparing the measure WR/WU from Table 4.4–M with the fraction of insured unemployment under all UI programs in Corson and Nicholson reveals striking similarities. While the magnitude of our utilization measure is significantly higher because it describes the behavior of what is essentially a young prime-age male, the time patterns are almost identical. From 1980 to 1984 both the aggregate measure and our value declined by 17 basis points i.e., 0.51 to 0.34 and 0.974 to 0.805 respectively.

On the other hand, our findings based on imputed measures of UI eligibility convey different patterns than those put forward in other work. Specifically, Blank and Card find decreasing take-up rates and relatively constant measures of the fraction of eligible unemployment, while the WR/WE and WE/WU measures in Tables 4.4 and 4.2 exhibit just the opposite patterns. Further research is needed to reconcile these disparities.

5. A General Estimation Approach

This section considers several issues relevant in designing an empirical model that enables one to measure the influence of UI policies on the duration of unemployment. The following analysis not only provides a basis for the subsequent empirical work, it also offers a useful framework for integrating and evaluating other empirical findings in the literature.

5.1 *Alternative Estimation Schemes*

To characterize the various procedures for analyzing the amount of unemployment experienced by individuals over some time horizon, the discussion below relies on the following definitions:

$$
\begin{aligned}
U =&\ \text{weeks of unemployment;}\\
R =&\ (B, T) = \text{ UI policy regime;}\\
B =&\ \text{rules of a UI program that define individuals' UI entitlements;}\\
T =&\ \text{rules of a UI program that determine the taxation scheme used}\\
&\quad\quad \text{to finance the program;}\\
E =&\ \text{UI entitlement variables;}\\
H =&\ \text{work history;}\\
\delta =&\ \text{indicator of UI receipt;}\\
Z =&\ \text{demographic characteristics;}\\
M =&\ \text{macroeconomic variables;}\\
PA =&\ \text{population attributes consisting of elements in } H,\ Z \text{ and } M; \text{ and}\\
f(w|X) =&\ \text{density or probability function of the variables } w\\
&\quad\quad \text{conditioning on the variables } X.
\end{aligned}
\tag{5.1}
$$

Attaching a subscript "i" to a variable designates the i^{th} observation of this variable. An observation refers to a variety of potential occurrences of unemployment. Thus, one may specify U_i to measure the number of weeks of unemployment that occurs in a spell of unemployment, or the total number of weeks of unemployment occuring within either a nonemployment spell or some fixed time interval. The variable R_i designates the rules of the UI program applicable when U_i occurs. The T component of R encompasses such features as the experience-ratings relevant for firms in making their contributions into the UI system, and the B component of R determines the values of E assigned to individuals according to their work experiences H. The variables E_i include the weekly benefit amount and the number of weeks of UI eligibility that an individual qualifies for who experiences U_i. The attributes H_i summarize various dimensions of the individual's past work experience when U_i occurs. The indicator variable δ_i equals 1 if the individual experiencing U_i collects UI benefits and equals 0 otherwise. The variables Z_i provide information on the demographic characteristics of the person at the time of U_i, and M_i incorporates variables capturing exogenous macroeconomic determinants of unemployment durations.

Knowledge of the distribution $f(U|R,\ PA)$ for a judicious choice of the conditioning variables PA provides the principal information needed to assess the consequences of changing aspects of UI programs on the extent and the composition of unemployment. Inclusion of the variables Z among the covariantes PA specifies a distribution for a particular demographic group; inclusion of H in PA determines a distribution for various worker types; and incorporating M in PA admits adjustments for macroeconomic conditions. Fitting the distribution $f(U|R,\ PA)$ determines how U varies as one alters policy instruments incorporated in R for a population characterized by the attributes making up the covariates PA.

Estimating $f(U|R,\ PA)$ is not an easy task for two reasons. First, there is no simple way to quantify R. Programs differ quite substantially in their rules for determining individuals' weekly benefits and weeks of eligibility, and these rules are not readily summarized by a set of explanatory variables that vary along some continuous spectrum. Second, estimating the effects of R on the distribution of unemployment requires one to hold a population's composition constant as one varies the value of R. The primary source of variation in R arises from differences in UI policies across states. Recognizing that the characteristics of states' populations also differ, one typically encounters a situation in which shifts in the policy parameters R occur simultaneously with changes in population composition. Not accounting for these composition changes results in invalid inferences about the influence of R. As a consequence of the difficulties involved in obtaining a direct estimate of $f(U|R,\ PA)$, empirical research on the effects of UI on unemployment utilizes other estimation approaches.

Specifically, this research tends to focus on estimating some variant of the distributions: $f(U|\delta = 1, E, PA)$, $f(U|\delta, PA)$, and $f(U|E, PA)$. Studies analyzing program data from State UI offices (e.g. Moffitt (1985), Meyer (1988), Katz and Meyer (1988a, 1988b)) estimate a specification of $f(U|\delta = 1, E, PA)$, which corresponds to the distribution describing the duration of unemployment for a UI recipient who qualifies for UI entitlements E and who comes from a population and an environment characterized by the attributes PA — in such analyses U measures number of weeks of UI receipt. Studies using survey data from such sources as the CPS, PSID or NLS estimate variants of $f(U|\delta, PA)$ and $f(U|E, PA)$. Empirical analyses comparing the hazard rates of UI recipients and non-UI recipients (e.g. Katz (1986) and Katz and Meyer (1988b)) in essence explore differences in the distribution $f(U|\delta, PA)$ when $\delta = 1$ and $\delta = 0$. Other work concerned with predicting the effects of UI entitlements on unemployment (e.g., Clark and Summers (1982a) and Topel (1983, 1985)) rely on some specification of $f(U|E, PA)$ as the basis for their estimation.

5.2 *Assessing the Influence of UI on Unemployment*

A key question that has gone unanswered in the literature concerns what can be learned about the distribution $f(U|R, PA)$ from estimated variants of the densities $f(U|\delta = 1, E, PA)$, $f(U|\delta, PA)$ and $f(U|E, PA)$. In particular, if one finds that higher UI entitlements E imply a shift in these distributions of U indicating greater unemployment, can one conclude, as is typically done in the literature, that a more generous UI policy regime will lead to more unemployment? The answer to this question is no unless one incorporates the appropriate measures of work history variables H to serve as controls among the covariates PA.

To ensure that estimated effects associated with UI entitlement variables have the interpretation typically given to them in the literature, the variation in E admitted in empirical specifications must reflect purely differences in policy regimes. While UI programs differ quite substantially in terms of the rules they apply to determine benefits, all programs define benefits using information on only a few aspects of a person's recent work history. As outlined in Section 2.1, these aspects include such items as base period earnings (BPE), high quarter earnings (HQE), average weekly earnings (AWE), the circumstances under which employment terminated (e.g. quit, fire, etc.), and whether previous employment was covered by the UI system. Incorporating these items among the work history variables H, there essentially exists a functional relationship linking H and a UI policy regime R to UI entitlements E. In particular, one can specify functions of the form

$$E = \Phi(H, M, R) = \Phi(H, M, B), \tag{5.2}$$

which show how a person's UI weekly benefit amount and weeks of eligibility are assigned given this individual's past work experiences and the rules of the UI program. The inclusion of the macroeconomic variables M as arguments of the function Φ accounts for the fact that some program features such as extended benefits depend on the levels of state unemployment rates. The second expression for Φ given in (5.2) recognizes that only the B component of R determines the entitlements of a system.

In estimation, the only source of variation in E of interest for drawing inferences about the influence of UI policies operates through the regime variables R or B. Inspection of the functions Φ highlight the point that E varies across observations in a sample not only due to shifts in R, but also as a consequence of differences in the work histories of individuals and possibly due to changes in values of M either across states or over time. If one incorporates the group of work history and macroeconomic variables included in H and M appearing in (5.2) as elements of the conditioning variables PA in the distributions $f(U|\delta, E, PA)$ or $f(U|E, PA)$, then all variation in E may be attributed to differences in the generosity of UI systems. Under such circumstances, one can interpret estimated effects associated with entitlements as reflecting responses to varying the characteristics of UI policy. These policy shifts arise as the consequence of considering individuals covered by different state programs or as the result of changes in UI policy over time.

The importance of including work history variables among the covariates to obtain reliable estimates of entitlement effects has long been recognized in the empirical literature on UI and unemployment. Surveys of this topic (e.g. Welch (1977), Hamermesh (1977) and Danziger, Haverman and Plotnick (1981)) discuss a variety of possible biases that might be present as a consequence of not capturing the appropriate source of variation in the variables E. However, while virtually all empirical studies account for some measure of H in their analyses, none of which we are aware includes the specification of controls needed in theory to purge E of variability other than that due to shifts in R.

One finds a variety of work history variables incorporated in empirical analyses of UI effects. The most popular choice for H consists of a single measure of an individual's average weekly earnings (AWE). Researchers typically enter AWE through some representation of a "wage replacement ratio", and quite often AWE is introduced in an after-tax form to capture the notion of opportunity cost more accurately. All UI systems use many work history variables in addition to AWE to determine benefits. Consequently, a specification of H consisting of only AWE is incomplete. The use of an after-tax form of AWE is likely to introduce even more serious sources of bias in estimation because UI benefits are based on the before-tax values of AWE rather than on after-tax quantities. It is not uncommon to find empirical studies incorporating many work history variables other than AWE in their analysis – including such quantities as base period or high quarter earnings which actually go into the determination of entitlements – but we know of no attempt to account for the full complement of variables and interactions needed to characterize the benefit structure of UI programs. Without accounting for this structure, UI entitlement and receipt variables E and δ in part perform the task of identifying worker types, with higher values of E and δ signifying those types who experience more unemployment. Such an occurrence in principle leads to incorrect inferences about the role of these variables as determinants of unemployment. Of course, the inclusion of only a subset of the relevant work history variables may be sufficient to avoid any serious biases in estimation.

5.3 *Measuring the Impact of Shifts in UI Policy*

Predicting comprehensive effects of UI policies on unemployment requires some formulation of the distribution $f(U|R, PA)$. As noted above, the direct estimation of this quantity involves a number of complications. A more attractive approach for constructing $f(U|R, PA)$ consists of combining information on estimated variants of $f(U|\delta, E, PA)$, and $f(\delta|E, PA)$, which represent the types of distributions analyzed in the literature. The distribution $f(U|\delta, E, PA)$ indicates the extent to which unemployment differs across UI and non-UI recipient populations according to levels of UI entitlements. The divergence between

$f(U|\delta = 1, E, PA)$ and $f(U|\delta = 0, E, PA)$ offers a measure of the shift in unemployment attributable to participation in UI programs. The second distribution $f(\delta|E, PA)$ determines the probability that individuals characterized by attributes PA become UI recipients when facing values of entitlements equal to E. Even if the difference in unemployment between UI and non-UI recipients is small, a modification in a UI program could have a large effect if it results in a big adjustment in the probability of UI participation.

Developing the relationship that enables one to construct $f(U|R, PA)$ from these other distributions requires several steps. According to familiar results in statistics,

$$f(U|R, PA) = \sum_{\delta, E} f(U|\delta, E, R, PA)\, f(\delta|E, R, PA)\, f(E|R, PA). \tag{5.3}$$

The summation sign used here assumes that all distributions are discrete — if they were continuous an integral sign would be used instead — with the summations carried out over the admissible range of the variables δ and E. The right-hand-side of formula (5.3) merely represents the joint distribution of the variables U, δ and E conditional on R and PA, with all the variables other than U integrated out.

A substantial simplification occurs in this representation of $f(U|R, PA)$ if one fully exploits the linkage relating entitlements, work history and policy regimes conveyed by the functions (5.2). According to these functions, as long as one includes sufficient information in H, the functional relationship linking E, H, M and B given by (5.2) means that knowledge of E and H eliminates the need to know B. This observation allows one to simplify or to avoid estimating the distributions appearing in formula (5.3). With respect to the first two distributions, one obtains

$$\begin{aligned} f(U|\delta, E, R, PA) &= f(U|\delta, E, T, PA) \\ f(\delta|E, R, PA) &= f(\delta|E, T, PA). \end{aligned} \tag{5.4}$$

One can eliminate B as conditioning variables because E, H and M implicitly summarize all the essential information in B. The ability to ignore B in specifying these distributions substantially reduces the problem of estimating them because one need not tackle the difficult task of quantifying B. Concerning the third distribution, $f(E|R, PA)$, appearing in formula (5.3), there is not even a need to estimate this quantity. Knowledge of H and R determines

E exactly. Alternatively, one can express this result as

$$(5.5) \qquad f(E|R,\ PA) = \Phi(H,\ M,\ R)$$

where the function Φ is given by (5.2).

Combining these results, provides the relationship that permits construction of $f(U|R,\ PA)$ from distributions that are more readily analyzed in empirical work. Substituting (5.4)–(5.5) into (5.3) yields

$$(5.6) \qquad f(U|R,\ PA) = \sum_{\delta,\ E} f(U|\delta,\ E,\ T,\ PA)\ f(\delta|E,\ T,\ PA)\ \Phi(H,\ M,\ R).$$

One can estimate specifications of the distributions $f(U|\delta,\ E,\ T,\ PA)$ and $f(\delta|E,\ T,\ PA)$ using micro data. The functions Φ are known depending on the UI policy under consideration. Formula (5.6) shows how to combine these quantities to compute an estimate of $f(U|R,\ PA)$.

5.4 *An Alternative Formulation*

When the variable U measures the accumulative number of weeks of unemployment that occur over some period of time – which is the type of measure analyzed in the subsequent empirical work – it is not convenient for estimation purposes to work directly with a parameterization of the distribution $f(U|\delta,\ E,\ T,\ PA)$ appearing in formula (5.6). If one presumes that a standard duration model describes spells of unemployment and spells in other labor market activities as well, then the implied specification for distribution of U (i.e., of total weeks of unemployment over a time horizon) is quite complex.

To avoid such complexities in developing a specification for the distribution $f(U|\delta,\ E,\ T,\ PA)$, an attractive alternative involves decomposing U into two components and specifying the distributions for these separate components. In particular, define $U = \rho\ell$ where ℓ = the length of the relevant time horizon over which total nonemployment is measured, and ρ = the fraction of ℓ classified as unemployment. From the two conditional distributions $f(\ell|\delta,\ E,\ T,\ PA)$ and $f(\rho|\ell,\ \delta,\ E,\ T,\ PA)$, one can infer the distribution associated with U via the formula

$$(5.7) \qquad f(U|\delta,\ E,\ T,\ PA) = \sum_{\ell=1}^{\infty} \sum_{\rho=U/\ell} f(\rho|\ell,\ \delta,\ E,\ T,\ PA)\ f(\ell|\delta,\ E,\ T,\ PA).$$

The quantity $f(\ell|\delta, E, T, PA)$ represents a conventional duration distribution that describes the spell length ℓ; and we refer to $f(\rho|\ell, \delta, E, T, PA)$ as a time-proportion distribution because it characterizes the portion of a duration ℓ spent in a particular status.