LOOKING AHEAD:

YOUNG MEN, WAGE GROWTH AND LABOR MARKET PARTICIPATION

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Abstract: Despite the current economic boom, employment among young men is lower today than it was in the late 1960s. This decline has been largely driven by a 17 percentage point reduction in the proportion of young high school dropouts working even a single week per year. One common explanation for this trend, declining real wages, ignores the fact that the value of working today depends on future returns to experience, particularly for young workers. Since both wage levels and returns to experience have varied considerably over time and have different policy implications, this paper examines their relative importance. Specifically, I estimate a model of labor supply with returns to experience as an explanatory variable using data on cohorts of young workers from the Current Population Survey. For young people, the classic myopic labor supply model (in which only the current wage matters) is rejected in favor of one that includes forward-looking considerations, embodied in returns to experience. For high school dropouts, decreasing returns to experience explain 30% of the decline in participation between 1967 and 1977. Changes in wages do not explain any of this trend. During the 1980s, declining wages result in an under-prediction in the annual participation of college graduates. Rising wage growth rates explain the higher rates of participation.

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1 Introduction

Recent media attention has focused on the improving labor market opportunities for young people during this time of economic expansion (cf. Nasar and Mitchell, 1999). However, the present rate of employment among young men still lags far behind those attained during the late 1960s. As figure 1a indicates, the proportion of high school dropouts with one to five years of experience who worked at least one week in a given year declined 17 percentage points from 0.95 in 1967 to 0.78 in 1997.[1] While past studies have attributed the change to declining wage levels or factors affecting unearned income (cf. Juhn, 1993; Parsons, 1980; Welch, 1997), this paper argues that young men are forward-looking and take into consideration the opportunity for future wage growth as well as current wage levels in making their labor market choices. Making the distinction between these stories is important. The decline in participation represents a large loss in productive capacity and considerable resources are allocated toward increasing the labor market participation of young people through such mechanisms as training programs and the earned income tax credit. While these programs try to improve wage levels, they do not take wage growth into consideration and, as a result, they neglect an important work incentive.

The traditional static model of labor supply is based on the assumption that the current wage level is a sufficient statistic for the value of employment. Such a model ignores the fact that employment also provides work experience and concomitant wage growth. For young people, wage growth is particularly high and because they have a long time to benefit, returns to experience are likely to comprise a large part of the value of current employment. As wage growth changes, so too does the value of employment. For instance, in the early 1970s high school dropouts experienced real average wage growth of 8 percent a year over their first 10 years of labor market experience. By the early 1980s average wage growth for dropouts had declined to about 4 percent. At a starting wage of $10.00/hour this difference in wage growth means the difference between earning $18.00 an hour versus $14.00 an hour after 10 years of experience. This finding is in keeping with the research suggesting that the quality of jobs available to many workers has declined (cf. Bound and Freeman, 1992; Bluestone and Harrison 1986; Gittleman and Howell 1995). Whereas many of these studies focused on the level of

[1] Definitions of terms and a description of the data used will be discussed in the next section of the paper.

wages as the primary measure of job quality, we extend the definition to include wage growth potential.

Dynamic labor supply models which allow future wages to depend on past work experience (endogenous wage models) are not new to the literature.[2] Yet none of the studies examine whether changes in returns to work experience can explain observed trends in labor market participation. Few even explore the impact of changes in returns to experience on labor supply. An exception is Shaw (1989) who examines a human capital model of life-cycle labor supply among men. She finds that the interaction between past labor market experience and wages encourages college graduates to work more at the beginning of their lives. In a study comparing the early labor market experience of blacks and whites, Wolpin (1992) notes that if blacks had the wage distribution of white workers, including the higher returns to experience, the work experience of blacks would increase considerably. The findings of these studies are based on the same intuition that motivates this work, but the authors take a very different approach, estimating structural models and simulating results. Their work uses panel data and does not address the issue of how changes in returns to experience have affected labor supply over time.

This study examines the relationship between labor market participation, wage levels and wage growth among 31 cohorts of young workers who entered the labor market between 1967 and 1998. The model is estimated at the cohort level on data from the Current Population Survey using an error-in-variables technique. The model requires a measure of expected wage growth that is exogenous to worker behavior. For the primary analysis I use the return to experience estimated from a log wage regression which is linear in experience. The return to experience is allowed to vary by cohort and education group. This measure implicitly assumes that workers have perfect foresight of their average cohort/education group wage growth. To test the validity of this assumption I compare these results with several other measures of expected wage growth including lagged wage growth and cross-sectional wage growth. The initial assumption of perfect foresight with respect to cohort/education group wage growth fits the model well.

[2] Weiss (1986) provides a review of the theoretical literature. Early empirical estimation of such models includes Heckman (1976a and 1976b).

The findings support the hypothesis that young men do consider returns to experience when determining their labor supply. A 10 percent increase in wage growth rates increases the proportion of young men working at least one week in a year by 0.0064 percentage points, while the increase in annual hours conditional on positive employment is 25 hours. Although these effects may seem small, they are between one-third and one half as large as the effect of changes in wage levels. They become even more significant in light of the large variation in wage growth over the past 30 years. Declining wage growth among high school dropouts can explain about 34 percent of the decline in annual participation over the 1970s. This is a particularly important finding because models examining wages alone have been largely unable to explain the decline in participation in this period. For college workers, rising wage growth rates during the early 1980s explain their steady participation in the face of declining wage levels.

This work makes several contributions to the existing literature. First, it demonstrates empirically the importance of forward-looking considerations in the labor supply decisions of young men. Although this issue has received considerable theoretical attention, it is not often considered in applied research or public policy. Current policies aimed at increasing the labor market participation of young workers, particularly disadvantaged young workers, focus on training and the entry-level wage. These programs tend to ignore whether the jobs provide wage growth opportunities. Tax policies also ignore wage growth. The evidence presented here suggests that tax policies should also be reexamined in light of the finding that young men are concerned with wage growth. For instance the phase-out of the Earned Income Tax Credit attenuates wage growth, which can now be seen as a disincentive to employment.[3]

Second, the study demonstrates that changes in wage growth are a key to understanding changes in employment over time, particularly among low-skilled young men. For instance Juhn (1992) and Welch (1997) examine whether changes in the level of wages can explain the decline in labor market participation. Although they find that the change in wages can explain a significant portion of the change in participation during the 1980s, they both find evidence of a shift in the labor supply curve in the 1970s. The results presented here indicate that a large part of that shift can be explained by changes in wage growth conditional on the wage. There is also

[3] The phase-out also produces a high marginal tax rate, which is a separate widely studied disincentive to employment. Another way to think about the issue is that the level of the earned income tax credit determines the effective wage level, while the phase-out determines the effective wage growth.

another possible interpretation. Traditional labor supply analysis plots participation against the wage. If instead we plot participation against the present discounted value of employment then we can see the decline in labor market activity over the 1970s as a movement along this newly defined labor supply curve. During the 1970s the decline in the present discounted value of wages was largely due to the decline in wage growth.

Third, this paper makes a methodological contribution by using the CPS to perform cohort analysis. Although the technique for this type of analysis has been formalized since Deaton (1985) and Browning et al.(1985), it is rarely performed on U.S. data. The analysis here extends the methodology laid out in those papers by examining selection and simultaneous equations in this framework.[4] Although there are several panel data sets on which this analysis could be performed, the CPS has several advantages. At least 30 years of data are available, allowing for a exploration of the trends in employment over time. Furthermore, the large sample sizes allow for more detailed analysis of sub-samples of the population.

The next section briefly describes the data used in the analysis. Section three provides preliminary evidence of the relationship between wages, wage growth, and employment for young workers. Section four describes a simple two-period labor supply model with human capital accumulation, which illustrates that under common assumptions labor supply can be written as a function of returns to experience. The fifth section describes the empirical approach and results. The last section concludes.

2 Data

The data used in this paper are drawn from the 1968 to 1998 March Demographic Supplements to the Current Population Survey. The employment and wage data refer to the year prior to the survey so the actual period examined is 1967 to 1997. The data are limited to men organized into cohorts based on year of entry into the labor market, education and, in some cases, race. Men are grouped into two samples: the employment sample and the wage sample. The employment sample consists of men with no more than 30 years of experience who are not in school, retired, or in the armed forces at the time of the interview and who did not list

[4] Deaton (1985) provides an IV estimator, but it does not allow for correlation between the measurement error in the instruments and the other explanatory variables. Blundell et. al (1994) perform a cohort analysis in a simultaneous equations framework; however, they ignore the issue of measurement error raised by Deaton.

schooling or retirement as a reason for working less than a full year in the year prior to the interview.[5] The wage sample is a subset of the employment sample that excludes men without wage and salary employment in the year prior to the survey and men with over $100 dollars in income from self-employment or farming. CPS March supplement weights are used to weight the samples.

CPS data on earnings are top-coded. The top coding is not indexed to inflation, but is instead changed at intervals, affecting very different numbers of men in each year. In order to eliminate top-coded individuals in a consistent way, men with annual wage and salary income above the 98th percentile in each year are excluded. Hourly wages are constructed as annual wage and salary income divided by annual hours worked. This results in some extremely low reported wage values. Men reporting hourly earnings of less than $1.35 in 1997 dollars, about one-half the 1982 minimum wage, are therefore eliminated.[6] All earnings data are adjusted to 1997 dollars using the personal consumption expenditure deflator from the Bureau of Economic Analysis. For the purposes of this paper, young men are defined as being between the ages 18 and 30 with 1 to 5 years of potential labor market experience.[7] These men are referred to as being new labor market entrants or at the start of their careers. The employment of men with only 1 year of potential experience is referred to as starting employment and their wage and salary earnings as starting wages. The results discussed below are not sensitive to any of the specifications described above including the use of weights or the definition of potential experience.

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[5] The CPS is a survey of the non-institutionalized population, therefore individuals in prison are not included. Individuals living on military bases are not surveyed for the same reason. As a result most young men in the military are excluded from the survey altogether.

[6] Several points should be kept in mind with respect to the wage restrictions. Trimming of the right tail of the data eliminates individuals with top coded income in a way that is consistent across years. This restriction eliminates virtually no young men. Second, many young men report very low earnings, so even these minimal restriction eliminate roughly 2 percent of the sample of men in their first year of labor market experience. My hope here is to eliminate spurious responses without completely eliminating the sample of low wage men. None of the trends are substantively affected by the choice of the top or bottom censoring points although there is a somewhat larger decline in starting wages without the restriction on low hourly wages.

[7] Potential experience is defined as min(age-education-7, age-17). I have chosen age-education -7 as the cut-off rather than the more common age-education-6, to reduce the likelihood that I include individuals who are only out of school for only part of the year.

Prior to 1976 the variable on the number of weeks worked in the year prior to the interview is reported as a categorical variable only. Furthermore, until that year, there is no variable on the usual hours worked in the year prior to the survey, although there is a variable reporting hours worked at the time of the survey. Therefore both these variables are imputed. The imputation procedure is described in the appendix 1. Imputed values for these variables are used for the entire time period. Analysis of the post-1975 time period using the actual or imputed variables gives comparable results.

3 Participation, Wages, and Wage Growth

3.1 Trends in Labor Market Participation

Figures 1a and 1b summarize the labor market activity from 1967 to 1997, by education group, of men with 1 to 5 years of experience. Figure 1a depicts an index of average annual participation, defined as the proportion of individuals working at least one week in a given year. Data are smoothed using a three-year moving average in order to highlight the trends although there is considerable cyclical variation in participation. The figure shows that high school dropouts have experienced the largest decline in participation. In 1997, participation was 18 percent lower than it had been in 1967. Workers in other education groups have also decreased their annual participation, but the decline is much lower: between 2 and 5 percent. Figure 1b illustrates an index of annual hours worked conditional on positive employment. The annual hours of low-skilled workers trended downward between 1967 and 1982 at which time it was 22 percent lower than at the start of the period. Since then there has been considerable cyclical variation but no clear trend. It is currently about 8 percent lower than in the late 1960s. College graduates have actually experienced an increase in annual hours, which has been largely driven by an increase in hours worked per week.[8]

3.2 Trends in Wage Growth and the Value of Work

[8] One obvious explanation for the decline in participation among young men with low levels of education is that as average levels of education have increased, only those with low ability or other unobserved characteristics negatively correlated with employment fail to complete high school. In this section I do not attempt to control for such compositional changes. However, the issue is addressed in the more rigorous empirical analysis in section 5 (see footnote 25 in particular).

The wage is a poor measure of the value of employment for young workers because they also gain considerable wage growth as a result of employment. Table 1 presents data on starting wages and total wage growth after the first ten years of work for workers entering the labor market during the given time periods. Wage growth is calculated as the growth in average cohort wages.[9] Because the rate at which workers accumulate experience differs across groups of workers defined by education level, race, or date of entry into the labor market, potential experience is a poor measure of true experience. As a result, the ten-year wage is considered to be the wage in which the accumulated experience for that group is closest to 10 regardless of the level of potential experience.[10]

Two features of the patterns of wage growth are worth pointing out. First, wage growth over the first ten years of the career is large, averaging about 51 percent. Second, the data indicate significant variation in wage levels and wage growth across time and across groups of workers defined by education and race. During the late 1960s and early 1970s groups with lower levels of education had a higher level of wage growth (71%) than did their peers with more education (44% for college graduates). Wage growth was also higher for black workers (71%) than for white workers (61%). This pattern is of course the opposite of that observed for wage levels indicating that over the lifecycle wage growth served to reduce at least some of the gap in between group starting wages. During the mid-1970s, however, wage growth rates among low-skilled workers and black workers declined to about 40% over 10 years, while wage

[9] This raises the question of what causes the variation in wage growth. On the one hand, wage growth may be seen as something created by the worker's own effort. A positive relationship between wage growth and employment could result if workers who are willing to put high effort into their work have high labor force participation and high wage growth. On the other hand, wage growth could stem from wage setting mechanisms, technology, demography, or macroeconomic forces that are exogenous to the worker (Aaronson 2000a). Moreover, if workers with different levels of education or of different races do not have access to the same employment opportunities or if they are differentially affected by aggregate phenomena then they may differ systematically in their wage growth, regardless of individual characteristics. In the discussion in this section, these various sources of wage growth are not distinguished. The point is to simply show the importance of wage growth in the earnings of young adults. In the econometric specification we use a measure of wage growth that is exogenous to the worker.

[10] Defining a year of experience as 2000 hours, in 1967 the actual average experience of high school drop-outs after ten years of potential experience was 8.2 years, for high school graduates it was 9.7 years, for those with some college it was 9.8 and for college graduates it was 11. Over the time period, in question, average experience for high school drop-outs declined by almost a year to 7.3 between 1982 and 1984 and then started to rise again. For other workers, the change in average cohort-education group experience was never more then 3 tenths of a year. The wage growth measure used in this section accounts for the variation in the relationship between actual and potential experience across groups and the less important differences across time.

growth among high-skilled workers and white workers increased, reaching nearly 60 percent in the early 1980s. The result is that during the late 1970s and early 1980s wage growth exacerbated inequality.[11] In the latest periods for which data are available, the pattern is less clear. While the wage growth rate for high school dropouts was much higher for the cohort entering the labor market between 1985 and 1987 than for the cohort immediately preceding it, the return to experience for high school graduates remained low. Meanwhile the return to experience for college graduates has been somewhat volatile.

Perhaps less noticeable from the table is the fact that this variation in wage growth results in appreciable changes in the value of employment. For example, think of a worker with a ten-year work horizon. The present discounted value of hourly earnings if a person works in all ten years can be written

$$pdv\ work = w_1 + w_1(1+g)/R + \ldots + w_1(1+g)^9/R^9, \qquad (1)$$

where w_1 is the starting wage, g is the annualized wage growth rate, and R is the discount factor. The present discounted value of working in every period except the first is

$$pdv\ don't\ \ work = 0 + w_1/R + \ldots + w_1(1+g)^8/R^9. \qquad (2)$$

Now define the value of working today as the difference between these two streams of income,)PDV. Table 2, shows values for)PDV calculated, using a discount factor of 1.03, for three cohorts of workers, along with wage levels and annual participation rates.[12] For cohorts entering the labor market between 1967 and 1969,)PDV was $12.20 per hour. The starting wage during this period was $7.56. By 1979-1981,)PDV for new entrants had declined to $9.52, a 22% decline. The starting wage during this period declined only 2 %. Annual participation during this period declined 11 %. Between 1979-1981 and 1985-1987,)PDV remained relatively unchanged at $9.61, while the starting wage declined to $6.23, a 16 % decline. Yet during this period annual participation remained relatively constant. These simple statistics suggest that

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[11] Trends in lifetime earnings are described in Aaronson 2000b.

[12] The annualized wage growth rates, *g*, are calculated from the data presented in table 1, which control for differences in actual work experience cross-sectionally and over time by calculating wage growth at the time when each cohort/education group attained ten years of actual experience. In this exercise, individuals are assumed to earn that rate in each of ten years. Because it also takes longer for more recent cohorts of low-skill workers to actually attain a given level of wage growth, this exercise underestimates the decline in the present discounted value of work due to declining returns to experience.

participation is not consistently correlated with changes in wages alone, but is quite sensitive to changes in)PDV, which combines both the present and future value of employment.

Figure 2a summarizes the data on wage levels and wage growth for dropouts. The figure depicts wage profiles for 6 cohorts, spaced five years apart. The bottom point in each wage profile is the starting wage, which is declining throughout most of the period. The figure also demonstrates that the wage profiles were much steeper in the late 1960s and early 1970s than they are in the 1980s. The value of current work depends on changes in both the wage level and in wage growth. A young dropout entering the labor market in 1967 earned an hourly wage of about $11.50 after 10 years in the labor market. A comparable worker entering the labor market in 1987 earned just over $9.00 an hour. Figure 2b superimposes starting average annual hours (including people who don't work) for each cohort on the graph in grey.[13] The graph makes clear that annual hours fell throughout the 1970s, at the same time that the value of employment was declining.

4 A Simple Life Cycle Labor Supply Model

The evidence suggests that changes in wage growth have had a significant impact on the value of employment over time. As such, wage growth is likely to be an important determinant of labor supply for young workers. This section describes a two-period model of labor supply with human capital investment and endogenous wages. It is intended to make the simple point that wage growth should be considered in a model of labor supply.

In this model, individuals have identical utility functions strictly concave in consumption and leisure. The function is constant and additively separable over time. It is also additively separable in its arguments, consumption and leisure. Individuals pick consumption (c) and leisure (l) in both periods to maximize the sum of their discounted utility, subject to their budget constraint. Income in the model comes only through labor market participation (h). There is a time constraint so that in each period $l + h = 1$. People can save and borrow at an interest rate of 0. The price of the consumption good is constant and is normalized to 1.

[13] The dots represent actual data. The lines connecting them are there simply to improve their visibility.

This is a model of post schooling employment with human capital investment and endogenous wages.[14] The starting wage is based on human capital accumulated in school, prior to the first period. It is assumed that people make an optimal schooling choice based on preferences and expected wage levels and wage growth. Once schooling is complete they have to determine their labor supply. At this point, the wage and wage growth can be thought of as predetermined. Wage growth between the first and second period is the result of costless learning on the job. The wage in the second period is equal to

$$w_2 = w_1 \left(1 + rh_1\right) \tag{3}$$

In this model *r* can be interpreted as the return to experience in a Mincer-type wage equation. However it is not necessary that the equation actually represent human capital accumulation. The important point here is that an individual's wage in the second period is a function of labor market experience in the first period and some exogenous component, *r*.[15] If the person doesn't work in the first period then he is faced with the starting wage in the second period. In contrast, in a model with exogenous wage growth, we would have $w_2=w_1(1+r)$.

Utilizing the fact that $l = 1 - h$, the consumer maximizes the following utility function with respect to h_1, h_2, c_1, and c_2.

$$\max_{c_1, c_2, h_1, h_2} U\left(c_1\right) + V\left(1 - h_1\right) + \beta\left[U\left(c_2\right) + V\left(1 - h_2\right)\right], \text{ subject to} \tag{4}$$

$$w_1 h_1 + w_2 h_2 - c_1 - c_2 = 0$$

where β is the discount factor. The first order condition for an interior solution with respect to h_1 is:

$$V'\left(1 - h_1\right) = \lambda w_1 + \lambda w_1 r h_2 , \tag{5}$$

where λ is the Lagrange multiplier. Concavity is sufficient to ensure the second order conditions are met.

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[14] Declines in expected wage growth for workers with low levels of education may induce individuals to stay in school longer. The impact of changing levels of educational attainment is explored in section 5.

[15] There are many possible alternative explanations. Wages may grow on the job due to learning about the quality of a job match or if there is back-loading for wages. Furthermore, it does not matter whether the wage growth takes place on the job (returns to tenure) or as the result of job turnover.

The first order condition implicitly defines a Frisch supply function for labor, $h_1(w_1,r,8)$ in which labor supply is a function of the starting wage, the marginal utility of wealth, and the return to experience. Although for some specifications of the utility function, a closed form solution is possible, it is not tractable. However, using the first order condition, we can still analyze the impact of changes in the returns to experience on labor supply. The left-hand side of equation 5 is the marginal utility of leisure, the cost of working an extra hour. The first term on the right-hand side represents the benefit of working an extra hour. These two terms constitute the first order condition in the classic case with exogenous wages. In the case of human capital accumulation, the marginal benefit increases by the second term, which represents the additional utility gained from working an extra hour in the form of higher consumption in the next period. This implies that *ceteris paribus* an increase in r will cause people to choose higher labor market participation. The question is whether this is more generally true. To determine this we must solve for dh_1/dr. Totally differentiating equation 5 and solving for dh_1/dr yields

$$\frac{dh_1}{dr} = \frac{-1}{V''(1-h_1)}\left[l\, w_1\left(h_2 + r\frac{dh_2}{dr}\right) + w_1(1+rh_2)\frac{d\, l}{dr}\right] \qquad (6)$$

The sign of this condition is ambiguous, which is not surprising since r is simply a price and therefore changes in r result in both income and substitution effects. Furthermore, because an increase in r raises second period wages without changing the first period wage there will also be intertemporal substitution effects. The term outside the brackets is positive; from the second order condition. The first term in the brackets is the substitution effect. The term

$\frac{l\, w_1 h_2}{V''(1-h_1)}$ is the partial effect of r on h_1, *ceteris paribus*. Using the implicit function theorem and the second order condition for h_1, this can be shown to be positive. The second part of the substitution term captures the intuition that the more a person is going to work in the second period the more they will benefit from the wage growth, increasing the substitution effect, however, it is not possible to demonstrate unambiguously that this term will be positive.[16] The last term represents an income effect. It can be shown that d8/dr is negative. Intuitively this

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[16] Although it is possible to substitute for $\frac{dh_2}{dr}$ in equation 6, the resulting equation still cannot be signed and it is not easy to interpret.

makes sense since 8 is the marginal utility of income, and an increase in *r* should increase income.

Although the comparative static cannot be signed for this general case, there are several cases in which the sign is clear. First, as long as the substitution effects are larger than income effect the comparative static is likely to be positive. Second, for workers deciding whether or not to enter the labor market, there is no income effect (since a non-working individual doesn't earn anything, income is unaffected by the increase in *r*) and the derivative will be positive. Third, using a model in which there is no saving or borrowing also eliminates the income effect (since an increase in *r* changes only the second period wage, which can no longer be borrowed against) and results in a positive derivative. It is also informative to compare these results to those of a model based on exogenous wages. The first order condition in a model with exogenous wages is not directly a function of the returns to experience: there is no substitution effect. It is, however, a function of 8, and *d*8/*dr* is negative. Therefore in the exogenous wage growth case, labor supply should unambiguously decrease.

To summarize, the model shows that when future wages depend on current labor supply, returns to experience will influence the labor supply decision. Labor supply can be written as $h(w_1,r,8)$. The question of whether labor market participation is positively or negatively correlated with these returns is an empirical question to which we next turn our attention.

5 Empirical estimation

5.1 Empirical Specification

We want to test the hypothesis that young men who expect high wage growth work more than those individuals with low expected wage growth conditional on their wage levels. As noted the first order condition for labor supply implicitly defines a Frisch supply function for labor that is a function of the wage, wage growth, and 8, the Lagrange multiplier on the budget constraint. The hours of work function implied by the first order condition is nonlinear in the variables and parameters. Estimating such a structural model requires strong functional form assumptions. Therefore, I assume that the function can be approximated by a linear equation. Ignoring for now the possibility that hours of work can be zero, the labor supply equation for an individual *i* in cohort *c* and education group *g* at time *t* can be written

$$N_{icgt} = b_1 \ln W_{icgt} + b_2 r_{icg} + b_3 X_{icgt} + h_i + m_g + x_t + e_{icgt} \quad (7)$$

where N_{icgt} is a measure of labor supply, lnW_{icgt} is the natural log of the hourly wage, r_{icg} is the return to experience, and X_{icgt} is potential experience.[17] It is necessary to include the experience terms in order to capture the difference in participation between two men at the same stage in their careers but facing different wage profiles. If we omit these terms then we also capture differences in participation due to intertemporal substitution as people move along their own wage profiles.[18] The variable O_i is an individual effect, which captures differences across individuals in lifetime resources for instance. The term $:_g$ is an education group effect. This accounts for the fact that workers with different levels of education have different levels of labor market participation, even conditional on other observable factors. The variable $>_t$ represents a time-shock and g_{icgt} is a mean zero error term. The year effects eliminate the possibility that the positive correlation between wage growth (or wages) and labor market participation is due to the fact that both are high during economic expansions.

Although this is an individual level model, it can be easily adapted to the case of cohort level data (Browning, et al. 1985). Averaging the equation over individuals in a given cohort/education group we have the cohort model of labor supply

$$\overline{N_{cgt}} = b_1 \overline{\ln W_{cgt}} + b_2 \overline{r_{icg}} + b_3 \overline{X_{cgt}} + h_i + m_g + x_t + \overline{e_{cgt}} \quad (8)$$

This equation can be easily estimated using repeated cross-sections of CPS data. But we cannot use simple ordinary least squares. The sample means observed in the data are only error-ridden measures of the underlying cohort population means. Specifically, we observe

$$\bar{W}_{cgt} = W^*_{cgt} + f_{cgt} \quad (9)$$

[17] Throughout this part of the paper potential experience is used in place of actual experience. The reason is that actual experience is calculated as a function of annual participation and annual hours of work, hence it is a function of the dependent variable. Alternative estimation procedures which used actual experience instrumented with potential experience or actual experience itself did not affect the results.

[18] Adjustments in labor supply in response to wage changes resulting from movements along the wage profile involve intertemporal substitution. In a model with perfect foresight, there are no income effects involved with these changes. As a result, the intertemporal elasticities are larger than the compensated and uncompensated substitution effects (unless income and wealth effects are zero). At test of the intuition underlying this model, I ran the same regression omitting potential experience from the regression. As is expected, the coefficients on wages and wage growth are larger. For a detailed discussion see MaCurdy 1981 and 1985.

where $\overline{W}$ is the sample cohort mean, W^* is the population cohort mean and N is measurement error due to sampling error. Therefore an error-in-variables model is required for estimation (cf. Deaton, 1985 and Fuller, 1987). From equation 9 it is clear that the true population mean is equal to the sample mean minus the measurement error, which is unknown. However the variance-covariance matrix of the measurement error can be estimated using the individual level data.

This implies the following estimator

$$\left(X'X - \Sigma_{xx} \right)^{-1} \left(X'Y - \Sigma_{xy} \right) \qquad (10)$$

Where *X'X* and *X'Y* are the sample moment and cross-product matrices and E_{xx} and E_{xy} are the variance-covariance matrices of the measurement error. The sample means converge at rate n_{cg}^{-1} (where n_{cg} is the number of individual observations in cohort *c* and group *g*). In contrast, the individual observations from all cohorts and time periods (*T*) may be used in calculating E_{xx} and E_{xy}. Therefore these covariances converge at rate $(Tn_{cg})^{-1}$. Since they converge in *T* as well as in n_{cg} they may be treated as known.[19]

Several other aspects of this estimation procedure require attention. We do not observe the average individual fixed effect. However since the cohort population is assumed to be constant over time we can use a cohort dummy 0_c to identify the average effect. By construction, dummy variables are measured without error. As can be seen in equation 8, the error term is an average of individual error terms and is therefore heteroskedastic by construction given that the sample size for each cohort/group varies. To address this problem all variables are multiplied by the square root of the n_{cgt} before estimation. Standard errors reflect the measurement error as well as the fact that some of the explanatory variables are predicted, as described below. The sample includes young men with one to five years of experience.

5.2 Missing Wages

[19] This description assumes a constant number of individuals in each cohort/education group. Due to changes in the size of the sample collected by the Census in each year as well as variation in the number of individuals meeting the inclusion criteria, there is variation over time in the number of individuals in each cohort/education group cell. This means that the sample means actually converge at rate n_{cgt}^{-1} and covariances at rate $(E_T\, n_{cgt})^{-1}$. Table 3 includes the cell sizes for each cohort/education group in each year.

To estimate this labor participation equation and the return to experience it is necessary to know the wages of those who don't work. Since these are not observed, they are imputed as follows. Individuals in a given cohort with positive employment are divided into cells based on their potential experience (single years), education (4 categories) and race (black/non black). Mean log hourly wages are calculated for each cell and assigned to individuals with missing wage data who have matching characteristics. The primary disadvantage of this method is that it assumes that to the extent that there is selection in participation on unobserved characteristics, it does not affect the distribution of wages. [20]

5.3 Estimating Wage Growth

The theory underlying the model is that individuals have some expectation of their wage growth conditional on working and that they take this into account when determining their labor supply. Of course we do not observe an individual's expected wage growth directly and therefore must estimate it. For the initial analysis we assume that an individual's expected wage growth is the actual *ex post* average wage growth of individuals in their cohort/education group. We do not assume that a young man has perfect foresight of his own individual wage growth, but rather that they know on average the wage growth opportunity available to someone with their level of education who enters the labor market at the same time. Even this is a strong assumption that will be tested later.

The theory offers a simple way to measure the *ex post* cohort/education group wage growth. Taking logs of both sides of equation 3, we get a simple Mincer-type wage regression,

[20] Specifically, it assumes that within a given cohort/experience/education/race cell $E(W|H=0) = E(W|H>0)$. I have explored this hypothesis using data from panels of the matched CPS. With this data I can compare the wages of individuals who are out of the labor market for one of the two years with those who are employed at least some time in both. I find that the mean wage of those who spend a year out of the labor market is marginally lower, conditional on observed characteristics. There are a few well-known attempts to deal with this issue, starting with Heckman (1974c). These include estimating a reduced form equation or estimating wages and participation jointly, which requires assumptions about the distribution of the covariance term between wages and participation. Juhn (1992) observes that hourly wages are positively correlated with weeks of work. Therefore she imputes missing wages using the wages of those with 1-13 weeks. This method of imputation conditions wages on the phenomenon to be explained. However, I estimate participation and annual hours separately, and this induced correlation would not seem to be a problem for the annual participation equation where the imputation is required. When I estimate the participation model using wages predicted in this manner, the results are comparable to those presented in the main text of the paper. The coefficient on wage levels decreases from 0.077 to 0.063 and the coefficient on wage growth decreases from 1.52 to 1.49.

in which r is coefficient on experience, usually referred to as the return to experience. In terms of our current notation, this can be rewritten as

$$\overline{\ln W_{cgt}} = d_{cg} + r_{cg} X_{cgt} + \overline{z_{cgt}} \qquad (11)$$

where w_1, the log starting wage is captured by the intercept, $*_{cg}$, and X, experience, replaces h_1, since we now have multiple years of data. The error term $._{cgt}$ is assumed to be log-normal. Ten years of data are used to predict the return to experience for each cohort/education group.[21] The results of the regressions used to estimate the rate of return to experience are typical. For each cohort and education group the return is positive and significant at the 99 percent level. The estimated returns can be seen in table 4. The returns range from 0.02 to 0.07.

Measuring wage growth in this way may result in an underestimate of the correlation between wage growth and annual participation or annual hours for two reasons. First, using potential experience as the measure of experience ignores the fact that annual hours worked and thus actual experience varies across cohorts and education groups. In particular, the measure is likely to underestimate wage growth for groups with low work experience and overestimate wage growth for high work experience groups, which may reduce the overall variation.[22] Second, the measure of potential experience may pick up returns to aging, if they exist, as well as returns to experience. As we saw in the theory section, exogenous wage growth such as returns to aging result in reduced current labor market participation.

Another relevant question is whether it is appropriate to treat the returns to experience as an exogenous variable. By construction, the return to experience is equal to the covariance of

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[21] The estimated returns to experience are sensitive to the number of years of data included in the regressions; therefore it is necessary to include the same number of years of data for each cohort. Each additional year of data included in the wage growth regression reduces the number of cohorts that can be analyzed. Ten years was chosen to balance the need for good estimates of wage growth with the need to include a large number of cohorts.

[22] As was noted in footnote 9, actual experience does not vary much over time within cohort-education groups, thus within groups, using potential experience rather than actual experience is not likely to affect the estimation of wage growth over time. However, while high school graduates and those with some college education accrue approximately ten years of average experience over ten years of potential experience, college graduates earn closer to 11 years of experience. Thus the wage growth of high school drop-outs will be somewhat attenuated in our estimation, while that of college graduates will be somewhat augmented. It should be noted that alternative estimation, which used actual experience instrumented with potential experience, or simply actual experience itself did not result in significantly different results.

wages and experience divided by the variance of experience. As is discussed below because of how hourly wages are calculated, they risk having a spurious negative correlation with hours worked. However, this should not affect the covariance between wages and experience. There is, however, an underlying process that generates returns to experience, which may also affect participation. The final regression includes cohort, year and education dummy; variables which should capture many of these omitted variables.

Even so, some endogeneity may remain. To test whether wage growth is endogenous we instrument returns to experience using variables which capture the proportion of individuals in each of 9 industries in the year of entry into the labor market. The motivation for using industry distribution as an instrument is that different industries offer different wage growth paths, which are exogenous to the worker. An F-test rejects the hypothesis that the coefficients on the industry variables are jointly zero in the first stage regression of returns to experience on industry. In order for these industry variables to be good instruments we must also be able to exclude them from our labor supply equation. Tests of over-identifying restrictions support this restriction. These findings indicate that the industry variables are adequate instruments. Nonetheless, a Hausman test fails to reject the equality of the ordinary least squares and two-stage least squares coefficients in the labor supply regression. Therefore returns to experience are treated as an exogenous variable.

5.4 The Endogeneity of Wages

The CPS does not contain a measure of the hourly wage. Therefore it is calculated as annual wage and salary income divided by the product of annual weeks of work and usual hours per week. If hours of work are measured with error, this procedure results in a spurious negative correlation between wage and any measure of labor supply based on annual hours (cf. De Vanzo et al., 1976; Juhn, 1992; Welch, 1997). As discussed above, it may also be the case that observed wages are not independent of hours of work (cf. Heckman, 1976c; Killingsworth, 1983). Evidence supports this concern: a Hausman test for the equality of ordinary least squares and two-stage least squares coefficients in a labor supply equation as specified in equation 8, rejects the hypothesis. The p-value for the test is 0.0002. Therefore an instrumental variables approach is used. Variables representing the proportion of individuals in their first ten years of experience in each of 9 broad industry groups are used as the excluded instruments. It is still necessary to account for the existence of measurement error in both the variables of the structural equation and in the excluded instruments. Therefore, the iv estimator which does this is given by:[23]

$$\left[\left(X'W - \Sigma_{xw} \right) \left(W'W - \Sigma_{ww} \right)^{-1} \left(W'X - \Sigma_{wx} \right) \right]^{-1} \times$$
$$\left[\left(X'W - \Sigma_{xw} \right) \left(W'W - \Sigma_{ww} \right) \left(W'Y - \Sigma_{wy} \right) \right] \qquad (12)$$

where, *W* represents the matrix of instruments and X is the matrix of explanatory variables. In this case, Σ_{wx} is the variance-covariance matrix of the measurement error associated with the variables in *X* and *W;* Σ_{ww} is the variance-covariance matrix of the measurement error of the variables in *W*; and Σ_{wy} is the variance-covariance matrix of the measurement error associated with the variables in *W* and *Y*.[24]

5.5 Estimation of Labor Supply Equations and Results:

Two measures of labor supply are used in the analysis: annual participation and annual hours conditional on positive employment. At the cohort level annual participation becomes the proportion of individuals working at least one week in the year. Dividing labor supply in this way is similar to estimating a separate probit and regression at the individual level. This raises the question of how to deal with selection in the annual hours equation. The problem is the same

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[23] Deaton (1985) provides the formula for the IV estimator in which the measurement error in the instruments is not correlated with the measurement error in the other variables. However that estimator is not an appropriate for our case as we use instruments which are contemporaneous with the dependent and explanatory variables. The asymptotic variance-covariance matrix for the estimator in equation 12 is given in appendix 2.

[24] There are two labor supply equations, one involving annual hours of work conditional on employment and the other involving whether or not a person works. This allows the decision whether or not to work to vary from the decision of how many hours to work, conditional on employment. The labor supply equations are estimated on two different samples (workers and all young men), each requiring a different wage measure. The first requires a wage measure for people who work and the second requires the wage for all individuals. Therefore, if the regressions were run in two stages rather than using an iv technique, two separate first stage regressions would be required. The results of these first stage regressions can be found in appendix table 1.2. The results are as expected. A test that the coefficients on the instruments are jointly equal to zero is rejected. Because there are 9 industry variables, tests of over identifying restrictions were also performed. In no case is the hypothesis that the coefficients on the industries are jointly equal to zero in the labor supply equation rejected.

as correcting for selection in panel data. Assuming that selection enters the equation as a fixed individual effect (which may be correlated with the explanatory variables) then using fixed effect estimation provides consistent estimates of the parameters of interest (cf. Wooldridge, 1995). In the model depicted here, the fixed effects within each cohort are captured by a cohort effect and fixed effects that vary by education group are captured by the education dummy variables. Therefore the annual hours equation should provide consistent estimates.[25,26]

In summary the equation to be estimated is of the following form:

$$\overline{N_{cgt}} = b_1 \overline{\ln \hat{W}_{cgt}} + b_2 \hat{r}_{icg} + b_3 X_{cgt} + h_c + m_g + x_t + \overline{e_{cgt}} \tag{13}$$

in which N_{cgt}, is either log annual hours conditional on positive employment or annual participation, $\ln \hat{W}_{cgt}$ is the log wage, for which we instrument, $\hat{r}_{cg}$ is the estimated return to experience and X_{cgt} is potential experience. There are also 3 vectors of indicator variables, O_c captures cohort effects, $\therefore_g$ captures education with dropouts the left-out group, and $>_t$ is a vector of time dummy variables. If we used a separate time dummy for each year, it is difficult to identify the dummies in the early years.[27] Therefore, the year effects are captured as pairs of

[25] Even if the selection is time-varying, estimating the labor supply equation in two parts may still be the best approach, particularly in the absence of clear exclusion restrictions, as is the case here (cg. Hay et al., 1987; Manning et al., 1987; and Leung and Yu, 1996).

[26] A full set of cohort/education interactions would more completely capture fixed effects, however, due to the limited numbers of degrees of freedom, this is not possible. I have run a model that allows for cohort/education effects that change smoothly overtime, which is a reasonable specification, if we think that changes in selection across cohort/education groups are due to the changing composition of the groups overtime due to long term educational and demographic trends. This model includes the proportion of individuals in each cohort in each education group interacted with an education dummy variable, which captures (without loss of generality) how the annual participation or annual hours of high school drop-outs varies with the proportion of individuals who are high school drop-outs. Including these variables strengthens the coefficient on wage growth and weakens the coefficient on the wage level in both the annual participation and annual hours equations. Note, that this specification also accounts more fully for changes in cohort quality over time.

[27] Since I restrict my sample to those cohorts for whom I observe the first year of labor market participation and because I only include individuals in their first five years of work, there are only 4 observations in 1967 (an observation for the first year of experience for each of the four education groups).

years, with 1967/1968 being the left-out pair.[28] The bars over the variables indicate cohort means. The mean values of the dependent and explanatory variables are given in table 5.

Table 6 presents the results of these regressions. The marginal effects have been converted into semi-elasticities which report the change in annual hours or annual participation resulting from a 10 percent increase in the hourly wage or return to experience ()y /%)x). The elasticities are calculated at the means of the variables. T-statistics are included in parentheses. In both the equations the effect of wage growth is positive and statistically significant, supporting the theory that individuals with higher expected wage growth work more, conditional on their starting wage. This is also a rejection of the theory that wages are exogenous or that wage growth simply represents returns to aging, since as we saw in section 4, this would imply a negative coefficient. The first column presents the results of the regression with annual participation as the dependent variable. We see that a 10 percent increase in the return to experience increases the proportion of men working at least one week per year by 0.0061: a 0.6 percent increase in annual participation. Although this may seem small, it is nearly as large as the contribution of a 10 percent increase in wages, which is 0.0072.

The second column of table 6 shows the results from the regressions of annual hours on the explanatory variables. A 10 percent increase in the return to experience induces a 24-hour increase in annual hours worked, about one-half of a standard work-week. Again this is comparable to the 28 hours increase in annual hours induced by a 10 percent increase in wage levels. Although in this case, the coefficient on the hourly wage is not statistically significant.

We can use these results to calculate the effect of a change in wage growth on the unconditional expected annual hours of work. The expected value of annual hours can be written as

$$E(H) = E(H \mid H > 0) \cdot \Pr(H > 0). \tag{14}$$

The marginal effect of the return to experience (r) on expected annual hours is therefore

$$\frac{\partial E(H)}{\partial r} = \frac{\partial E(H|H>0)}{\partial r} \cdot \Pr(H>0) + E(H|H>0) \cdot \frac{\partial \Pr(H>0)}{\partial r} \tag{15}$$

28 Instead of year effects, the model has also been specified using detrended GDP as a way to capture cyclical effects. It does not substantively change the results. Since the year effects are more flexible, we present that specification.

Using the marginal effects and sample averages listed in tables 5 and 6, we find that the total marginal effect of returns to experience on unconditional annual hours of work is 34 hours, or nearly one 40-hour work week. Of this, 23 hours can be accounted for by the marginal effect of annual hours conditional on work (the first term on the right hand side). The remainder is due to the change in the expected hours of work resulting from the change in the probability of working at all (see table 6).

Before proceeding it is worthwhile to comment on some of the other results of the estimation. The cohort effects may capture either a change in cohort quality, a change in the demand for young workers, or a shift in the labor supply curve. F-tests reject the hypothesis that they are all equal. Interestingly the cohort effects do not show a monotonic decline in either of the specifications, which eliminates a simple story such as declining school quality. In fact, in the annual participation equation the effects are highest for cohorts entering the labor market during in the late 1970s and early 1980s, when labor market participation had already declined quite a bit. However, the cohort effects for more recent cohorts are lower, particularly in the annual hours equation.

The year effects capture cyclical changes in labor market participation. As figures 1a and 1b suggest, the labor supply of young men is very sensitive to cyclical effects. Throughout the 1970s and early 1980s the year effects tend to be negative, particularly during the recessions of 1973-1975 and 1981. In the annual hours equation the year effects are positive during the expansion of the 1980s, but they remain negative in the annual participation equation, suggesting that participation declined during this period across all cohorts relative to the level in 1967/1968.

The results presented above were calculated assuming a 10 percent change in hourly wages or the return to experience. However without knowing the variation in the actual data it is still difficult to judge the relative importance of these factors. Between the beginning of the period and the early 1980s dropouts and high school graduates experienced a 40 percent decline in wage growth. In contrast, wage levels generally didn't decline by more then 10 or 15 percent over the entire period.

The large percent change in wage growth relative to wage levels suggests that the changes in the return to experience may explain a large part of the change in labor market participation since the late 1960s. Figures 3a to 3c provide evidence of this conjecture for high school drop-outs, high school graduates, and college graduates. The figures graphs actual annual participation and predicted annual participation based on the regression results described above. Also graphed is a prediction of annual participation that uses the regression coefficients and the same data, with the exception that wage growth is held constant at the 1967 level. Looking at Figure 1a, we see that high school drop-outs entering the labor market between 1967 and 1977 experienced a 7.5 percent decline in annual participation. Changes in wage levels predict almost none of the decline, whereas changes in wage growth are able to predict 40 percent of the decline. The difference in the predictive power of wages and wage growth is even more significant for high school graduates. Among high school graduates the prediction that allows wage growth to vary matches the data very closely and predicts the levels of participation very well throughout the 1970s. In contrast, wage levels greatly over-predict labor market participation during this period.   For instance in 1977, the actual annual participation rate was about 0.97 and the predicted participation rate was about 0.96. In contrast, the wage growth constant predicted participation rate was over 1. These findings are in accordance with other findings in the literature (cf. Juhn, 1992 and Welch, 1997) that changes in wage levels do not predict declines in labor market participation in the 1970s. These studies attribute the decline to a downward shift in the labor supply curve. We can now see that at least one-third of this shift can be explained by declining wage growth rates. In the later period, changes in wage levels explain the changes in participation fairly well but there is a significant difference between the actual annual participation and the predicted participation holding wage growth constant due to the sharp decrease in wage growth for low-skilled workers during the period.

Although we are primarily interested in explaining the decline in labor market participation among low-skilled workers, it is important to note that this model also explains changes in participation among those with high skills. Figure 3c focuses on college graduates. It can be seen that holding constant wage growth significantly under predicts annual participation for college graduates during the 1980s, because wage levels were declining during this period. However wage growth was increasing, encouraging college graduates to remain in the labor market despite their low starting wages. Therefore, labor supply among these workers remained relatively high and much higher than would be predicted by the changes in wages holding wage growth constant.

Finally, it is important to note that the labor market participation of low-skilled workers would have been considerably higher in the late 1980s if young workers entering the labor market had received the same wage growth as their peers who entered the labor market in the 1960s. Based on the regression results we can predict that the participation rate among high school drop-outs and graduates in 1988 would have been 4 percentage points higher given 1967 wage growth rates.

5.6 Estimation Using a Time-Varying Measure of Expected Wage Growth:

One of the limitations of the given results is that they are based on a specification in which wage growth is assumed to be constant, despite the fact that wage growth is higher when young and then tapers off. Since we only estimate wage growth over the first ten years of the career, this may not be a bad assumption. However, it can be tested. In this time-varying wage growth model I calculate the 5-year average wage growth rate as: $\frac{\left(\ln \hat{w}_{c(t)} - \ln \hat{w}_{c(t-5)}\right)}{5}$,

where $\ln \hat{w}_{ct}$ is the predicted log wage in year *t*. Predicted wages are obtained by regressing log-wages on a quadratic in experience for each cohort/education group using a sample of individuals with between 1 and 10 years of potential experience.

Table 7 provides the semi-elasticities of annual hours and annual participation for the original measure of wage growth as well as the time-varying results. Wage growth is positive and significant at the 99 percent level in both equations. A 10 percent change in wage growth yields a 0.0048 increase in annual participation and a 13-hour increase in annual hours. The effects are somewhat smaller than when the constant wage growth measure is used. This could be due to the fact that in some years the coefficient on the quadratic term is not statistically significant and so the measure of wage growth may be noisy. It may also be related to the fact that, due to data limitations, we consider only a 5-year wage growth rate.

5.7 Estimation Using Alternative Measures of Expected Wage Growth:

The analysis is based on the assumption that a young man's expectation of his own wage growth is his cohort/education group wage growth and that he knows this wage growth perfectly. However, it is easy to imagine that young men might hold other expectations. For instance, a young man might look at the wage growth experienced by his older siblings and friends. Alternately he might look at the wage levels of older individuals in that same time period to extrapolate his expected wage growth. To test the reasonableness of the assumption of perfect foresight against these alternative hypotheses, we compare the original regression results to results when we use other measures of expected wage growth. The results of these alternative specifications appear in table 7.

The first measure we examine is representative of the case in which an individual looks at the experience of someone 5 years older than himself in forming his expectations. Although the wage growth effect in the annual participation equation is still positive it is not statistically significant and it is only about 15% as large as in the case when young men have perfect foresight. It is not economically significant. In the annual hours equation the effect is also insignificant. The reason for this finding is that lagged wage growth contains very little information about current wage growth. A regression of current wage growth on lagged wage growth yields an insignificant coefficient. This result is not surprising when we take into consideration the fact that wage growth among drop-outs declined by over 40 percent in ten years.

Another possible measure of wage growth to which young men might have access is cross-sectional wage growth. This measure captures the possibility that an individual forms his expectations by looking at the difference in wages between himself and someone older than himself in a given year. I calculate the cross-sectional wage growth as the return to experience in a regression of log wages on potential experience by year and education group using cross-sectional individual level data for young men with between 1 and 10 years of potential experience. This measure is more successful than the lag, resulting in statistically significant effects in the annual participation equation. In fact, the semi-elasticity of annual participation with respect to a 10 percent increase in wage growth is 0.0077, a bit larger than the affect of the actual *ex post* wage growth. The affect on annual hours is not statistically significant and is only one-third as large as when actual wage growth is used: about 8 hours per year.

Overall, the actual cohort/education group wage growth has the most impact on labor supply, particularly in the annual hours equations. However, it is still unclear where young men might get this information. Therefore, I test one other possibility. It may be that young men combine information on wage growth in the cross-section with some information that they have on their own future wage growth. In the final specification, I predict the actual cohort/education group wage growth using the cross-sectional wage growth. (The best prediction of wage growth is the projection of actual wage growth in the cross-sectional wage growth space.) The results, which appear in the last row of table 7, are very strong. A 10 percent increase in wage growth increases annual participation by 0.023, over two percentage points. This is nearly 4 times as large as the effect of the actual cohort/education group wage growth. The increase in annual hours due to the same increase in wage growth is 23 hours per week, nearly as large as the effect in the basic cohort/education group wage growth model, however the effect is not statistically significant. These results suggest that young men may base their expectations both on information about the wages of older workers and on speculation on their future prospects that is highly correlated with their *ex post* wage growth.

6 Conclusions

Typical explanations for the decline in labor market activity among men have generally focused on static considerations such as falling real wages or rising outside opportunity costs such as increased social benefits or increased returns to criminal activity and other "informal" economic activities. These explanations, however, neglect the dynamic aspects of labor market participation. In particular they ignore the fact that the value of employment includes not only current wages but also future wage growth resulting from returns to experience. Since starting wages are relatively low while wage growth for young workers is particularly high, returns to experience encompass a large portion of the value employment.

This paper advances past work on the topic by including forward-looking considerations into a labor supply model aimed at explaining trends in employment. The findings suggest that indeed young men are forward-looking when making their labor supply decisions. Coefficients on returns to experience are significant and positive in equations determining both annual hours and annual participation, implying that increases in potential wage growth do increase labor market participation *ceteris paribus*. The elasticities are of a sufficient magnitude that changes in returns to experience can have an important impact on labor market activity, particularly the decision of whether or not to participate in the labor market at all. Simple simulations indicate that among high school dropouts, the group which experienced the largest fall in labor market activity, declining returns to experience can account for about 30 percent of the decline in labor supply between 1967 and 1977. Changes in the level of wages cannot explain any of the decrease in participation.

Previous studies that have focused on changes in wage levels alone suggested that because a large part of the decline in labor market participation in the 1970s could not be explained by wages there must have been a shift in the labor supply curve. The search for the cause of this decline has usually led to an examination of welfare benefits, income from other family members or criminal activity. According to the results related here, the large decline in the return to experience offers a possible alternative explanation. This explanation complements recent research suggesting that there has been a large increase in so-called dead-end jobs and the implication is that these jobs discourage workers not only because their wages are low but also because they provide few opportunities for advancement.

Finally, these findings have implications for policies aimed at improving the labor market activity of young low-skilled workers. In particular they suggest that unless wages are particularly high, jobs offering little chance for wage growth do not offer a great enough work incentive. As we saw, if wage growth among low-skilled workers in the late 1980s had attained the levels achieved during the late 1960s then annual participation among these workers would have been 4 percentage points higher. Furthermore, although this analysis was performed on pretax wages it has implications for tax policy. Taxes clearly impact not only wage levels but also wage profiles. While it is common to analyze the distortionary impact of changes in the levels after-tax income on labor market activity, this paper suggests that it would also be wise to examine the implications of such policies on wage growth.

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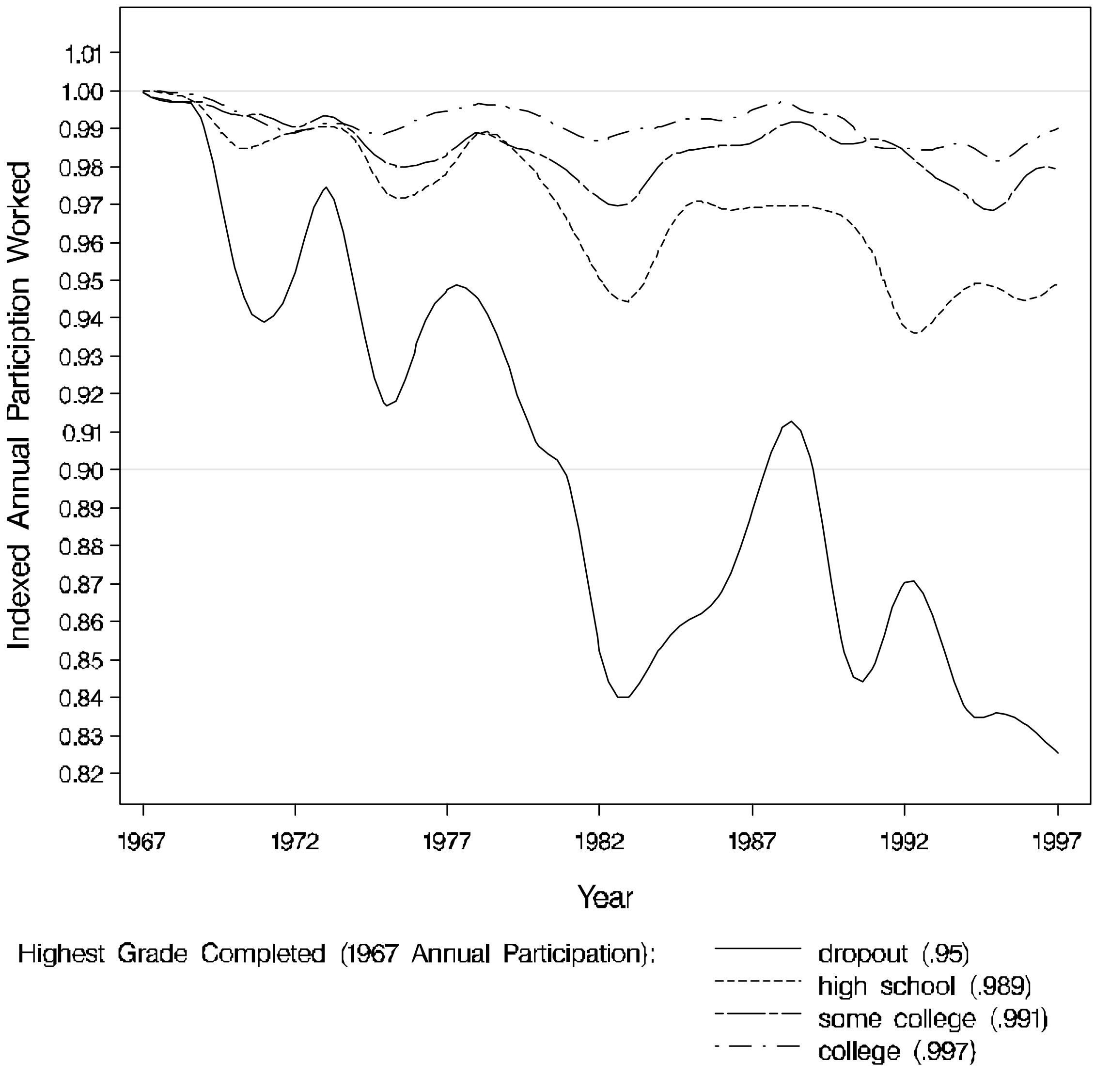
Figure 1a

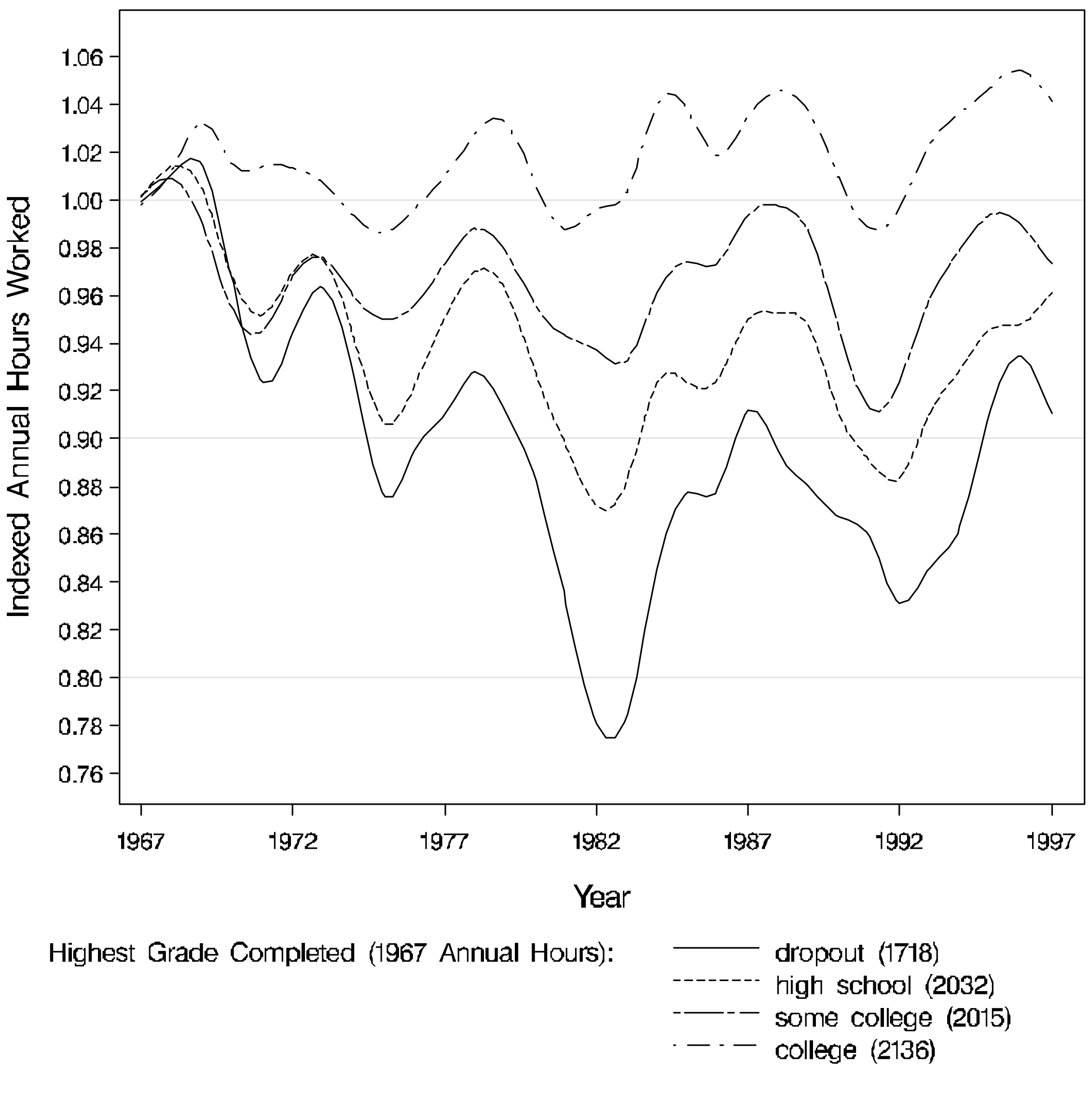
Men in the First Five Years of Potential Experience
Index of Annual Participation
by education 1967−1997



Notes: 1. Data are from the March Demographic Supplement to the Current Population Survey
2. Annual participation is calculated as the proportion of all men working at least, one week in the given year. The index scales by the annual participation in 1967. Variables and sample inclusion criteria are described in section 1.2 and section 1.3.

Figure 1b

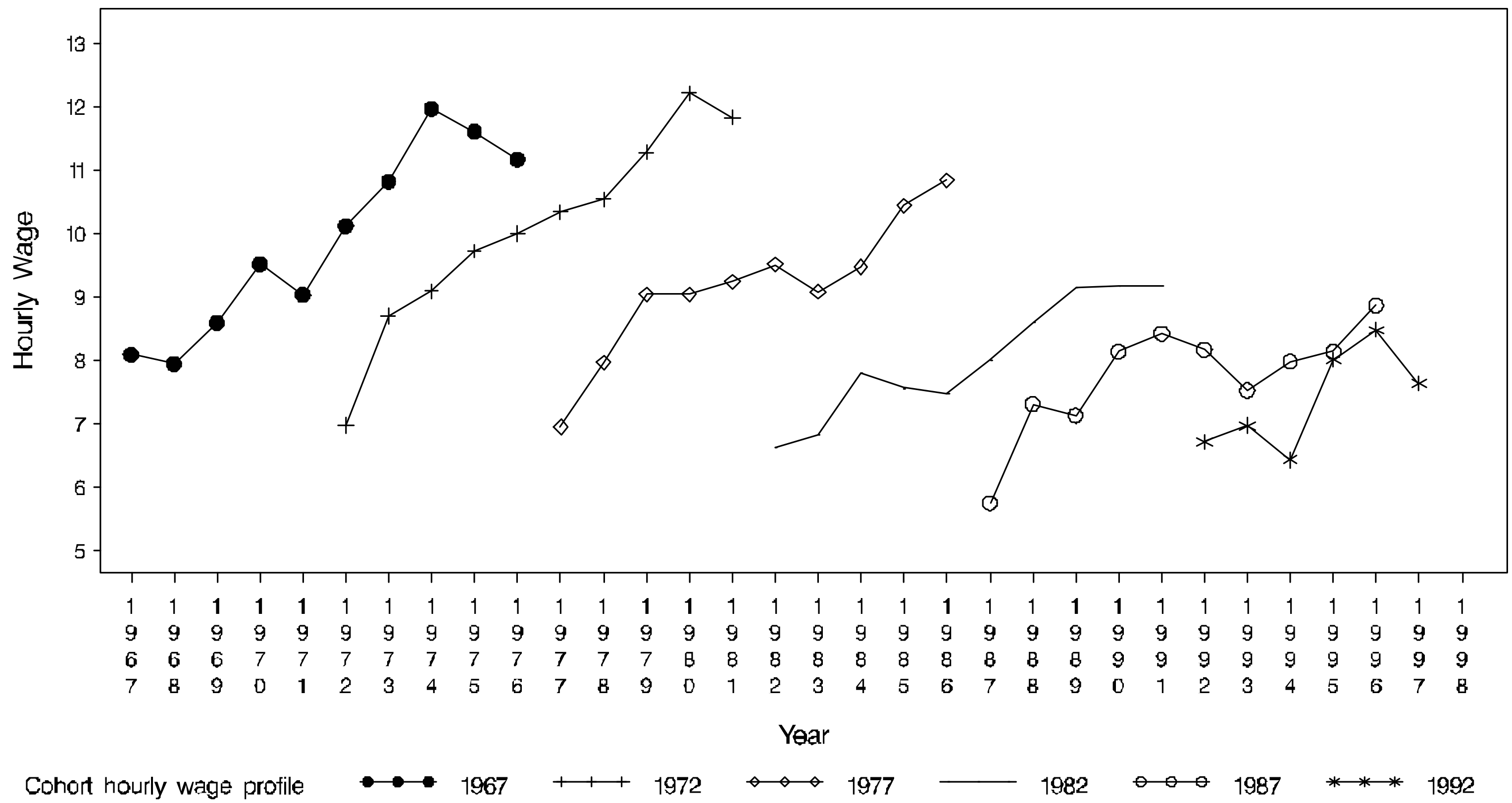
Men in the First Five Years of Potential Experience
Index of Annual Hours Worked
by education 1967–1997



Notes: 1. Data are from the March Demographic Supplement to the Current Population Survey
2. Indexed annual hours is calculated as the average annual hours worked per year conditional on positive employment. The index scales by annual hours in 1967. Variables and sample inclusion criteria are described in Section 2 and Section 3.

Figure 2a

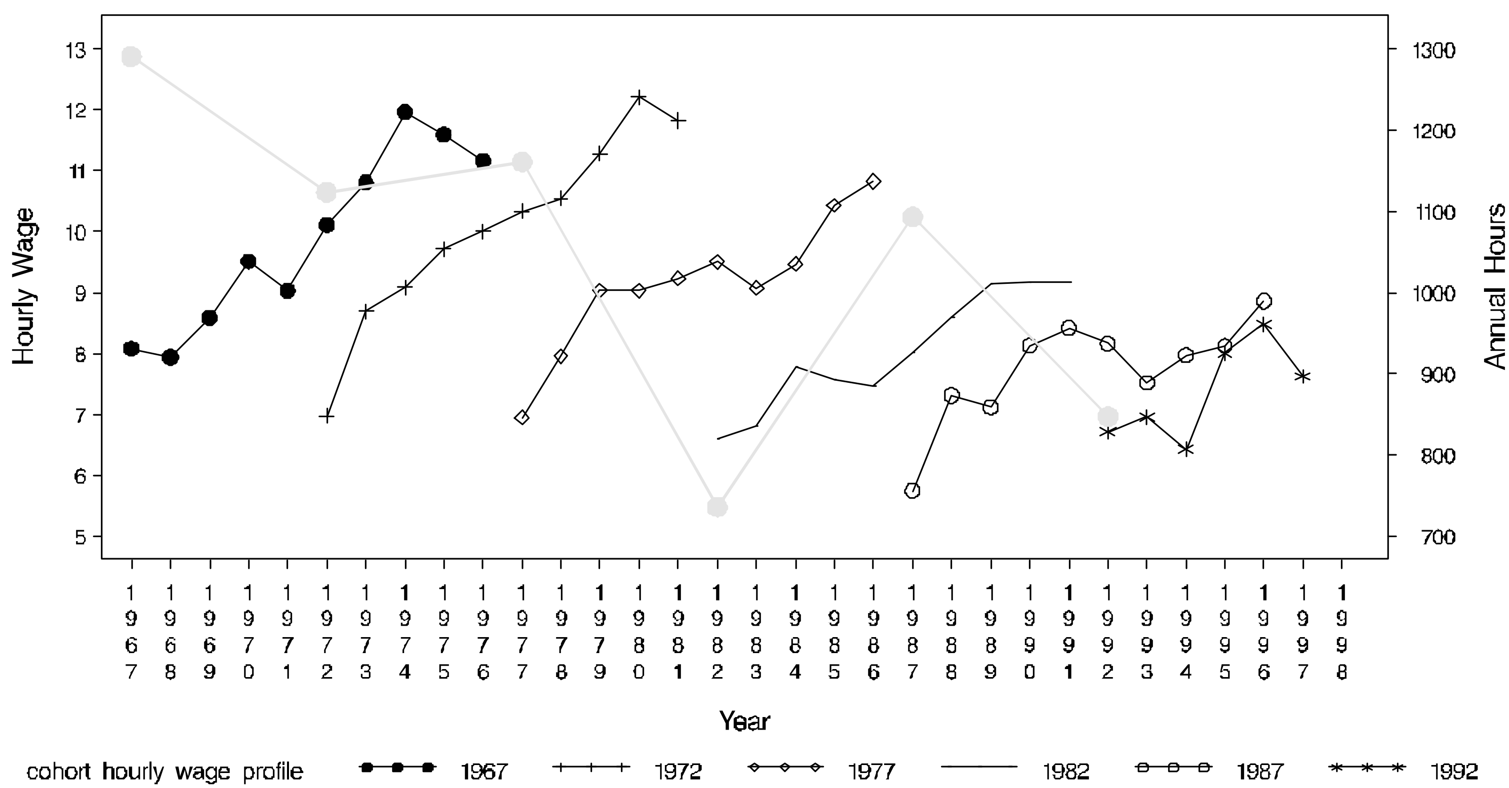
Hourly Wage Profiles
for Selected Cohorts of High School Dropouts



Notes: 1. Data are from the March Demographic Supplement to the Current Population Survey
2. Wage profiles are calculated for workers only. Variables and sample inclusion criteria are described in section 1.2 and section 1.3.
3. Wages are deflated using the Consumption Expenditure Survey (1992=100).

Figure 2b

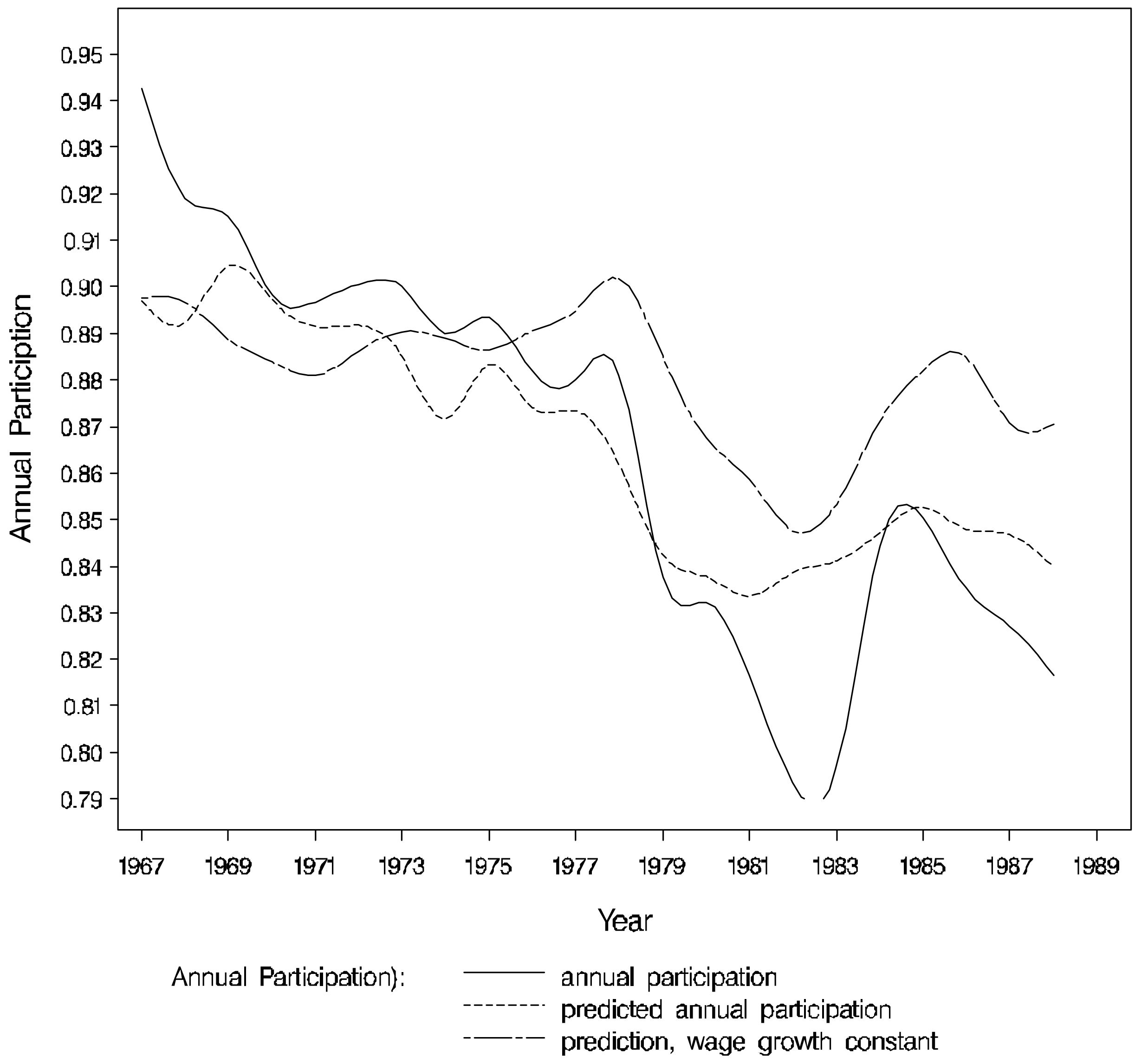
Hourly Wage Profiles and Starting Annual Hours for Selected Cohorts of High School Dropouts



Notes: 1. Data are from the March Demographic Supplement to the Current Population Survey.
2. Average annual hours includes individuals who are not working. Wage profiles are calculated for workers only. Variables and sample inclusion criteria are described in section 1.2 and section 1.3.
3. Wages are deflated using the Consumption Expenditure Survey (1992=100).

Figure 3a

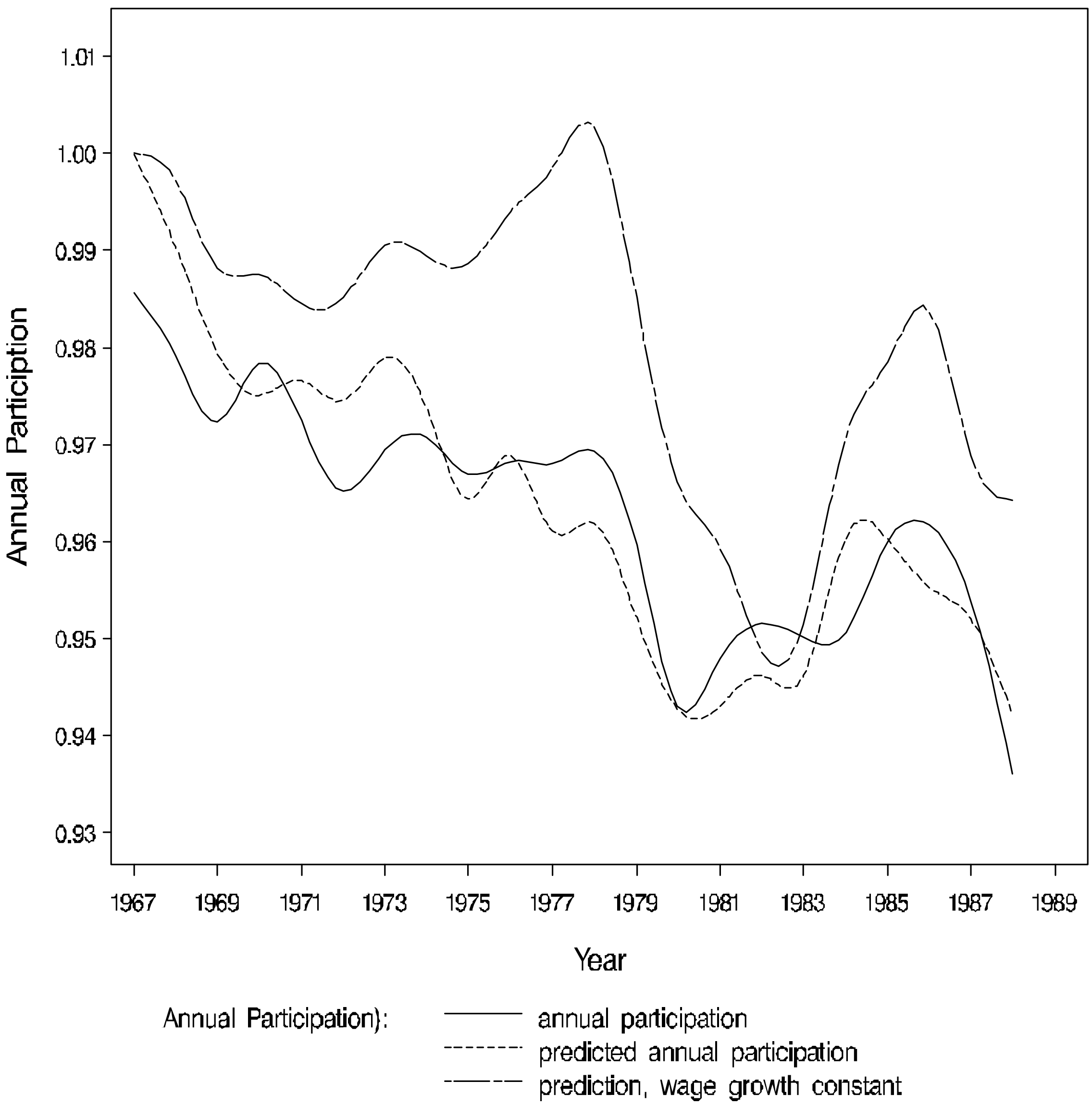
Annual Participation and Predicted Participation among high school drop–outs 1967–1988



Notes:
1. Data are from the March Demographic Supplement to the Current Population Survey
2. Annual participation is calculated as the proportion of all men working at least one week in the given year.
3. Predictions are based on regressions of annual participation on wages and wage growth, described in section 1.5. See appendix tables for full regression results.
4. The wage growth constant prediction holds wage growth at the 1967 level.

Figure 3b

Annual Participation and Predicted Participation among high school graduates 1967–1988

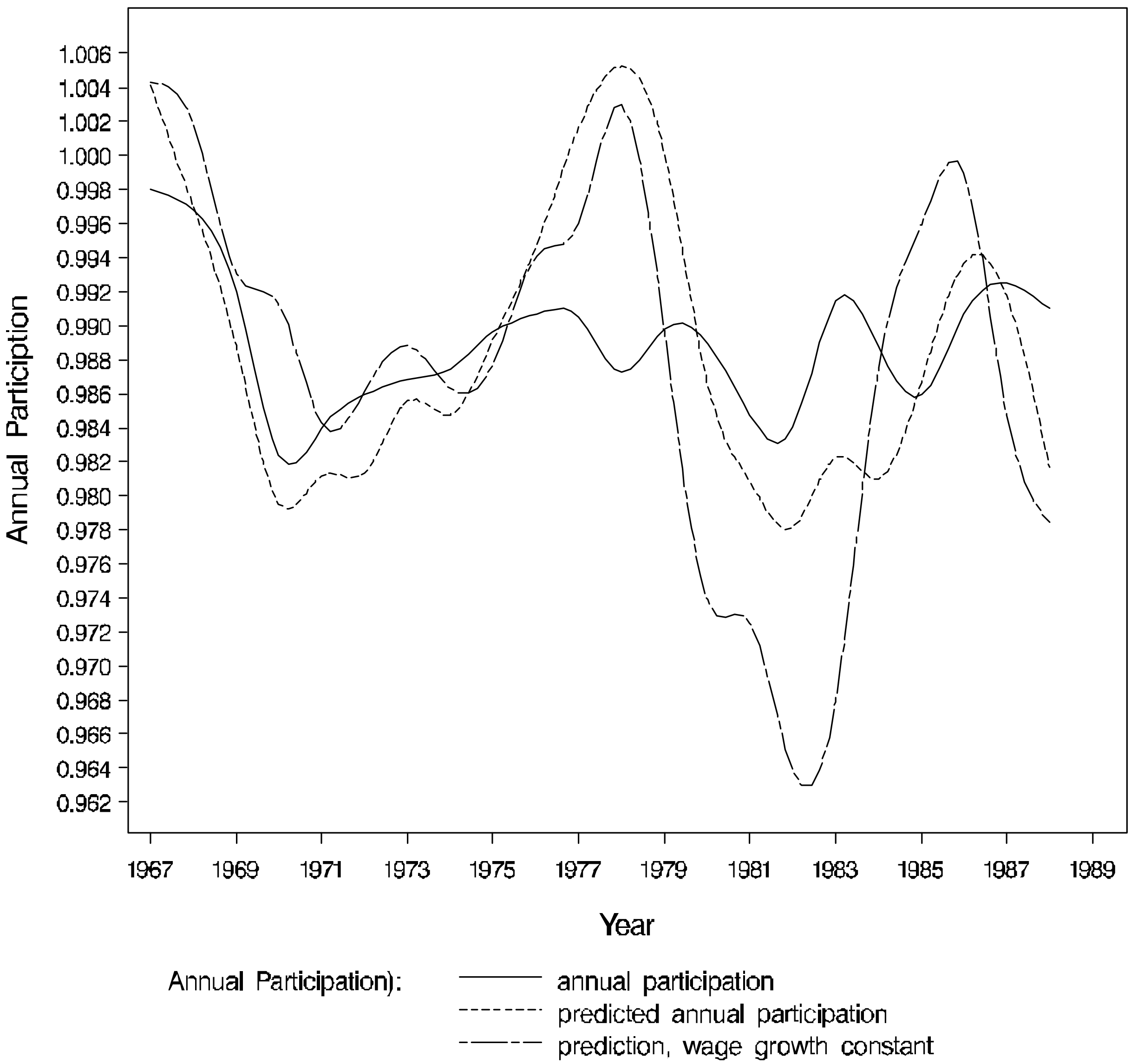


Notes:

1. Data are from the March Demographic Supplement to the Current Population Survey
2. Annual participation is calculated as the proportion of all men working at least one week in the given year.
3. Predictions are based on regressions of annual participation on wages and wage growth, described in section 1.5. See appendix tables for full regression results.
4. The wage growth constant prediction holds wage growth at the 1967 level.

Figure 3c

Annual Participation and Predicted Participation among college graduates 1967–1988



Notes:
1. Data are from the March Demographic Supplement to the Current Population Survey
2. Annual participation is calculated as the proportion of all men working at least one week in the given year.
3. Predictions are based on regressions of annual participation on wages and wage growth, described in section 1.5. See appendix tables for full regression results.
4. The wage growth constant prediction holds wage growth at the 1967 level.

Table 1
Average starting wages and 10 year wage growth for young men[a]

Year		1967-1969	1970-1972	1973-1975	1976-1978	1979-1981	1982-1984	1985-1987
Total	Wage Growth Starting Wage	63% 10.12	55% 10.37	51% 10.25	50% 10.13	50% 10.06	58% 9.12	54% 9.27
Education								
Drop-out	Wage Growth Starting Wage	71% 7.56	60% 7.03	41% 7.66	43% 7.26	39% 7.42	40% 6.98	57% 6.23
High school graduates	Wage Growth Starting Wage	66% 9.46	56% 9.51	48% 9.77	44% 9.61	40% 9.41	47% 8.11	50% 7.96
Some college	Wage Growth Starting Wage	59% 10.57	55% 10.63	51% 10.11	53% 10.41	46% 10.31	53% 9.29	57% 8.83
College	Wage Growth Starting Wage	44% 13.67	31% 14.49	41% 13.30	44% 13.09	48% 13.56	59% 12.41	41% 13.49
Race								
Non-Blacks	Wage Growth Starting Wage	61% 10.39	54% 10.54	51% 10.35	50% 10.23	47% 10.19	57% 9.25	53% 9.41
Blacks	Wage Growth Starting Wage	71% 8.00	55% 8.58	36% 8.96	39% 8.87	51% 8.22	74% 7.48	54% 7.62

[a] Notes:

1. Data are from the March Demographic Supplement to the Current Population Survey 1968-1998. See Section 2 for sample inclusion criteria and a description of the wage data.
2. Starting wages are hourly wages for workers with 1 year of labor market experience. Wage growth is the percent change in wages between the first and tenth year of actual experience (see Section 3 for description). Wages are deflated using the Personal Consumption Price Deflator (1992=100).

Table 2
Wages, value of working today,
and annual participation for new entrants
with no high school degree[a]
(%change compared to 67-69 in parentheses)

	1967-1969	1979-1981	1985-1987
) PDV	$12.20	$9.52 (-22%)	$9.61 (-21%)
Wage Level	$7.56	$7.42 (-2%)	$6.23 (-18%)
Annual Participation	0.95	0.85 (-11%)	0.86 (-10%)

[a] Notes:

1. Data are from the March Demographic Supplement to the Current Population Survey 1968-1998.
2.) PDV is the difference in the present discounted value of hourly wages over 10 years between a person working today or not, given that he works in the remaining periods. See Section 3.

Table 3
Number of observations per cohort/education group
for workers with one year of experience
March Demographic Supplement to the Current Population Survey, 1968-1987

Cohort	Education Group	# Obs.		Cohort	Education Group	# Obs
1	Dropout	141		12	Dropout	189
1	High School	134		12	High School	384
1	Some College	114		12	Some College	239
1	College	104		12	College	212
2	Dropout	165		13	Dropout	256
2	High School	164		13	High School	469
2	Some College	113		13	Some College	280
2	College	130		13	College	233
3	Dropout	150		14	Dropout	239
3	High School	138		14	High School	486
3	Some College	98		14	Some College	261
3	College	99		14	College	217
4	Dropout	166		15	Dropout	204
4	High School	187		15	High School	428
4	Some College	167		15	Some College	223
4	College	138		15	College	219
5	Dropout	183		16	Dropout	166
5	High School	246		16	High School	442
5	Some College	166		16	Some College	222
5	College	161		16	College	187
6	Dropout	152		17	Dropout	164
6	High School	307		17	High School	376
6	Some College	208		17	Some College	221
6	College	175		17	College	179
7	Dropout	149		18	Dropout	155
7	High School	328		18	High School	327
7	Some College	227		18	Some College	246
7	College	174		18	College	188
8	Dropout	137		19	Dropout	150
8	High School	341		19	High School	321
8	Some College	203		19	Some College	211
8	College	196		19	College	193
9	Dropout	166		20	Dropout	165
9	High School	335		20	High School	324
9	Some College	203		20	Some College	222
9	College	176		20	College	204
10	Dropout	199		21	Dropout	139
10	High School	406		21	High School	274
10	Some College	224		21	Some College	208
10	College	234		21	College	207
11	Dropout	192		22	Dropout	147
11	High School	460		22	High School	275
11	Some College	231		22	Some College	186
11	College	205		22	College	185

Table 4
Average returns to experience over the first ten years of working[a]

Cohort	Dropout	High School	Some College	College
1	0.050	0.053	0.047	0.038
2	0.046	0.048	0.045	0.034
3	0.062	0.048	0.046	0.036
4	0.058	0.044	0.050	0.029
5	0.057	0.048	0.049	0.037
6	0.053	0.045	0.046	0.034
7	0.047	0.045	0.038	0.036
8	0.037	0.043	0.047	0.037
9	0.050	0.036	0.046	0.039
10	0.037	0.037	0.037	0.038
11	0.037	0.028	0.041	0.043
12	0.023	0.026	0.033	0.039
13	0.021	0.031	0.034	0.045
14	0.031	0.038	0.043	0.047
15	0.032	0.041	0.052	0.043
16	0.045	0.052	0.053	0.047
17	0.042	0.049	0.052	0.048
18	0.034	0.046	0.041	0.033
19	0.031	0.041	0.043	0.033
20	0.024	0.033	0.043	0.034
21	0.035	0.043	0.046	0.043
22	0.029	0.038	0.050	0.040

[a] Notes:

1. Average wage growth is calculated as the coefficient on potential experience in a log wage equation.
2. Data are from the Match Demographic Supplement to the Current Population Survey, 1968-1998. The employment sample is used. Data and sample inclusion criteria are described in Section2.

Table 5
Descriptive statistics
Means and Standard Deviations[a]

	Mean	Standard Deviation
Annual Hours Conditional on Positive Employment	1881	256
Log Annual Hours Conditional on Positive Employment	7.43	0.214
Annual Participation	0.95	0.057
Hourly Wage Conditional on Positive Employment	11.29	2.98
Log Hourly Wage Conditional on Positive Employment	2.28	0.287
Hourly Wage	11.22	3.03
Log Hourly Wage	2.27	0.289
Average 10 year return to experience	0.041	0.008

[a] Notes:

1. Data are from the March Supplement of the Current Population Survey, 1968-1991. Variables are described in Section 2 and Section 5.
2. Wage data are deflated using the Consumption Expenditure Deflator (1992=100).

Table 6
Semi-elasticities of labor market participation with respect to wage levels and wage growth[a]

Change in annual hours or annual participation resulting from a ten percent change in wages or returns to experience ()y/%)x) or workers with 1 to 5 years of experience
(t-statistics in parentheses)

Explanatory Variable	Dependent Variable		
	(1) Annual Participation	(2) Annual Hours	(3) Total Effect
Hourly Wage	0.0072 (1.78)	28 (0.61)	40
Return to Experience	0.0061 (8.58)	24 (5.54)	34

[a] Notes:

1. Data include male workers with 1 to 5 years of potential experience. For the annual hours equation the workers sample is used. For the annual participation equation the employment sample is used. Variables and sample inclusion criteria are described in Section 2 and Section 5.
2. Equations are estimated using linear regression with a correction for measurement error. Covariates included in each regression are the log hourly wage, the return to experience, 22 cohort dummies, 3 education dummies (high school dropouts are the left-out group), year effects, and a quadratic in potential experience. The regression is run without an intercept. Full regression results appear in appendix table 1.2.

Table 7
Semi-elasticities of labor market participation
for alternative measures of wage growth[a]

Change in annual hours or annual participation resulting from a ten percent change in returns to experience ( ) y/%) x)
for workers with 1 to 5 years of experience
(t-statistics in parentheses)

Measure of Wage Growth	Dependent Variable	
	Annual Participation	Annual Hours
Cohort Return to Experience	0.0061 (8.58)	24 (5.54)
Time-Varying Return to Experience	0.0048 (5.84)	13 (3.69)
5 Year Lag of Cohort Return to Experience	0.00068 (1.03)	1 (0.20)
Cross-sectional Return to Experience	0.0077 (9.31)	8 (0.92)
Cohort Return to Experience Instrumented with the Cross-sectional Return to Experience	0.023 (3.79)	23 (0.92)

[a] Notes:

1. Data include male workers with 1 to 5 years of potential experience. For the annual hours equation the worker sample is used. For the annual participation equation the employment sample is used. Variables and sample inclusion criteria are described in Section 2 and Section 5.
2. Equations are estimated using linear regression with a correction for measurement error. Covariates included in each regression are the log hourly wage, a measure of wage growth, 22 cohort dummies, 3 education dummies (high school dropouts are the left-out group), year effects, and a quadratic in potential experience. The regression is run without an intercept.

Appendix

An Instrumental Variables Estimator with Measurement Error Correlated Across Endogenous Variables and Instruments

Deaton (1985) proposes an iv estimator to be used in cases when creating panel data from a time series of cross-sections. However, the estimator does not allow for the possibility that the measurement error in the instruments is correlated with the measurement error of the endogenous variables. The following estimator allows for this possibility. The asymptotic variance-covariance matrix and it's empirical analogue are also provided.

Let X be the observed matrix of structural variables, W be the observed matrix of instruments and Y be the observed vector of the dependent variable. The variables are measured with error so that

$$X = X^* + u; \quad (1)$$
$$Y = Y^* + d; \quad (2)$$
$$W = W^* + h \quad (3)$$

where u, $*$, and 0 are measurement error with respective variances $s_u^2, s_d^2, and\, s_h^2$. The measurement error is also allowed to co-vary, such that the variance-covariance matrix of 0 and $*$ is E_{0*} and the variance-covariance matrix of 0 and u is E_{0u}. and Let M_{xw}, M_{ww}, and M_{wy} be the sample moment and cross-product matrices and let S_{xw} and S_{ww} be the moment and cross-product matrices of the unobservable variables X^* and W^*.

Therefore

$$E(M_{ww}) = \Omega_{ww} + \Sigma_{ww}; \text{ and} \quad (4)$$
$$E(M_{wy}) = \Omega_{wx} b + \Sigma_{wy} - \Sigma_{wx} b \ . \quad (5)$$

Then the consistent iv estimator of $\$$ is

$$\tilde{b}_{IV} = \left[(X'W - T\Sigma_{uh})(W'W - T\Sigma_{hh})^{-1}(W'X - T\Sigma_{hu}) \right]^{-1} (X'W - T\Sigma_{uh})(W'W - T\Sigma_{hh})^{-1}(W'Y - T\Sigma_{hd}) \quad (6)$$

where T is the number of observations.

The derivation of the asymptotic variance-covariance matrix follows Deaton (1985). Assume that the variance-covariance matrix of the measurement error is known. To simplify the notation let $(_1$ indicate the first part of the estimator and $(_2$ the second part:

$$g_1 = \left[\left(M_{xw} - \Sigma_{xw} \right) \left(M_{ww} - \Sigma_{ww} \right)^{-1} \left(M_{wx} - \Sigma_{wx} \right) \right]^{-1} \tag{7}$$

and

$$g_2 = \left(M_{wx} - \Sigma_{wx} \right) \left(M_{ww} - \Sigma_{ww} \right)^{-1} \tag{8}$$

The matrices $'_1$ and $'_2$ represent the analogous matrices based on the unobserved “true” data.

$$\Gamma_1 = \left[\Omega_{uh} \Omega_{hh}^{-1} \Omega_{hu} \right]^{-1} . \tag{9}$$

$$\Gamma_2 = \Omega_{uh} \Omega_{hh}^{-1}$$

By adding and subtracting $'_1\ '_2(M_{wy}\text{-E}_{0*})$ we can rewrite equation 6 as

$$\tilde{b}_{IV} - b = \Gamma_1 \Gamma_2 \left[M_{wy} - E\left(M_{wy} \right) \right] + \left(g_1 g_2 - \Gamma_1 \Gamma_2 \right) \left(M_{wy} - \Sigma_{hd} \right) . \tag{10}$$

Now by adding and subtracting $'_1\ '_2[M_{wx}\$\text{-}E(M_{wx}\$)]$ we find that

$$\begin{aligned} \tilde{b}_{IV} - b &= \Gamma_1 \Gamma_2 \left[\left(M_{wy} - M_{wx} b \right) - \left(E\left(M_{wy} \right) - E\left(M_{wx} \right) b \right) \right] \\ &+ \Gamma_1 \Gamma_2 \left(M_{wx} b - E\left(M_{wx} b \right) \right) + \left(g_1 g_2 - \Gamma_1 \Gamma_2 \right) \left(M_{wy} - \Sigma_{hd} \right) \end{aligned} \tag{11}$$

From this equation we see that the variance of $\tilde{b}_{IV}$ will depend on the variance of $M_{wy} - M_{wx} b$. It can be shown that

$$M_{wy} - M_{wx} b = \left(W^* + h \right) \left(e + d - u' b \right) . \tag{12}$$

One of the properties of the normal distribution is that $Var\left(ab \right) = E\left(\left(ab \right)^2 \right) - \left(E\left(ab \right) \right)^2$, where a and b are random variables. Using this property it is possible to show that

$$\begin{aligned} Var\left(M_{wy} - M_{wx} b \right) &= \left[E\left(M_{ww} \right) \left(s_e^2 + s_d^2 - 2 s_{du}' b + b' \Sigma_{uu} b \right) \right] \\ &+ \left[\left(\Sigma_{hd} - \Sigma_{hu} b \right) \left(\Sigma_{hd} - \Sigma_{hd} b \right)' \right] \end{aligned} \tag{13}$$

Based on equations 12 and 13, the asymptotic variance-covariance matrix of $\tilde{b}$ is

$$TVar\left(\tilde{b} \right) = \Gamma_1 \Gamma_2 \left\{ \begin{aligned} &\left[E\left(M_{ww} \right) \left(s_e^2 + s_d^2 - 2 s_{du}' b + b' \Sigma_{uu} b \right) \right] \\ &+ \left[\left(\Sigma_{hd} - \Sigma_{hu} b \right) \left(\Sigma_{hd} - \Sigma_{hd} b \right)' \right] \end{aligned} \right\} \Gamma_2' \Gamma_1' . \tag{14}$$

The sample analogue can be derived by noting that $\tilde{\Gamma}_1 = g_1$ and $\tilde{\Gamma}_2 = g_2$. If we define

$$w = \left(s_e^2 + s_d^2 - 2s_{du}'b + b'\Sigma_{uu}b \right) \quad (15)$$

then

$$\tilde{w} = \frac{1}{T}\left(Y - X\tilde{b}\right)'\left(Y - X\tilde{b}\right) = \frac{1}{T}e'e\,. \quad (16)$$

Furthermore, based on equation 12 we find that

$$\Sigma_{hd} - \Sigma_{hu}b = M_{wy} - M_{wx}b = \frac{1}{T}W'e\,. \quad (17)$$

Substituting equations 16 and 17 into equation 14, and using sample analogues where appropriate, we see that the sample variance-covariance matrix is

$$TVar\left(\tilde{b}\right) = g_1 g_2 \left[T^{-1}M_{ww}e'e + T^{-2}W'ee'W\right]g_2' g_1' \quad (18)$$