A MINIMUM WAGE STUDY: TEENAGE SCHOOL ENROLLMENT AND ACADEMIC PERFORMANCE

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INTRODUCTION

For the teenage group, employment is a major alternative to education. By attending school, students are forgoing the hourly wage that they would have earned if they were working. In other words, the hourly wage is actually the opportunity cost of schooling. On the other hand, schooling increases the expected earnings in the future, which means that the opportunity cost of working is actually the future expected income forgone if the individual had remained in school. Because of the fact that most teenagers enter the labor market as low-skilled workers paid at the minimum wage, teenagers often make school/work decisions based on comparisons between the minimum wage and the expected return from additional years of schooling. As the minimum wage level changes, teenagers may alter their enrollment and employment decisions. An interesting question, then, is: whether a higher minimum wage would induce some teenagers to leave school for employment? Studying the impact of the minimum wage is valuable to policymakers not only because of the question of whether a higher minimum wage would reduce employment, but also because it may alter the investment in human capital that would, to some extent, adversely affect the long run economic growth and the welfare of the society as a whole.

While there are numerous past literatures studying this popular labor-economic issue, this research paper attempts to build on the existing literature by examining the relationship between student academic performance and the effects of the minimum wage on teenage enrollment.

Academic performance is an interesting research issue because the prospects of additional schooling are taken into consideration when teenagers are making school/work decisions. Teenagers who possess strong academic performance (high-GPA) will generally have better prospects continuing their education. The notion of "good prospects" constitutes the completion of secondary diploma, earning a higher income after high school graduation, and the possibility of pursuing post-secondary education, all of which are closely knitted with the academic achievement of the individual. The question, then, is: given an increase in the minimum wage, will teenagers with strong academic performance forsake their good prospects by leaving school for employment? More generally, do the effects of the minimum wage on enrollment and employment decisions of teenagers depend on their academic performance?

This paper investigates the relationship using 1980-1984 data from National Longitudinal Survey of Youth 1979 (NLSY79), by estimating a multinomial logit model to obtain derivatives of school/work probabilities with respect to the minimum wage.

The empirical evidence in this paper suggests that a higher minimum wage reduces part-time employment and increases full-time employment. There is an overall disemployment effect because the reduction of part-time employment outweighs the increase in full-time employment. Because part-time jobs are more difficult to be obtained, teenagers are more likely to return to full-time schooling. This paper finds that some students do dropout from high school for employment at the higher minimum wage. These dropouts are more likely to be teenagers with poor academic performance, while those who possess good academic standing are more likely to remain in school. Another important finding is that the inclusion of year, state, or regional dummies in the empirical model will lead to misleading results because these dummy variables are highly correlated with the minimum wage variable.

This paper will proceed by introducing some related past studies in the literature survey. Following the literature survey, I will describe the NLSY79 dataset and the methodology in two separate sections. Subsequently, the results section will present the key findings in the paper, which will then lead to the conclusion.

LITERATURE SURVEY

Brown et al. (1983) find that a 10% increase in the minimum wage is associated with a reduction in teenage employment of 1% to 3%. The disemployment effect is less severe for 20-24-year-olds than it is for younger teenagers. The shortcoming of this research, however, lies in the fact that it uses time-series data on the federal minimum wage, on workers covered by the federal minimum wage, and on the aggregate labor market (Neumark and Wascher 1992). Neumark and Wascher claim that time-series data may have relatively small variation in minimum wage over time, and this variation may be correlated with various social welfare and training programs. It is therefore difficult to isolate the effects of the minimum wage by using time-series datasets.

Using state-level cross-sectional data from 1960 and 1970 U.S. Censuses, Cunningham (1981) tests his prediction that a higher minimum wage would reduce part-time employment and increases full-time employment. This is based on his postulation that the same worker is more productive working full-time than part-time, and hence, employers adjust their demands for full-time and part-time labor accordingly. Teenagers, responding to the increase in demand, will have more incentives to leave school for full-time employment at the higher minimum wage. Consistent with Cunningham's prediction, the evidence from the data suggests that a higher minimum wage reduces school enrollment, reduces part-time employment, and increases full-time employment for white teenagers of both sexes, with the reduction in part-time employment outweighing the increase in full-time employment. This implies that there is a net disemployment effect. Generally, the vast majority of the minimum wage literature confirmed that the minimum wage reduces part-time employment. The ambiguity, however, remains in the effects of the minimum wage on teenage enrollment and full-time employment.

In contrast to Cunningham, Mattila (1981) finds that a higher minimum wage will lead to an increase in teenage enrollment. Mattila claims that the minimum wage creates barriers to employment and that additional schooling may be one strategy to overcoming those barriers. Utilizing 1947-1977 time-series data from the Current Population Survey (CPS), he finds that increases in the minimum wage are positively associated with teenage enrollment rates. Mattila also finds that the increase in enrollment is matched by the reduction in working teenagers. He explains that teenagers are returning to school because additional schooling is required in order to become more qualified for the jobs paid at the higher minimum wage. Similar to Brown et al. (1983), the use of time-series data in Mattila's research is often pointed out as a deficiency. Nevertheless, Mattila's findings suggest that a higher minimum wage creates a disemployment effect for the teenage group, and that the unemployed teenagers tend to return to school.

Ehrenberg and Marcus (1980) carry out a more profound analysis studying the relationship between family income and the effects of the minimum wage on teenagers. They predict that the effects of the minimum wage on teenage enrollment and employment may depend on the financial background of teenagers. They argue that, since part-time jobs are more difficult to obtain, teenagers from low-income families are more likely to dropout of school for full-time employment following a minimum wage increase, while teenagers from high-income families are more likely to remain in school because they can afford to do so without a job. Using data from 1966 National Longitudinal Survey (NLS) of Young Males, their conditional logit estimates provide evidence that strongly supports their predictions. The evidence suggests that, for white male teenagers, an increase in the minimum wage induces a shift from part-time employment to full-time schooling for the teenagers from high-income families. For teenagers from low-income families, however, such an increase would induce a shift from part-time employment while in school to full-time employment. They also find that a higher minimum wage has no significant effect on the enrollment and employment outcomes of nonwhite male teenagers from high-income families. For nonwhite male teenagers from low-income families, however, an increase in the minimum wage would induce a shift from full-time education to full-time employment.

Based on pooled repeated cross-sectional May CPS data, Card and Krueger (1995) find no evidence that a higher minimum wage reduces teenage employment; in some specifications, employment actually increases. Such findings support the Monopsony model.[50] Burkhauser et al. (2000) argue that because only one observation is drawn from each year, the inclusion of year dummies in the specification of Card and Krueger (1995) will eliminate all variation in the minimum wage variable due to changes in federal policy. Thus, including the year dummies will lead to insignificant and misleading results. Using 1979-1997 CPS data, Burkhauser et al. (2000) attempt to mitigate the problem of completely excluding the federal policy by collecting twelve monthly observations from each year. When year dummies are added to their specification, however, the estimation still removes 93% of the variation in the minimum wage. Apart from the criticism of Card and Krueger (1995), their finding suggests that the elasticity of teenage employment with respect to the minimum wage lies in the range of -.2 to -.6.

[50] The definition of the term "monopsony" is "sole buyer". Under the monopsony model, firms are allowed to choose the wage they pay to their workers. A firm that wants to recruit more workers, or to recruit workers more quickly, will have to pay a higher wage rate. This is different from the conventional assumption that firms can hire all the workers they want at the current wage rate. In the monopsony model, firms operate with ongoing vacancies. This is because if they offer a higher wage for an additional unit of worker, they will have to raise the wage rate to the same level for all their current workers. A profit-maximizing firm will hire an additional unit of labor at a wage rate equal to the marginal product minus the additional wages that must be given to all its current workers. Hence, firms choose to pay a wage rate lower than the marginal product and operate with some level of vacancy. A small increase in minimum wage will increase the employment of these firms because a higher minimum wage law forces firms to pay a higher wage rate for current employees. This will allow firms to hire more workers at the minimum wage, without the need to raise the wage paid to all their current employees. In the case when the increase in the minimum wage is too much, firms will choose to cut back employment, similar to the conventional model.

In a symposium introduction in *Industrial and Labor Relations Review*, Ehrenberg (1992) summarizes, "it is significant that none of the studies suggest that at current relative values of the minimum wage, large disemployment effects would result from modest future increases in the minimum wage – increases up to, say, 10%." Neumark and Wascher (1995b) argue that, however, reporting the disemployment effects at an aggregate level may not be adequate to explain the dynamics within population subgroups. Neumark and Wascher stress that although the net teenage disemployment effect may be small and insignificant, the minimum wage's effect on the transition dynamics within teenage subgroups may be significantly large. Aggregation may conceal interesting transitions within the teenage subgroups: some teenagers may shift from full-time schooling to part-time or full-time employment; some may be displaced from their current job, and consequently, they return to school or become neither enrolled nor employed. The aggregate estimation, however, may overlook these transitions and yield an insignificant net effect.

Neumark and Wascher (1995b) divide teenagers into four activities: in school and not employed (SNE), in school and employed (SE), not in school and employed (NSE), and not in school and not employed (NSNE). For simplicity, throughout the rest of this paper, I will utilize Neumark and Wascher's abbreviations of the four activities (SNE, SE, NSE, NSNE).

Using data from repeated May Current Population Survey (CPS) from 1973 through 1989, Neumark and Wascher (1995a) find that an increase in the minimum wage has an overall insignificant disemployment effect for an average teenager. In addition, they find that a higher minimum wage reduces the proportion of teenagers enrolled in school (SNE and SE) and increase the proportion of teenagers who are not in school and not employed (NSNE). They provide two explanations for these results.

The first explanation is the *substitution hypothesis*, which predicts that a higher minimum wage induces a substitution effect towards enrolled, and thus higher quality, teenagers (SNE and SE). Such an increase in the labor demand for enrollees will bid up their market wages, and hence, there are additional incentives for enrollees to leave school for employment. Under this scenario, these high-quality teenagers displace low-quality teenagers who are not in school and employed (NSE) at or near the old minimum wage level. Consequently, the displaced teenagers become not in school and not employed (NSNE).

The second explanation is the *queuing hypothesis*. This hypothesis suggests that a raise in the minimum wage reduces enrollment because enrollees leave school to queue for employment at the higher minimum wage. In this case, these high school dropouts may experience difficulty in acquiring jobs at the higher minimum wage, and consequently, they wind up queuing for jobs without any displacement of the teenagers who are currently employed.

In their subsequent study, Neumark and Wascher (1995b) utilize individual-level panel data from the May Current Population Surveys (CPS) for the period from 1979 to 1992. The estimates from a multinomial logit model are transformed into derivatives of the probability of each activity (SNE, SE, NSE, NSNE) with respect to the minimum wage. Neumark and Wascher compute the marginal effects of the minimum wage on, conditional on the individual's initial activity, the transition probabilities of the four activities. The estimates are summarized in *Table 1*.

Looking at *column (i)*, for teenagers who are initially in school and not employed (SNE), a higher minimum wage will significantly increase the probability of becoming not in school and not employed (NSNE). This result provides evidence supporting the queuing hypothesis. The negative and significant effect on the probability of becoming in

school and employed (SE) suggests that the teenagers who are originally in school and not employed (SNE) do not displace low-quality worker by combining school and work (SE). In addition, the increase (although insignificant) in the probability of becoming not in school and employed (NSE) implies that some high school dropouts actually find jobs, consistent with the substitution hypothesis.
As *column (ii)* reports, for the teenagers who are initially in school and employed (SE), a higher minimum wage significantly reduces the probability of remaining in the same activity, and increases the probability of becoming not in school and employed (NSE). Consistent with the substitution hypothesis, these results suggest that the teenagers who are initially in school and employed (SE) may displace low-quality workers by dropping out to work for more hours. The positive and significant effect on the probability of becoming not in school and not employed (NSNE) supports the queuing hypothesis, reflecting the individuals who dropped out from school to queue for full-time jobs at the higher minimum wage.

For those who are initially not in school and employed (NSE), *column (iii)* shows that an increase in the minimum wage significantly increases the likelihood of becoming not in school and not employed (NSNE). This is again consistent with the substitution hypothesis, which suggests that low-quality workers are being displaced by the high-quality teenagers who are initially enrolled in school (SNE or SE). Moreover, the estimates suggest that the teenagers who are initially not in school and employed (NSE) are less likely to return to school (SNE or SE).

As *column (iv)* reports, teenagers who are initially not in school and not employed (NSNE) are more likely to remain in the category of NSNE because a higher minimum wage reduces job opportunities. Although they have trouble finding jobs, these teenagers are less likely to return to school (SNE or SE) as minimum wage increases. This result is inconsistent with Mattila's claim that teenagers return to school in order to become more qualified for minimum wage jobs.

Overall, Neumark and Wascher find that an increase in the minimum wage reduces the probability of school enrollment. This is in stark contrast to the findings of Mattila (1981), who suggests the opposite. Both studies agree that employment is more difficult to obtain. The difference, however, lies in the enrollment decisions of teenagers. Mattila suggests that the unemployed teenagers return to school, while Neumark and Wascher suggest that they queue up for jobs and become not in school and not employed (NSNE).

Summing up the literature survey, none of the papers examines the possibility that the effects of minimum wage on teenage school leaving may be associated with the academic performance of individual teenagers. Cunningham (1981) suggests that the association lies in the productivity of individual teenagers, and hence part-time jobs are harder to obtain than full-time jobs. Similarly, Mattila (1981) points out that the employers are looking for teenage employees with higher level of education, and it is therefore beneficial for teenagers to return to school. Ehrenberg and Marcus (1980) provide evidence suggesting that the effects of the minimum wage on teenage school/work decisions depend on the family income level of individual teenagers. Lastly, Neumark and Wascher (1992, 1995a, 1995b) provide results that divulge valuable insight regarding the school/work transitions within teenage subgroups. Nevertheless, none of the abovementioned studies has incorporated the academic performance of teenagers as a control factor in their empirical models to examine the relationship between student academic achievement and the effect of the minimum wage on teenage enrollment.

THE DATA

The individual-level panel data comes from the National Longitudinal Survey of Youth 1979 (NLSY79). The sample consists of 11087 observations, which are the panel data of teenagers from 16- to 19-year-old from 1980 to 1984. After 1984, none of the sample members in NLSY79 is younger than the age of 20. The definitions, constructions, sources, and descriptive statistics of all variables are summarized in the Data Appendix.

High school graduates, college enrollees, and teenagers in military services are excluded from the sample because they do not have the same school/work options as high school enrollees and dropouts. High school graduates are likely to be employed or in the process of job searching, but they do not have the option of returning to high school. College enrollees, also, will not be returning to high school. Moreover, the effect of the minimum wage on college enrollees is likely to be different from that on high school teenagers. This paper will only examine the school/work decisions of high school students and dropouts. Prior to the exclusion of high school graduates and college enrollees, the original dataset has 19010 observations of teenagers from 16- to 19-year-old. The exclusion reduces the sample size by 7668 observations, which is approximately 40% of the original sample. Most of the excluded teenagers are the 18- and 19-year-olds who have graduated from high school a few years earlier than the others have.

The NLSY79 data with geographic micro data specifies the current state of residence for each individual. Using this information, the individual-level data are matched with state-level variables, which are the minimum wage, the average hourly earnings in manufacturing industry, and the unemployment rate. Sampling weights, provided by NLSY79, are used throughout the empirical analysis to adjust for the over sampling of certain demographic groups.

Studying the minimum wage during the period from 1980 to 1984, however, may be criticized for being dated. Although this period is not selected intentionally, 1980-1984 does appear to be very suitable for minimum-wage study. *Table 2* shows that the federal minimum wage has increased three times from 1979 to 1984. This will create much variation in the minimum wage variable and will help the sensitivity of the empirical analysis.

Figure 1 and Figure 2 portray the economic environment during the period 1960 – 2000 in terms of national annual GDP growth rates and unemployment rates, respectively. The GDP growth rates from 1980 to 1984 are high, averaging to approximately 9.1% per annum. In 1982, however, the growth rate is cut to 4.1%. At the same time, unemployment rates also show some variation with its peak centered at the year 1982. Overall, the business cycle from 1980 to 1984 does reflect some up-down swings rather than a one-sided trend.

In comparison with Neumark and Wascher's data (1995b), my sample from the NLSY79 panel data is selected and surveyed randomly while their sample has to be matched across CPS surveys. Neumark and Wascher claim that about 65% of the eligible teenagers in each year could be matched to a record in the following year, and that this raises the possibility of sample selection bias, if the unobservable characteristics associated with both successful matches and school/work outcomes are correlated with the independent variables.

Another major distinction is that Neumark and Wascher utilize an enrollment status variable that can only distinguish teenagers as "enrolled" or "not enrolled". As a result, they are unable to exclude high school graduates, college enrollees, and teenagers in military service from their sample. Lastly, Neumark and Wascher's CPS dataset containing 36,021 matched records is collected from 1979 to 1992, which is superior to the dataset used in this paper in terms of sample size and data variations across time.

METHODS

A. Lagged Relative Minimum Wage Variable

Previous empirical analyses studying the effects of the minimum wage on school/work decisions of teenagers typically equate the minimum wage variable as

$$RMW\_1 = \frac{\text{Higher of the federal or state minimum wage lagged by one year}}{\text{Average hourly wage in manufacturing lagged by one year}} \quad \text{(I)}$$

where RMW_1 is the lagged relative minimum wage variable. It is worth clarifying the reasons for formulating the relative minimum wage equal to the ratio of the minimum wage (higher of the federal or state) to the average hourly wage (manufacturing industry) in the state. First, although the federal minimum wage is constant across states at a given time, the minimum wage level and its coverage vary across states,[51] as each state may set its own minimum wage equal to or higher than the federal minimum wage. Secondly, the average hourly wage is also a state-specific variable. For States that have a lower average hourly wage, the minimum wage is relatively more attractive than other states that have a higher average hourly wage. The relative minimum wage variable is therefore a ratio adjusting for the relative attractiveness of the minimum wage across states. A number of past studies have also adjusted for the differences in the coverage rate between different states.[52] Neumark and Wascher (1995b) point out, however, that it is problematic to obtain an accurate measure of the coverage rate in most states, and that it is plausible to disregard this factor because the results are very similar with or without the coverage adjustment. Because of these reasons, the relative minimum wage variable in this paper will not be adjusted for the coverage difference across states. Lastly, the relative minimum wage variable is lagged by one year to account for the lags in the effects of minimum wage changes due to inability to adjust to other forms of input quickly, or due to high cost of hiring and training (Neumark and Wascher 1992).[53]

B. Multinomial Logit Estimation

The empirical approach in this paper will be very similar to that of Neumark and Wascher (1995b). The utility from each activity indexed by j (SNE, SE, NSE, or NSNE),[54] for individual k in state i at period t is

$$U_{kjit} = X_{it}\beta_j + A_{kit}\gamma_j + J_{kit-1}\pi_j + S_i\delta_j + Y_t\theta_j + \varepsilon_{kit}, \quad \text{(II)}$$

where X is a set of state-level variables that includes the lagged relative minimum wage (RMW_1) and unemployment rate, A is a set of individual-level variables that includes age, sex, and race dummies, along with net annual family income, family size, and academic performance (*GPA*). J is another set of lagged activity dummies to account for individual school/work activity in the previous year. State (S) and year (Y) dummy variables are included to account for the unobserved fixed influences common to all individuals within states or years. Lastly, ε denotes the person-specific random error.

Every individual k chooses one of the activities (SNE, SE, NSE, or NSNE) such

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51 The coverage rate is the proportion of sectors that is covered by the minimum wage law. Each state has different laws that restrict certain industries to be covered by the minimum wage.

52 The coverage-adjusted relative minimum wage variable is formulated by multiplying the coverage rate to the relative minimum wage.

53 Strong lags in the minimum wage effects are sometimes considered unlikely because of the high turnover among low-wage workers, and because minimum changes are typically enacted earlier than the time they actually take effect (Brown et al. 1982).

54 The index j takes on the values {1, 2, 3, 4} for activity categories {SNE, SE, NSE, NSNE} respectively. That is, {Activity $_{j=1}$ = SNE, Activity $_{j=2}$ = SE, Activity $_{j=3}$ = NSE, Activity $_{j=4}$ = NSNE}.

that the utility function expressed by equation (II) is maximized. Assuming ε_k has an extreme value distribution, this will lead to a multinomial logit model (Neumark and Wascher 1995b).[55] If equation (II) is expressed in general form as

$$U_{kj} = W\alpha_j + \varepsilon_k, \qquad \text{(III)}$$

where W is a matrix containing the set of explanatory variable specified in equation (II) and α is a vector containing the parameters, multinomial logit estimation will calculate the α vector such that its elements maximize the U in equation (III) for each activity j (SNE, SE, NSE, NSNE). After multinomial logit estimation, the probabilities of being in each activity j can be computed as

$$P_j = exp\,(W\alpha_j)\,/\,[1 + \Sigma_j\, exp\,(W\alpha_j)].^{56} \qquad \text{(IV)}$$

However, the coefficients of interest are not the probabilities, but the derivatives of these probabilities with respect to the lagged relative minimum wage. The derivative of the probability of being in activity j with respect to the m^{th} element of the matrix W is calculated as (Neumark and Wascher 1995b)

$$\partial P_j/\partial W_m = P_j\,[\,\alpha_{mj} - \Sigma(P_j\alpha_{mj})].^{57} \qquad \text{(V)}$$

In this paper, the m^{th} element of interest is the lagged relative minimum wage. The expression in equation (V) yields the percentage change in the probability of being in each of the activity j (SNE, SE, NSE, NSNE) with respect to a unit change in the lagged relative minimum wage variable specified in equation (I). Put differently, equation (V) computes the marginal effect of the lagged relative minimum wage on the probabilities of being in each activity j.

It is important to note that the probabilities and the derivatives in equation (IV) and (V) depends on the values of every elements in matrix W, which are the values of all explanatory variables specified in equation (II). The typical way to compute the derivatives is to evaluate them at the sample mean of all explanatory variables in matrix W. The results are the derivatives of the probability of being in activity j with respect to the lagged relative minimum wage for the entire sample, unconditional on their initial (lagged) activities. Intuitively, these derivatives are useful in estimating the overall effects of the minimum wage on teenage enrollment and employment, but they are insufficient in estimating the school/work transitions within teenage subgroups due to changes in the minimum wage. To calculate the transitions within teenage subgroups, the derivatives are computed conditional on the initial (lagged) activities.[58] The resulting sixteen coefficients (4 initial activities x 4 final activities) tabulated by Neumark and Wascher in *Table 1* are precisely computed using this method.

Because a unit change in the lagged relative minimum wage implies doubling the minimum wage level holding the average hourly wage constant, the derivative computed from equation (V) should be interpreted as the effects of a 100% raise in the minimum wage level on the probability of being in each activity j. A more useful

[55] For more explanation for the multinomial logit model, refer to Greene (2000), pp. 859-862.

[56] The summation of the probabilities of being in each activity j is
$\Sigma P_j = P_1 + P_2 + P_3 + P_4 = Prob\,(SNE) + Prob\,(SE) + Prob\,(NSE) + Prob\,(NSNE) = 1$.

[57] Since $\Sigma P_j = 1$, it follows that the sum of the derivatives of the probability of being in activity j with respect to the m^{th} element of W must be equal to zero. That is, $\Sigma_j\,(\partial P_j/\partial W_m) = 0$.

[58] For example, if the lagged activity dummies are {SNE_1, SE_1, NSE_1, NSNE_1}, the conditional setting for the teenagers who are initially in school and employed (SE), the derivatives from equation (V) will have to be calculated at {SNE_1 = 0, SE_1 = 1, NSE_1 = 0, NSNE_1 = 0, mean of all other explanatory variables}.

interpretation, then, is to divide the derivative by 10, which will be interpreted as the effect of a 10% raise in the minimum wage level on the probability of being in each activity j.

C. Endogeneity Problem of Academic Performance

The inclusion of academic performance (GPA) as a control factor in equation (II), however, may cause endogeneity problem in the multinomial logit estimation (Smith 2000; Sicular 2000). A teenager may choose an effort level in school that depends on their expectations of future enrollment and employment opportunities. This effort level consequently affects the academic performance (GPA) of the teenager. That is, GPA and school/work activities may be simultaneously determined, and that the causality may be bi-directional between the academic performance and the probability of being in one of the school/work activities (SNE, SE, NSE, or NSNE).

To address the endogeneity problem in the academic performance (GPA), I use ASVAB verbal score, ASVAB math score,[59] mother's education level, and father's education level as instrumental variables for GPA. This will require a two-stage method. In the first stage, I obtain the predicted value of GPA from the ordinary least square (OLS) regression of GPA on the instrumental variables. In the second stage, I perform the multinomial logit estimation using the predicted value of GPA, in place of the original GPA, as an explanatory variable. An alternative approach is to use the original GPA and the predicted residual from the first stage as explanatory variables in the second stage. In this case, the residual term is analogous to the correction term in the Heckman two-step method (Smith 2001).[60]

The two-stage method requires strict assumptions on the instrumental variables. The first assumption is that the correlation between GPA and the instrument must not be equal to zero. This assumption is easily testable by computing the sample correlation between GPA and the instruments. The second assumption is that the instruments must not be correlated with the random error (ε) in equation (II). This assumption is not testable, so it requires intuitive arguments that ASVAB scores and parental education level are uncorrelated with the error term.

The error term in equation (II) is the remaining variations in school/work transitions that are left unexplained after conditioning on the observable characteristics in the explanatory variables. One possibility is that an individual's preference in schooling and working may affect his/her enrollment and employment decisions. This preference factor is unobservable, and hence, is a component of the error term. In order to use the two-stage method under this scenario, I need to assume that the preference in schooling and working is uncorrelated with ASVAB scores and parental education level. Intuitively, this assumption entails arguments such as teenagers do not take their school/work preference into account when they are writing the ASVAB tests, and parental education level does not influence teenagers' school/work preference. I feel that the ASVAB scores assumption is more intuitively valid than the parental education assumption because it is unlikely that the performance in ASVAB tests will affect future prospects of schooling and employment, so that school/work preference is not likely a factor that influences the test scores. On the other hand, parental education level is likely to affect teenagers' attitude towards schooling and working. If this is the

[59] The Armed Services Vocational Aptitude Battery (ASVAB) is a multiple-aptitude test battery consisting of ten subtests on various subjects. The U.S. Department of Defense uses the ASVAB to test potential recruits on their abilities and knowledge on certain subjects, and to predict performance in certain academic areas such as English and mathematics.

[60] The Heckman two-step method is an approach to correct for selection biases in the sample.

case, ASVAB scores are clearly preferred to be the instrumental variables for academic performance.

RESULTS

A. The Choice of Specification

The multinomial logit estimates and implied derivatives from various specifications are reported in *Table 3* and *Table 4* (the values in parentheses denote the robust standard errors).[61] Panel A of *Table 3* and *4* reports the estimates of the multinomial logit model using SNE as the comparison group, and panel B reports the implied partial derivatives of the probabilities of being in each activity (SNE, SE, NSE, NSNE) with respect to the lagged relative minimum wage for the entire sample, unconditional on their initial (lagged) activities. The implied partial derivatives are computed at the sample means of all explanatory variables to derive $\partial P_j/\partial RMW\_1$ as described in equation (V).[62]

The specification in *column (1)* includes only the lagged relative minimum wage. This model predicts that a higher minimum wage will significantly increase the probability of becoming in school and not employed (SNE) or not in school and employed (NSE), while the probabilities of becoming in school and employed (SE) is significantly reduced. The minimum wage has no significant effect on the probability of becoming not in school and not employed (NSNE), although the sign of the coefficient is negative. Unemployment rate is added in *column (2)* to account for differences in labor markets and business cycles across states. The implied derivatives are generally the same as *column (1)* except that there is now a significant increase in the probability of becoming not in school and not employed (NSNE), and the reduction in probability of becoming in school and employed (SE) becomes even more substantial. In *column (3)*, age, race, and sex dummies are added to the model. The minimum wage effect on the probability of becoming in school and not employment (SNE) becomes small and insignificant, while the coefficients on the other activities (SE, NSE, NSNE) remain similar to that of *column (2)*.

In *column (4)*, lagged activity dummies are included in the model to account for the possibility that teenagers' school/work decisions depend on their initial activities (SNE_1, SE_1, NSE_1, or NSNE_1). The Pseudo R-squared of the model is substantially improved in this model, implying that teenage school/work decision does depend on their initial activity.[63] The effect of the minimum wage on the probability of being not in school and not employed (NSNE) remains positive but reverts to statistically insignificant, and the reduction in the probability of becoming in school and employed (SE) is noticeably weakened.

Year dummies are added in the specification in *column (5)* to capture the differences in economic environment across time. Although adding the year dummies will eliminate all of the influence of changes in the federal minimum wage policy (Burkhauser et al. 2000), the results are almost identical to that of *column (4)*. This may be because that the NLSY79 data stretches only from 1980-1984, implying that cross-sectional variation in the lagged relative minimum wage dominates over-time variation in the data. The year dummies are jointly insignificant at the 5% level, possibly because much of the business cycle fluctuations are captured by the unemployment rate variable.

State dummies are included in *column (6)* to account for cross-state differences in items such as compulsory schooling age, education

[61] The robust standard errors are reported because of sampling weights are used for the estimation.

[62] Recall from footnote (8) that the four implied derivatives in each column must sum up to zero.

[63] In fact, the joint significance of the lagged activity dummies is statistically significant at the 1% level in all specifications I estimated.

policies, and school quality. Under this specification, however, all implied derivatives become statistically insignificant. This does not imply that the minimum wage has no effect on teenage school/work transitions. Instead, it implies that the inclusion of year and state dummies in the specification will almost eliminate all variation in the lagged relative minimum wage across states. In fact, regressing (OLS) the lagged relative minimum wage on the year and state dummies yields an R-squared of .9956, which means that when year and state dummies are added into the multinomial logit model, the regression is very close to exhibiting multicollinearity. The results from such a model will be highly inefficient with extremely large standard errors, as shown in *column (6)*.

It is important to note that the specification in *column (6)* is exactly the one used by Neumark and Wascher (1995b). Given that only one minimum wage observation is drawn from each year from each state, it is astonishing to observe such significant values as tabulated in *Table 1*.[64] Although Neumark and Wascher's CPS data has a larger sample size and a longer time frame that stretches from 1979 to 1992, it is not convincing that such level of significance could be observed under such a high level of collinearity in their model.

To mitigate the collinearity problem, *column (7)* in *Table 4* uses regional dummies in place of the state dummies.[65] The purpose of adding regional dummies is to capture the differences in various social and economic policies across regions (Sicular 2001). The significance of the implied derivatives is substantially reduced from *column (5)*, but obviously not as severe as using the state dummies. In this specification, a higher minimum wage will reduce the probability of becoming in school and not employed (SNE), which is different from *column (5)*. The negative effect on the probability of becoming in school and employed (SE) has become statistically insignificant.

In *column (8)*, net family annual income and family size are added to account for the different family obligations that each teenager faces, which will influence the teenager's school/work decisions. The number of observations is reduced to 8482 due to invalid non-responses in the family income variable, which are treated as missing values. The family income variable is implemented in the study by Ehrenberg and Marcus (1980), as mentioned in the literature survey. It turns out that family income and family size are both significant at the 1% level in explaining school/work decisions of teenagers, and the Pseudo R-squared improves to .3353. The results from this specification are almost the same as *column (7)*. The only difference is that the derivative on in school and employed (SE) becomes positive, but it is still insignificantly different from zero.

Academic performance variable (GPA) is added to the specification in *column (9)*.[66] As mentioned in the literature survey, none of the past studies has incorporated GPA as a control factor in their empirical models. The GPA variable is significant at the 1% level, and the Pseudo R-squared climbs up to .3572. However, the implied derivatives on all four

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64 This argument is analogous to Burkhauser et al. (2000)'s criticism of the inclusion of year dummies in the specification of Card and Krueger (1995)

65 The regional dummies are provided by NLSY79, assigning each observation into one of the four regions (South, West, Northeast, and North Central).

66 Two variables are actually added into the specification. The first being the 4-point scale GPA, which is calculated based on all high school courses taken by the individual. The second variable is a dummy variable (zeroGPA), which takes on the value of one for individuals who have never taken a high school course, and takes on the value of zero for individuals who have taken one or more high school courses. The reason for this is to allow a different slope for teenagers who have never attended high school.

school/work activities become statistically insignificant. At this point, it seems that the lagged relative minimum wage has no significant effect on teenage school/work transitions under this specification. This result is misleading, however, because the year and regional dummies still remove 57% of the variation in the lagged relative minimum wage.[67]

With a more careful study of the correlation between the lagged relative minimum wage and the year and regional dummies, I find that the year and regional dummies are highly correlated with the lagged minimum wage level with an R-squared (OLS) of .9750, which means that minimum wage policies systematically differ across regions. In particular, the west and the northeast are observed to have a higher lagged minimum wage level than the south and the north central. The year dummies also play an important role in explaining the variation in the lagged minimum wage level, because they capture most of the increases in the federal minimum wage (Burkhauser 2000). Moreover, the year and regional dummies are also correlated with the lagged average hourly earnings with an R-squared (OLS) of .6622.[68] This implies that including year and regional dummies in the model will eliminate much of the explanatory power of the lagged relative minimum wage variable, similar to the scenario of including the year and state dummies.

In essence, the lagged relative minimum wage variable is extremely sensitive to the choice of other explanatory variables. Inclusion of highly correlated variables such as year, state, or regional dummies in the specification may lead to misleading results in terms of direction and statistical inference, because these dummy variables overlap the explanatory information given by the lagged relative minimum wage variable. Future study in this topic should consider using specific state-level variables such as welfare expenditure, education spending, and compulsory schooling age dummies instead of using year, state, or regional dummies to capture the whole environment.

B. Detecting Endogeneity of Academic Performance

The inclusion of the academic performance variable (GPA) in the model specified in *column (10)* raises the possibility of endogeneity bias (Sicular 2000; Smith 2000). To account for the problem, a two-stage method is applied as described in the Methods section. The results from the two-stage method are summarized in *Table 5*. The first column is directly transferred from *column (10)* of *Table 4* for the purpose of comparison. *Column (a)* uses ASVAB verbal and math scores as instrumental variables for GPA. The R-squared from the first-stage ordinary least squares estimation is .2996, which implies that the GPA and ASVAB scores are correlated. The results from the second stage using multinomial logit estimation (panel B) indicate that there is no noticeable difference from *column (10)*.

Column (b) uses parental education levels as instruments for GPA. The sample correlation between mother's education level and GPA is 0.2429, and the sample correlation between father's education level and GPA is 0.2335. The R-squared from the first-stage, however, is only .0862. Nevertheless, parental education level significantly explains the variation in GPA at the 1% level. Again, the results in panel B are essentially the same as *column (10)* except that the increase in the probability of becoming in school and not employed (SNE) has become slightly less significant.

The same implication applies to *column (c)*, which now uses the ASVAB scores and

[67] Regressing (OLS) the lagged relative minimum wage on the year and regional dummies yield an R-squared of .5702, which is also high and contributes to the less significant results.

[68] Recall from equation (I) that the lagged relative minimum wage is a function of the lagged minimum wage level and the lagged average hourly wage in manufacturing industry.

parental education together as instruments of the GPA variable. The only difference is that the SNE coefficient reverts to significant at the 10% level. Lastly, in *column (d)*, the original GPA variable and the predicted residual from first-stage as explanatory variables are used in the second-stage estimation. The results, again, are almost identical to that of *column (10)*.

In summary, the results in *Table 5* indicate that there are no distinguishable differences after the applying the two-stage method to correct for the endogeneity problem of academic performance (GPA). One possibility is that, optimistically, GPA is in fact not endogenous, given that the instruments satisfy the assumptions described in the Methods section. Another possibility is that, pessimistically, GPA, ASVAB scores, and parental education levels are all endogenous, and that they are all part of the whole system of choosing a school/work activity and an effort level in school. In this case, the two-stage method fails to detect the endogeneity problem because the assumption that the instrumental variables are uncorrelated with random error is violated. Nevertheless, I believe that the ASVAB scores are exogenous because it is unlikely that the performance in ASVAB tests will affect future prospects of schooling and employment. If this is indeed the case, *Table 5* conveys that the endogeneity bias is minimal in a model that contains teenage academic performance (GPA). Because of this reason, I decide to use the model specified by *column (10)* for further analyses.

C. Minimum Wage Effects on School/Work Activities

The implied derivatives in *column (10)* of *Table (4)* are very similar to that of *column (4)* of *Table 3*, of which the year and state dummies are not yet added in the specification.[69] The implied derivatives from *column (10)* indicate that a 10% raise in the minimum wage will reduce the probability of becoming in school and employed (SE) by 3.8%.[70] This implies that part-time employment is more difficult to obtain, which is consistent with most previous studies. A 10% increase in the minimum wage will raise the probability of becoming not in school and employed (NSE) by 2.1%. This is consistent with Cunningham (1981), who finds that a higher minimum wage will reduce part-time employment and raise full-time employment. Notice that the reduction in part-time employment outweighs the increase in full-time employment, indicating that there is an overall disemployment effect.

The 2% increase in probability of becoming in school and not employed (SNE) implies that teenagers who have lost their jobs are returning to full-time schooling, although this increase is only significant at the 10% level. Nevertheless, this result supports Mattila's (1981) time series evidence that an increase in the minimum wage is positively associated with teenage school enrollment. Lastly, the minimum wage has no significant impact on the probability of becoming not in school and not employed (NSNE).

Table 6 summarizes the changes in the probabilities of being in each activity before and after a 10% and 30% raise in the minimum wage. The numbers indicate that, given a modest increase in the minimum wage such as 10%, the effects of the minimum wage on the probability of each school/work activity are small. The minimum wage effects become much more apparent with a more generous 30% increase, especially for the reduction in the probability of becoming in school and employed (SE). The probabilities of becoming in school and

[69] This paper only reports the coefficient on the lagged relative minimum wage variable. For those who are interested in other variables, see Output Appendix.

[70] Recall from the Methods section that the implied derivatives correspond to a 100% increase in the minimum wage level, holding the average hourly wage constant. Dividing the coefficients by 10 thus implies a 10% increase.

not employed (SNE), and not in school and employed (NSE), have increased considerably. Realistically, the increases in the federal minimum wage rarely exceed 15% in the recent years, although increases larger than 30% have occurred frequently during the 1940s and 1950s.

D. Minimum Wage Effects on School/Work Transitions

So far, the analyses have examined the overall effects of the minimum wage on the probability of each school/work activity for the entire sample. A more in-depth study is to examine the transition between teenage subgroups conditional on their initial activities. That is, given the initial activity (SNE_1, SE_1, NSE_1, NSNE_1), what are the effects of an increase in the minimum wage on the probability of being in each activity *j* (SNE, SE, NSE, NSNE)?

The derivatives of switching to each school/work activity conditional on a given initial activity, are calculated by deriving $\partial P_j/\partial RMW\_1$ in equation (V) by setting the lagged activity dummy for the initial school/work activity being considered to one, and setting the others to zero (Neumark and Wascher 1995b). The resulting 16 transition derivatives (four initial activities x four final activities) are summarized in *Table 7*.[71]

Looking at all columns in *Table 7*, the first thing to notice is that the probabilities of becoming in school and employed (SE) are significantly reduced for all initial activities, implying that part-time employment is more difficult to obtain. Again, this is consistent with the majority of past literature.

From *column (i)*, for teenagers who are initially in school and not employed (SNE), a higher minimum wage will raise the likelihood of staying in the same activity (SNE). Because it is harder to find part-time jobs, students who opt to stay in school are less likely to become in school and employed (SE). This result is consistent with Mattila's finding that a higher minimum wage will create barriers to employment and thus, teenagers are more likely to stay in full-time education. The probability of becoming not in school and employed (NSE) is also significantly increased after a minimum wage hike. This result provides evidence that some full-time students do dropout to work full-time. In addition, the insignificant change in the probability of becoming not in school and not employed (NSNE) implies that high school enrollees do not dropout to queue for jobs at the higher minimum wage, which contradicts the queuing hypothesis suggested by Neumark and Wascher (1995b).

As *column (ii)* reports, for teenagers who are initially in school and employed (SE), a higher minimum wage significantly reduces the probability of remaining in the same activity, and increases the probability of becoming not in school and employed (NSE). These results suggest that some teenagers who are able to sustain their part-time jobs are more likely to dropout for full-time employment. The positive and significant effect on the probability of becoming in school and not employed (SNE) implies that teenagers initially in school and employed (SE) who lose their jobs tend to return to full-time education instead of queuing for jobs. Again, this refutes the queuing hypothesis.

For teenagers who are initially not in school and employed (NSE), *column (iii)* shows that an inflated minimum wage significantly increases the chance of staying in the same activity (NSE) and reduces the chance of becoming not in school and not employed (NSNE). This suggests that full-time workers are not being displaced, which is inconsistent with the substitution hypothesis of Neumark and Wascher (1995b). The estimates also suggest that teenagers who are initially

[71] This paper only reports the coefficient on the lagged relative minimum wage variable. For those who are interested in other variables, see Output Appendix.

working full-time (NSE) are less likely to return to school (SNor SE).

Lastly, *column (iv)* reports that teenagers who are initially not in school and not employed (NSNE) are less likely to remain NSNE after an increase in the minimum wage. The positive and significant probability of becoming full-time worker (NSE) suggests that teenagers who are originally not in school and not employed (NSNE) are successful in obtaining jobs after an increase in the minimum wage. The negative coefficients on SNE and SE indicate that teenagers who are initially not in school and not employed are less likely to return to school.

Summarizing the results from this subsection, the main finding is that a higher minimum wage does induce some students to dropout for full-time employment. The evidence supports the view of Cunningham (1981) that part-time employment is harder to be obtained and that there are more opportunities for full-time employment. On the other hand, the findings in this paper sternly refute ideas found in Neumark and Wascher (1995b), namely, the queuing and substitution hypotheses.

Intuitively, the queuing hypothesis violates common sense, since it is more sensible that teenagers would confirm employment before dropping out from high school (Wong 2000). In theory, schooling and working are the two major activities for the teenage group. Teenagers choose schooling or working by comparing the returns on schooling and the returns on working, while some teenagers choose to do both at the same time. A raise in the minimum wage will increase the returns on working and thus, causing some teenagers to alter their school/work decisions. This does not imply, however, that students (SNE or SE) will dropout to queue for jobs at the higher minimum wage (NSNE). If a working student (SE) loses his/her part-time job due to the minimum wage hike, he/she is likely to return to full-time schooling (SNE) because it is his/her next best alternative. For teenagers who are initially not in school and not employed (NSNE), there must be some activity, other than schooling and working, that yields a higher utility. An increase in the minimum wage will raise the returns on working, thus inducing some of these teenagers to look for jobs.

Technically, apart from the differences in the specification that is used by this paper and that by Neumark and Wascher's, the differences in the two datasets may also contribute to the disputing results. The inclusion of high school graduates and college enrollees in Neumark and Wascher's study may overestimate the increase in the probability of becoming not in school and not employed (NSNE), and may also overestimate the reduction in the probability of becoming in school and not employed (SNE). This is because high school graduates and college enrollees do not have the option to attend high school, and high school graduates are likely to be in the process of job searching (NSNE).

<u>E. Academic Performance and Minimum Wage Effect</u>

From the previous section, I find that a higher minimum wage does induce some teenagers to drop out for full-time employment. The analysis goes further to answer the question of whether the effects of the minimum wage on school/work transitions depend on their academic performance (GPA). The coefficients in *Table 8* and 9 are computed by splitting the sample into high-GPA group (GPA >= 2) and low-GPA group (GPA < 2), thus disaggregating the minimum wage effect between the two groups.

It is not difficult to observe that, after an increase in the minimum wage, teenagers with high-GPA *(Table 8)* are much more likely to stay in full-time schooling (SNE) than it is for teenagers with low-GPA *(Table 9)*. Likewise, teenagers with low-GPA are much more likely to dropout for full-time employment (NSE) than it is for the teenagers with high-GPA. Teenagers with high-GPA are also less likely to become working student (SE) than those with low-GPA. These evidence suggest that minimum wage hikes are more attractive to teenagers with low-GPA, while teenagers with high-GPA are not seriously affected by such increases.

Another approach to conduct the same experiment is to include an interaction term in the specification, which is the product of GPA and the lagged relative minimum wage variable. This approach is superior to the previous because it allows GPA to be continuous and statistical inference can be drawn from the coefficient on the interaction term (Sicular 2001). *Table 10* summarizes the minimum wage's effects on school/work activities. It is important to note that the effect of the lagged relative minimum wage is now embraced in both the RMW_1 variable and the interaction term (GPA x RMW_1). The joint significance of the lagged relative minimum wage and the interaction term is significant at the 1% level, implying that the minimum wage still has a significant effect on school/work activity under this specification. Moreover, the interaction term is individually significant at the 1% level, which implies that the effects of the minimum wage do depend on GPA.

The interaction term (GPA x RMW_1) provides evidence that teenagers who possess higher GPA are less likely to become not in school and employed (NSE) or not in school and not employed (NSNE). At the same time, teenagers with high-GPA are more likely to become in school and not employed (SNE) after an increase in the minimum wage. These results are consistent with the approach above. On the other hand, the result also suggests that teenagers with high-GPA are more probable to become working students (SE), which is inconsistent with the former approach. This raises the possibility that splitting the sample into two groups (high-GPA and low-GPA) may lead to sample selection biases. In this case, the interaction approach should yield results that are more reliable. Overall, the evidence from *Table 10* suggests that a teenager with higher GPA is more probable of studying in high school (SNE or SE) and less likely to dropout for full-time employment (NSE) or become not in school and not employed (NSNE).

Intuitively, this is because low-GPA teenagers are uncertain of their prospect of staying in school, and therefore an increase in the minimum wage provides incentives for them to dropout for employment. On the other hand, for teenagers with high-GPA, who have better prospects studying in school, are less affected by the same incentives. In other words, because teenagers with strong academic performance have higher returns on schooling, an increase in the minimum wage is less attractive for them in the sense that the returns on working, though raised by the minimum wage hike, is still less than their returns on schooling. The reverse statement applies to the teenagers with poor academic achievement: because they have lower returns on schooling, a raise in the minimum wage that increases their returns on working will provide strong incentives for them to dropout.

CONCLUSION AND POLICY IMPLICATIONS

Using NLSY79 data from 1980 to 1984, this paper finds many implications of the minimum wage policy that resemble the past literature. In particular, the reduction in the part-time employment and the increase in full-time employment are matched with the findings of Cunningham (1981). Moreover, the reduction in part-time employment outweighs the increase in full-time employment and thus creating an overall disemployment effect. The results also support the findings of Mattila (1981) that an increase in the minimum wage is positively associated with teenage school enrollment. At the same time, some teenagers who are original in school do dropout to work full-time at the higher minimum wage. These high school dropouts are more likely to have poor academic performance because they have considerably lower returns on schooling than the students who possess good academic achievement do.

In many ways, the findings in this paper contradict the study by Neumark and Wascher (1995b). First, this paper finds that the lagged relative minimum wage variable is extremely sensitive to the choice of explanatory variables in the specification. Inclusion of year and state dummies in Neumark and Wascher's study will yield misleading results in terms of both direction and statistical inference, because the year and state dummies eliminate 99.6% of variation in the lagged relative minimum wage. This argument is analogous to that of Burkhauser et al. (2000). Even in an attempt to mitigate this specification problem by using regional dummies instead of state dummies, the year and regional dummies still eliminate 97.5% of variation in the lagged minimum wage and 66% of the variation in the lagged average hourly wage.

Secondly, using multinomial logit estimation on a model without year, state, or regional dummies, this paper finds evidence that contradicts the queuing and substitution hypotheses suggested by Neumark and Wascher (1995b). The underlying theory against the queuing hypothesis constitutes common sense that teenagers would first secure employment before dropping out from high school. Moreover, a working student who loses his/her part-time job due to a higher minimum wage should return to full-time schooling because it is his/her next best alternative, rather than queuing for jobs at the higher minimum wage.

Policymakers are interested in the effects of the minimum wage on teenage school enrollment because the issue involves with human capital accumulation of the younger generation. This paper presents the idea that teenagers choose their school/work activities by comparing the returns on schooling and working, and that an increase in the minimum wage will raise the returns on working, thus inducing some teenagers to alter their school/work decisions. Nevertheless, the objective of each individual teenager is to maximize his/her returns by choosing a school/work activity optimally. This implies that teenagers will not choose to participate in activities that are not productive in response to a higher minimum wage. Highly productive students are more likely to stay in school, while not so productive students dropout to work. Teenagers who are unable to sustain job positions will return to full-time education. Moreover, the overall school enrollment increases under a higher minimum wage, and lastly, the top-ranked students are still in school. Given these behaviors of the teenage group, policymakers should be in a better position to determine the tradeoffs of raising the minimum wage.

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TABLES AND FIGURES

B) TABLE 1

Minimum Wage Effects on Transition Probabilities
Neumark and Wascher (1995b)

Final activity	Initial employment-enrollment activity SNE_1 (i)	SE_1 (ii)	NSE_1 (iii)	NSNE_1 (iv)
SNE	-.09 (.20)	.05 (.18)	-.12 (.13)	-.28* (.14)
SE	-.29* (.10)	-.56* (.18)	-.33* (.10)	-.19* (.05)
NSE	.17 (.14)	.39^ (.20)	.25 (.23)	-.02 (.20)
NSNE	.21* (.06)	.13* (.03)	.19* (.08)	.49* (.18)
# of observations	17233	8658	7079	3051

* Statistically significant at the 5 percent level
^ Statistically significant at the 10 percent level

Control factors: Lagged relative minimum wage,
prime-age male unemployment rate,
age, race, and sex dummies,
year dummies and state dummies
and lagged activity dummies.

C) TABLE 2

FEDERAL MINIMUM WAGE RATES UNDER THE FAIR LABOR STANDARDS ACT
HISTORICAL CHART OF THE MIMIMUM HOURLY WAGE

Source: U.S. Department of Labor, 2000

EFFECTIVE DATE	1938 ACT (1)	1961 AMENDMENTS (2)	1966 & SUBSEQUENT AMENDMENTS (3)	
			NONFARM	FARM
OCT. 24, 1938	$ 0.25			
OCT. 24, 1939	$ 0.30			
OCT. 24, 1945	$ 0.40			
JAN. 25, 1950	$ 0.75			
MAR. 1, 1956	$ 1.00			
SEPT. 3, 1961	$ 1.15	$ 1.00		
SEPT. 3, 1963	$ 1.25			
SEPT. 3, 1964		$ 1.15		
SEPT. 3, 1965		$ 1.25		
FEB. 1, 1967	$ 1.40	$ 1.40	$ 1.00	$ 1.00
FEB. 1, 1968	$ 1.60	$ 1.60	$ 1.15	$ 1.15
FEB. 1, 1969			$ 1.30	$ 1.30
FEB. 1, 1970			$ 1.45	
FEB. 1, 1971			$ 1.60	
May 1, 1974	$ 2.00	$ 2.00	$ 1.90	$ 1.60
JAN. 1, 1975	$ 2.10	$ 2.10	$ 2.00	$ 1.80
JAN. 1, 1976	$ 2.30	$ 2.30	$ 2.20	$ 2.00
JAN. 1, 1977			$ 2.30	$ 2.20
JAN. 1, 1978	$ 2.65 for all covered, nonexempt workers			
JAN. 1, 1979	**$ 2.90 for all covered, nonexempt workers**			
JAN. 1, 1980	**$ 3.10 for all covered, nonexempt workers**			
JAN. 1, 1981	**$ 3.35 for all covered, nonexempt workers**			
APR. 1, 1990 (4)	$ 3.80 for all covered, nonexempt workers			
APR. 1, 1991	$ 4.25 for all covered, nonexempt workers			
OCT. 1, 1996 (5)	$ 4.75 for all covered, nonexempt workers			
SEPT. 1, 1997	$ 5.15 for all covered, nonexempt workers			

(1) The 1938 Act was applicable generally to employees engaged in interstate commerce or in the production of goods for interstate commerce.

(2) The 1961 Amendments extended coverage primarily to employees in large retail and service enterprises as well as to local transit, construction, and gasoline service station employees.

(3) The 1966 Amendments extended coverage to State and local government employees of hospitals, nursing homes, and schools, and to laundries, dry cleaners, and large hotels, motels, restaurants, and farms. Subsequent amendments extended coverage to the remaining Federal, State and local government employees who were not protected in 1966, to certain workers in retail and service trades previously exempted, and to certain domestic workers in private household employment.

(4) Grandfather Clause: Employees who do not meet the tests for individual coverage, and whose employers were covered by the FLSA, on March 31, 1990, and fail to meet the increased annual dollar volume (ADV) test for enterprise coverage, must continue to receive at least $3.35 an hour.

(5) A subminimum wage -- $4.25 an hour -- is established for employees under 20 years of age during their first 90 consecutive calendar days of employment with an employer.

D) TABLE 3

Multinomial Logit Estimates of Minimum Wage Effects on Probabilities of School/Work Activities

	(1)	(2)	(3)	(4)	(5)	(6)
A. Model Estimates						
SE / SNE	-2.45*	-3.47*	-2.45*	-1.76*	-1.78*	7.52
	(.42)	(.47)	(.50)	(.53)	(.53)	(8.12)
NSE / SNE	1.07^	1.14^	3.88*	2.15*	2.53*	5.52
	(.58)	(.62)	(.72)	(.89)	(.89)	(11.84)
NSNE / SNE	-1.25*	.37	1.61*	.26	.41	10.19
	(.56)	(.57)	(.67)	(.80)	(.81)	(10.93)
RMW_1	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment rate	No	Yes	Yes	Yes	Yes	Yes
Age, race, sex dummies	No	No	Yes	Yes	Yes	Yes
Lagged activity dummies	No	No	No	Yes	Yes	Yes
Year dummies	No	No	No	No	Yes	Yes
State dummies	No	No	No	No	No	Yes
Regional dummies	No	No	No	No	No	No
Net family annual income	No	No	No	No	No	No
Family size	No	No	No	No	No	No
GPA	No	No	No	No	No	No
Log-likelihood	-13747	-13583	-11737	-9535	-9521	-9352
# of observations	11028	10972	10972	10972	10972	10972
# of parameters	6	9	27	36	48	189
Pseudo R-squared	.0027	.0080	.1428	.3036	.3046	.3170
B. Implied Derivatives	(1)	(2)	(3)	(4)	(5)	(6)
SNE	.36*	.41*	.09	.10	.08	-1.99
	(.09)	(.09)	(.11)	(.13)	(.13)	(1.74)
SE	-.53*	-.83*	-.70*	-.43*	-.45*	.95
	(.09)	(.10)	(.10)	(.11)	(.11)	(1.63)
NSE	.22*	.24*	.36*	.25*	.28*	.12
	(.06)	(.06)	(.05)	(.07)	(.07)	(.84)
NSNE	-.05	.18*	.25*	.08	.09	.92
	(.06)	(.06)	(.08)	(.10)	(.10)	(1.30)

* Statistically significant at the 5 percent level

^ Statistically significant at the 10 percent level

E) TABLE 4

Multiomial Logit Estimates of Minimum Wage Effects on Probabilities of School/Work Activities

	(7)	(8)	(9)	(10)
A. Model Estimates				
SE / SNE	.53	1.09	1.29	-1.69*
	(.75)	(.85)	(.86)	(.61)
NSE / SNE	2.67*	3.06*	2.04	2.14*
	(1.17)	(1.36)	(1.40)	(1.02)
NSNE / SNE	1.53	1.15	0.22	-.66
	(1.07)	(1.27)	(1.31)	(.94)
RMW_1	Yes	Yes	Yes	Yes
Unemployment rate	Yes	Yes	Yes	Yes
Age, race, sex dummies	Yes	Yes	Yes	Yes
Lagged activity dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	No
State dummies	No	No	No	No
Regional dummies	Yes	Yes	Yes	No
Net family annual income	No	Yes	Yes	Yes
Family size	No	Yes	Yes	Yes
GPA	No	No	Yes	Yes
Log-likelihood	-9488	-6983	-6753	-6810
# of observations	10972	8482	8482	8482
# of parameters	57	63	69	48
Pseudo R-squared	.3070	.3353	.3572	.3517
B. Implied Derivatives	(7)	(8)	(9)	(10)
SNE	-.30^	-.36^	-.29	.20^
	(.17)	(.20)	(.20)	(.14)
SE	-.04	.09	.21	-.38*
	(.15)	(.17)	(.18)	(.12)
NSE	.20*	.22*	.12	.21*
	(.10)	(.11)	(.09)	(.07)
NSNE	.14	.05	-.04	-.03
	(.14)	(.14)	(.13)	(.09)

* Statistically significant at the 5 percent level

^ Statistically significant at the 10 percent level

F) TABLE 5

Detecting the Endogeneity Problem for the GPA Variable
Using 2 Stage Least Squares Method
Multinomial Logit Estimates of Minimum Wage Effects on
Probabilities of School/Work Activities

A. Model Estimates	(10)	(a)	(b)	(c)	(d)
SE / SNE	-1.69*	-1.74*	-1.48*	-1.57*	-1.60*
	(.61)	(.61)	(.65)	(.65)	(.65)
NSE / SNE	2.14*	1.86^	1.81	1.96^	2.16^
	(1.02)	(1.04)	(1.13)	(1.16)	(1.17)
NSNE / SNE	-.66	-1.32	-1.61	-1.81	-1.55
	(.94)	(.96)	(1.07)	(1.10)	(1.11)
ASVAB verbal score (IV)	*No*	*Yes*	*No*	*Yes*	*Yes*
ASVAB math score (IV)	*No*	*Yes*	*No*	*Yes*	*Yes*
Mother's Education (IV)	*No*	*No*	*Yes*	*Yes*	*Yes*
Father's Education (IV)	*No*	*No*	*Yes*	*Yes*	*Yes*
R-squared in first-stage (OLS)	-	*.2996*	*.0862*	*.2845*	*.2845*
Predicted GPA from first-stage	No	Yes	Yes	Yes	No
GPA (original)	Yes	No	No	No	Yes
Residual from first-stage	No	No	No	No	Yes
Log-likelihood	-6810	-6757	-5736	-5541	-5425
# of observations	8482	8302	7042	6894	6894
# of parameters (MNL)	48	48	48	48	51
Pseudo R-squared	.3517	.3404	.3316	.3374	.3513

B. Implied Derivatives	(10)	(a)	(b)	(c)	(d)
SNE	.20^	.25^	.24	.26^	.26^
	(.14)	(.14)	(.15)	(.15)	(.15)
SE	-.38*	-.36*	-.31*	-.33*	-.36*
	(.12)	(.13)	(.14)	(.15)	(.14)
NSE	.21*	.21*	.21*	.21*	.19*
	(.07)	(.08)	(.08)	(.08)	(.07)
NSNE	-.03	-.10	-.14	-.14	-.09
	(.09)	(.10)	(.11)	(.10)	(.09)

* Statistically significant at the 5 percent level
^ Statistically significant at the 10 percent level

Control factors: Lagged relative minimum wage, unemployment rate age, race, and sex dummies, lagged activity dummies net family annual income, family size, and GPA.

G)
H) **TABLE 6**

Probability of School/Work Activities

	Initial Probability	Probability after 10% increase in the minimum wage	Probability after 30% increase in the minimum wage
SNE	49.8%	51.8%	55.9%
SE	29.9%	26.0%	18.4%
NSE	8.3%	10.4%	14.6%
NSNE	12.0%	11.7%	11.1%
Total	100.0%	100.0%	100.0%

Using the model specified by column (10) of Table 4

Control factc Lagged relative minimum wage, unemployment rate
age, race, and sex dummies, lagged activity dummies
net family annual income, family size, and GPA.

I) **TABLE 7**

Minimum Wage Effects on School/Work Transitions

Final activity	Initial employment-enrollment activity			
	SNE_1 (i)	SE_1 (ii)	NSE_1 (iii)	NSNE_1 (iv)
SNE	.25* (.12)	.30* (.12)	-.04 (.04)	-.01 (.08)
SE	-.32* (.11)	-.44* (.14)	-.21* (.09)	-.06^ (.04)
NSE	.08* (.03)	.13* (.04)	.73* (.21)	.54* (.17)
NSNE	-.01 (.05)	.01 (.04)	-.48* (.19)	-.47* (.19)
# of observations	4633	1960	788	1101

* Statistically significant at the 5 percent level

^ Statistically significant at the 10 percent level

Control factors: Lagged relative minimum wage,
unemployment rate,
age, race, and sex dummies,
lagged activity dummies
net family annual income, family size,
and GPA.

J) TABLE 8

Teenagers with High-GPA (GPA >= 2)

Minimum Wage Effects on School/Work Transitions

	Initial employment-enrollment activity			
Final activity	SNE_1 (i)	SE_1 (ii)	NSE_1 (iii)	NSNE_1 (iv)
SNE	.43* (.19)	.40* (.17)	.00 (.23)	-.30 (.44)
SE	-.46* (.19)	-.45* (.18)	-.63 (.45)	-.10 (.08)
NSE	.02 (.02)	.03 (.02)	.64 (.58)	.45 (.52)
NSNE	.01 (.02)	.02 (.02)	-.01 (.58)	-.05 (.53)
# of observations	2041	1078	77	134

* Statistically significant at the 5 percent level

^ Statistically significant at the 10 percent level

Control factors: Lagged relative minimum wage,
unemployment rate,
age, race, and sex dummies,
lagged activity dummies
net family annual income, family size,
and GPA.

K) **TABLE 9**

Teenagers with Low-GPA (GPA < 2)

Minimum Wage Effects on School/Work Transitions

Final activity	Initial employment-enrollment activity			
	SNE_1 (i)	SE_1 (ii)	NSE_1 (iii)	NSNE_1 (iv)
SNE	.13 (.17)	.16 (.16)	-.03 (.04)	.00 (.05)
SE	-.20^ (.12)	-.38^ (.20)	-.08^ (.05)	-.02 (.02)
NSE	.16* (.06)	.25* (.09)	.71* (.23)	.57* (.19)
NSNE	-.09 (.11)	-.03 (.09)	-.60* (.22)	-.55* (.20)
# of observations	2592	882	711	967

* Statistically significant at the 5 percent level

^ Statistically significant at the 10 percent level

Control factors: Lagged relative minimum wage,
unemployment rate,
age, race, and sex dummies,
lagged activity dummies
net family annual income, family size,
and GPA.

L) TABLE 10

GPA x Lagged Relative Minimum Wage Interaction

Minimum Wage Effects on School/Work Transitions

	Lagged Relative Minimum Wage (i)	GPA x Lagged Relative Minimum Wage (ii)
SNE	.15 (.15)	.10* (.02)
SE	-.59* (.13)	.15* (.02)
NSE	.32* (.08)	-.10* (.01)
NSNE	.12 (.10)	-.15* (.01)

* Statistically significant at the 5 percent level

^ Statistically significant at the 10 percent level

Note: Joint-significance of lagged relative minimum wage variable (RMW_1) and interaction term (GPA x RMW_1) is statistically significant at the 1% level.

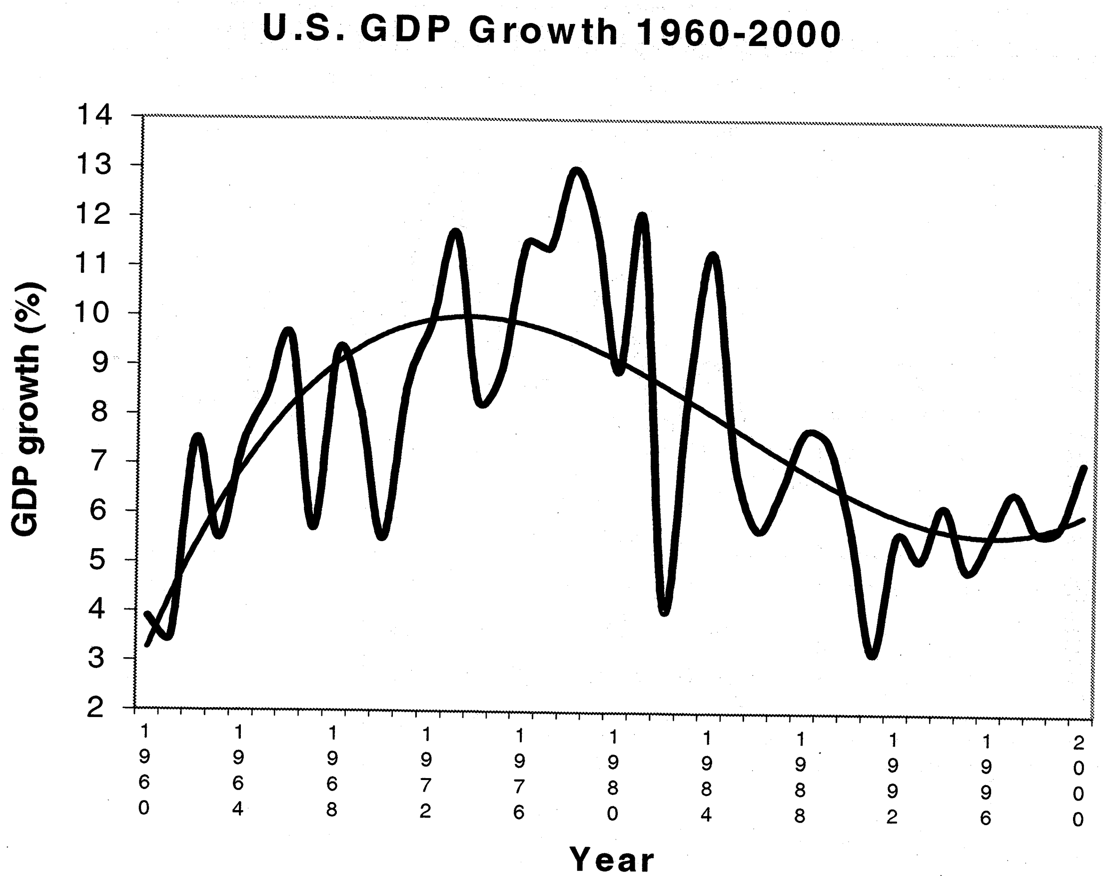
Control factors: Lagged relative minimum wage, unemployment rate, age, race, and sex dummies, lagged activity dummies net family annual income, family size,

Number of obs = 8482

Log likelihood = -6880

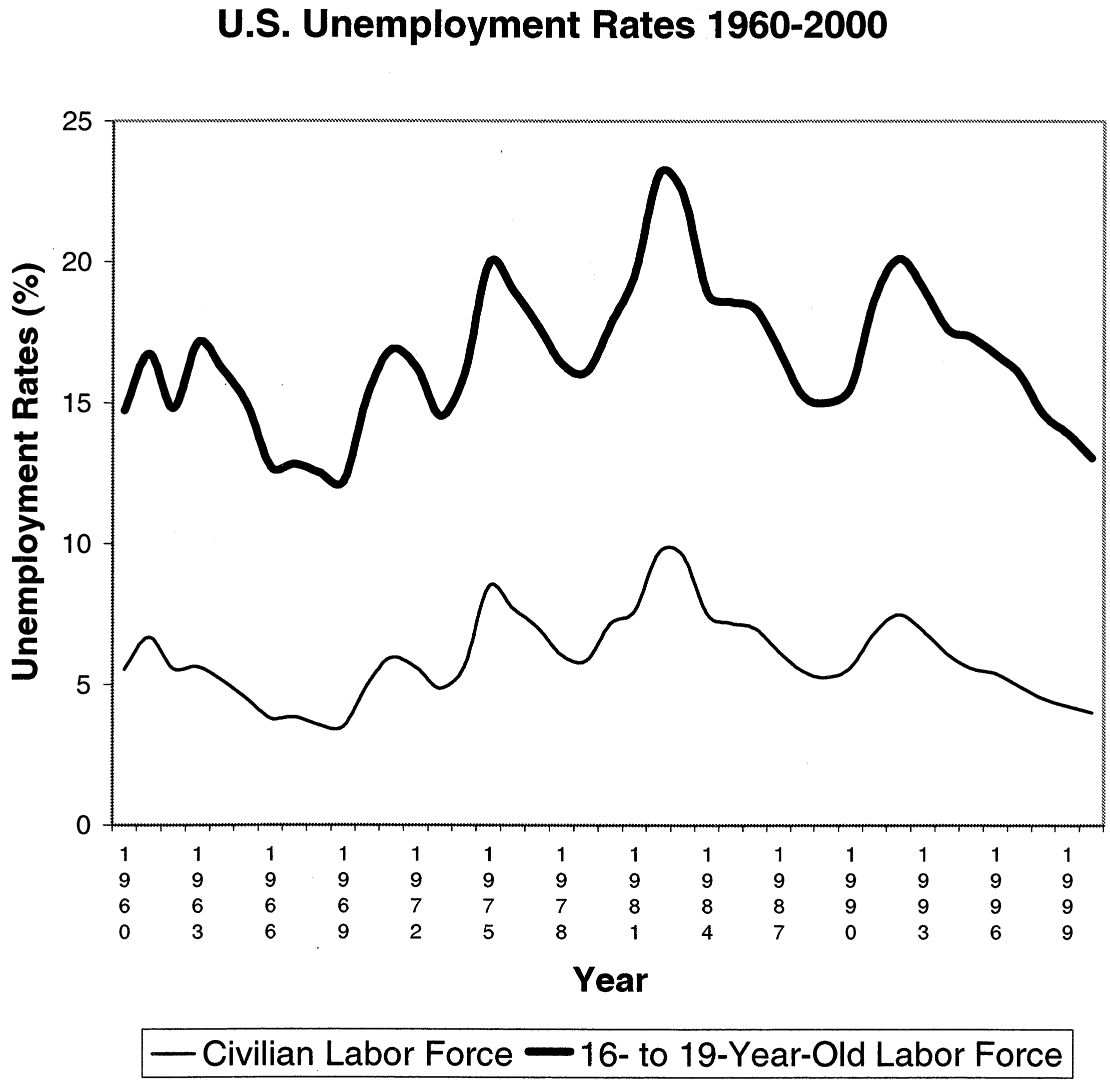
Pseudo R2 = 0.3451

M) FIGURE 1



1979: GROWTH RATE = 11.8%
1980: GROWTH RATE = 8.9%
1981: GROWTH RATE = 12.0%
1982: GROWTH RATE = 4.1%
1983: GROWTH RATE = 8.5%
1984: GROWTH RATE = 11.3%
Source: Bureau of Economic Analysis, 2001

N) FIGURE 2



Source: Bureau of Labor Statistics, 2000 (LSF21000000, LSF21000800)

DATA APPENDIX

Variable	Definition / Construction	Source
1. SNE - in school, not employed	Collapsed employment status from employment state recode, school enrollment from enrollment status as of May 1 survey year	NLSY79: KEYVARS
2. SE - in school, employed	"	"
3. NSE - not in school, employed	"	"
4. NSNE- not in school, not employed	"	"
5. Lagged activity dummy variables	Dummy variables for last year's activity of the individual (SNE_1, SE_1, NSE_1 , or NSNE_1)	NLSY79: KEYVARS
6. Lagged relative minimum wage	Higher of state or federal minimum wage level of each year, divided by average hourly wage (manufacturing sector) in the state, lagged by 1 year	Bureau of Labor Statistics
7. Unemployment rate	Unemployment rate for labor market of each year in the state	NLSY79: KEYVARS
8. Age dummy variables	Dummy variables for single-year age categories, ages 16-19	NLSY79: KEYVARS
9. Sex dummy variable	Dummy variable for individual's sex	NLSY79: KEYVARS
10. Race dummy variables	Dummy variables for black, Hispanic, and non-black/non-Hispanic	NLSY79: KEYVARS
11. Year dummy variables	Dummy variables for year 1980, 1981 1982, 1983, and 1984	NLSY79: KEYVARS
12. State dummy variables	Dummy variables for the state of residence of the individual: 50 states in total	NLSY79: GEO80,GEO81 GEO82, GEO83, GEO84
13. Net family annual income	Total net family income in past calender year	NLSY79: KEYVARS
14. Family size	Family size of respondent	NLSY79: KEYVARS

Variable	Definition / Construction	Source
15. GPA	Grade point average of the individual as of 1981. Averaging the grade points for all courses taken by the individual. Individuals who do not take any courses (thus, no GPA value) are assigned a GPA of zero. A dummy variable is generated which takes on the value "1" if the individual do not have a GPA value, and "0" otherwise.	NLSY79: TRANSURV
16. ASVAB verbal score	Verbal composite standandized ASVAB score	NLSY79: PROFILE
17. ASVAB math score	Average of standandized score of ASVAB: arithmetic reasoning, numerical operations, and mathematics knowledge.	NLSY79: PROFILE
18. Mother's education level	Highest grade completed by respondent's mother	NLSY79: FAMBKGN
19. Father's education level	Highest grade completed by respondent's father	NLSY79: FAMBKGN
20. Sampling weight	Adjustment for over sampling of certain demographic groups	NLSY79: KEYVARS

O) DATA MANAGEMENT

- The sample is restricted to individuals between 16-year-old and 19-year-old. All observations outside this range are dropped.
- The sample is restricted to individuals who are high school enrollees are dropouts. High school graduates, college enrollees, and army active forces are dropped.
- Invalid skips in parental education level are assigned a zero value. Valid skips are regarded as missing values.
- Non-responses in enrollment status are treated as missing values.
- Non-responses in employment status are treated as missing values.
- Non-responses in net family annual income are treated as missing values.
- Grade point assignment in each of the 64 courses is [{A=4}, {B=3}, {C=2}, {D=1}, {PASS=0.7}, {FAIL=0}].
- Valid skips in ASVAB scores are treated as missing values. There is no invalid skip.

P) DESCRIPTIVE STATISTICS

	Obs	Mean	Std. Dev.	Min	Max
Lagged Minimum Wage	11087	3.0995	0.1857	2.90	3.85
Lagged Average Hourly Wage	11028	7.2630	1.2534	4.87	12.33
Lagged Relative Minimum Wage	11028	0.4374	0.0669	0.2883	0.5955
GPA	11087	1.4571	1.1643	0	4
Unemployment Rate	11024	3.3472	1.0689	1	6
Net Family Annual Income	8561	18027	14260	0	75001
Family Size	11087	4.845	2.188	1	15
ASVAB verbal score	10816	41.369	10.69	20	62
ASVAB math score	10816	44.143	8.213	25	65.33
Mother's education level	10314	10.266	3.266	0	20
Father's education level	9433	10.033	4.227	0	20

Lagged activity distribution

	Freq.	Percent	Cum.%
SNE_1	6005	54.16	54.16
SE_1	2532	22.84	77
NSE_1	1041	9.39	86.39
NSNE_1	1509	13.61	100
Total	11087	100	

Current activity distribution

	Freq.	Percent	Cum.%
SNE	4584	41.35	41.35
SE	3001	27.07	68.42
NSE	1470	13.25	81.67
NSNE	2032	18.33	100
Total	11087	100	

Teenagers who do not have GPA

	Freq.	Percent	Cum.%
GPA exists	8122	73.26	73.26
GPA does not exist	2965	26.74	100
Total	11087	100	

Age of respondent at date of interview

	Freq.	Percent	Cum.%
16	2485	22.41	22.41
17	3830	34.54	56.96
18	2872	25.9	82.86
19	1900	17.14	100
Total	11087	100	

Race of respondent

	Freq.	Percent	Cum.%
Non-black/non-Hispanic	5884	53.07	53.07
Black	3016	27.2	80.27
Hispanic	2187	19.73	100
Total	11087	100	

Gender of respondent

	Freq.	Percent	Cum.%
Female	5161	46.55	46.55
Male	5926	53.45	100
Total	11087	100	

Year distribution in data

	Freq.	Percent	Cum.%
1980	4235	38.2	38.2
1981	3550	32.02	70.22
1982	2188	19.73	89.95
1983	865	7.8	97.75
1984	249	2.25	100
Total	11087	100	

Regional distribution in data

	Freq.	Percent	Cum.%
South	4297	38.76	38.76
West	2085	18.81	57.57
Northeast	2038	18.38	75.95
North central	2667	24.06	100
Total	11087	100	

OUTPUT APPENDIX

Table 4, column (10):

```
. mlogit ACT RMW_1 GPA zeroGPA unemprate age16 age17 age18 black hispanic male
>          SE_1 NSE_1 NSNE_1 faminc famsize [pweight=weight];

(sum of wgt is   2.3064e+09)
Iteration 0:   log likelihood = -10505.672
Iteration 1:   log likelihood =  -7558.224
Iteration 2:   log likelihood = -7041.2657
Iteration 3:   log likelihood = -6824.4355
Iteration 4:   log likelihood = -6810.7489
Iteration 5:   log likelihood = -6810.4671
Iteration 6:   log likelihood = -6810.4669

Multinomial regression                            Number of obs   =       8482
                                                  Wald chi2(45)   =    2294.38
                                                  Prob > chi2     =     0.0000
Log likelihood = -6810.4669                       Pseudo R2       =     0.3517
```

ACT	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
SE						
RMW_1	-1.693665	.6065107	-2.79	0.005	-2.882404	-.5049255
GPA	.1665238	.0501355	3.32	0.001	.06826	.2647876
zeroGPA	.1115587	.1490008	0.75	0.454	-.1804774	.4035949
unemprate	-.1374725	.0367259	-3.74	0.000	-.2094539	-.0654912
age16	-.1517362	.2015926	-0.75	0.452	-.5468504	.2433781
age17	.0762167	.1955797	0.39	0.697	-.3071124	.4595458
age18	.2636178	.2006952	1.31	0.189	-.1297376	.6569732
black	-.5926182	.0888868	-6.67	0.000	-.766833	-.4184033
hispanic	-.2942181	.0938166	-3.14	0.002	-.4780952	-.1103409
male	.0373698	.0733313	0.51	0.610	-.106357	.1810966
SE_1	1.683493	.0778809	21.62	0.000	1.530849	1.836137
NSE_1	1.5307	.5341715	2.87	0.004	.483743	2.577657
NSNE_1	-.1720983	.4252251	-0.40	0.686	-1.005524	.6613276
faminc	6.08e-06	2.50e-06	2.44	0.015	1.19e-06	.000011
famsize	.0089455	.0198674	0.45	0.653	-.0299939	.047885
_cons	-.1200341	.4232863	-0.28	0.777	-.9496599	.7095917
NSE						
RMW_1	2.143735	1.016408	2.11	0.035	.151613	4.135857
GPA	-1.209987	.09849	-12.29	0.000	-1.403024	-1.01695
zeroGPA	-1.734029	.2138393	-8.11	0.000	-2.153146	-1.314912
unemprate	-.2538202	.0634603	-4.00	0.000	-.3782001	-.1294402
age16	-3.021573	.2674114	-11.30	0.000	-3.54569	-2.497457
age17	-2.259431	.2094457	-10.79	0.000	-2.669937	-1.848925
age18	-1.297454	.1956524	-6.63	0.000	-1.680926	-.9139829
black	-1.448675	.1637855	-8.84	0.000	-1.769688	-1.127661
hispanic	.0404888	.1462499	0.28	0.782	-.2461558	.3271334
male	.3353778	.1345085	2.49	0.013	.071746	.5990095
SE_1	1.085757	.171338	6.34	0.000	.7499411	1.421574
NSE_1	5.422486	.4808375	11.28	0.000	4.480062	6.36491
NSNE_1	3.997203	.2491613	16.04	0.000	3.508856	4.48555
faminc	-.0000171	5.74e-06	-2.97	0.003	-.0000283	-5.82e-06
famsize	-.1903638	.0359145	-5.30	0.000	-.2607549	-.1199727
_cons	2.34057	.6480899	3.61	0.000	1.070338	3.610803
NSNE						
RMW_1	-.6572022	.939091	-0.70	0.484	-2.497787	1.183382

```
         GPA |  -1.216699   .0936407   -12.99   0.000    -1.400231   -1.033167
     zeroGPA |  -1.668139    .202269    -8.25   0.000    -2.064579   -1.271699
   unemprate |  -.0707291   .0561924    -1.26   0.208    -.1808643     .039406
       age16 |  -2.386374   .2226663   -10.72   0.000    -2.822792   -1.949956
       age17 |  -1.914165   .1885913   -10.15   0.000    -2.283797   -1.544533
       age18 |  -1.128344   .1825379    -6.18   0.000    -1.486112   -.7705765
       black |  -.9549562   .1442967    -6.62   0.000    -1.237773     -.67214
    hispanic |  -.0815824   .1409426    -0.58   0.563    -.3578249    .1946601
        male |  -.4620505   .1200676    -3.85   0.000    -.6973787   -.2267223
        SE_1 |   .5217209   .1673346     3.12   0.002     .1937511    .8496906
       NSE_1 |   4.418783   .4946659     8.93   0.000     3.449256     5.38831
      NSNE_1 |   4.230528   .2276525    18.58   0.000     3.784338    4.676719
      faminc |  -.0000518   6.06e-06    -8.54   0.000    -.0000637   -.0000399
     famsize |  -.0660156   .0301977    -2.19   0.029     -.125202   -.0068293
       _cons |   3.557201   .5729389     6.21   0.000     2.434262    4.680141
------------------------------------------------------------------------------
(Outcome ACT==SNE is the comparison group)

. mfx c, predict(outcome(1));

Marginal effects after mlogit
      y  = Pr(ACT==1) (predict, outcome(1))
         =  .49809822
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |    .203215      .14107    1.44   0.150  -.073275  .479705   .437112
     GPA |    .098041      .01299    7.55   0.000   .072587  .123495   1.50972
 zeroGPA*|   .1136643      .03306    3.44   0.001   .048875  .178454   .255129
unempr~e |   .0351538      .00872    4.03   0.000   .018055  .052252   3.36689
   age16*|   .2085509      .04108    5.08   0.000   .128043  .289058   .231785
   age17*|   .1636784      .03889    4.21   0.000   .087448  .239909   .354987
   age18*|   .0535642      .04145    1.29   0.196  -.027677  .134806   .250648
   black*|   .1954509      .01965    9.95   0.000   .156939  .233963   .253596
hispanic*|   .0455396      .02203    2.07   0.039   .002355  .088725   .192643
    male*|    .009047      .01763    0.51   0.608  -.025499  .043593   .533836
    SE_1*|  -.3171291       .0159  -19.95   0.000  -.348293 -.285966   .231078
   NSE_1*|  -.5361123      .01753  -30.59   0.000  -.570462 -.501763   .092903
  NSNE_1*|  -.4793885      .01736  -27.61   0.000  -.513419 -.445358   .129804
  faminc |   2.90e-06      .00000    4.13   0.000   1.5e-06  4.3e-06   18048.6
 famsize |    .010468      .00469    2.23   0.026    .00127  .019666   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, predict(outcome(2));

Marginal effects after mlogit
      y  = Pr(ACT==2) (predict, outcome(2))
         =  .29877897
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |   -.384135      .12466   -3.08   0.002  -.628466 -.139804   .437112
     GPA |   .1085627      .01114    9.75   0.000   .086731  .130395   1.50972
 zeroGPA*|   .1052017      .03211    3.28   0.001   .042274   .16813   .255129
unempr~e |  -.0199873      .00745   -2.68   0.007  -.034583 -.005392   3.36689
   age16*|   .0745199       .0418    1.78   0.075  -.007414  .156454   .231785
   age17*|   .1221473      .03932    3.11   0.002   .045081  .199214   .354987
   age18*|    .119333      .04292    2.78   0.005   .035207  .203459   .250648
   black*|  -.0635182       .0169   -3.76   0.000  -.096647  -.03039   .253596
hispanic*|  -.0575761      .01753   -3.28   0.001  -.091929 -.023224   .192643
    male*|   .0165174      .01509    1.09   0.274   -.01306  .046094   .533836
```

```
     SE_1*|   .3243099      .01839    17.63   0.000    .28826   .36036   .231078
    NSE_1*|  -.2311599      .02294   -10.08   0.000  -.276124 -.186196   .092903
   NSNE_1*|  -.2999312      .01696   -17.69   0.000  -.333167 -.266696   .129804
    faminc |   3.56e-06      .00000     6.20   0.000   2.4e-06  4.7e-06   18048.6
   famsize |   .0089519      .00409     2.19   0.029   .000938  .016966   4.76598
---------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, predict(outcome(3));

Marginal effects after mlogit
      y  = Pr(ACT==3) (predict, outcome(3))
         =  .08266605
---------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+-----------------------------------------------------------------------
   RMW_1 |   .2109404      .07035     3.00   0.003   .073063  .348818   .437112
     GPA |  -.0837537      .00735   -11.40   0.000  -.098153 -.069354   1.50972
 zeroGPA*|  -.0909978      .00978    -9.31   0.000  -.110161 -.071835   .255129
unempr~e |  -.0151481      .00437    -3.47   0.001  -.023708 -.006588   3.36689
   age16*|  -.1304509       .0107   -12.19   0.000  -.151423 -.109479   .231785
   age17*|   -.130026      .01326    -9.80   0.000  -.156022  -.10403   .354987
   age18*|  -.0756926      .01019    -7.43   0.000  -.095663 -.055722   .250648
   black*|  -.0706762      .00844    -8.38   0.000  -.087211 -.054142   .253596
hispanic*|   .0111361      .01062     1.05   0.294  -.009684  .031956   .192643
    male*|   .0289089      .00908     3.18   0.001   .011106  .046712   .533836
    SE_1*|   .0234651      .01376     1.71   0.088  -.003494  .050425   .231078
   NSE_1*|   .5196639      .03734    13.92   0.000   .446477  .592851   .092903
  NSNE_1*|    .272694      .03158     8.64   0.000   .210805  .334583   .129804
   faminc |  -9.29e-07      .00000    -2.25   0.024  -1.7e-06 -1.2e-07   18048.6
  famsize |  -.0139993      .00259    -5.39   0.000  -.019085 -.008913   4.76598
---------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, predict(outcome(4));

Marginal effects after mlogit
      y  = Pr(ACT==4) (predict, outcome(4))
         =  .12045675
---------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+-----------------------------------------------------------------------
   RMW_1 |  -.0300203      .09204    -0.33   0.744  -.210407  .150367   .437112
     GPA |    -.12285      .00958   -12.82   0.000   -.14163  -.10407   1.50972
 zeroGPA*|  -.1278682      .01279   -10.00   0.000  -.152939 -.102797   .255129
unempr~e |  -.0000184      .00545    -0.00   0.997  -.010695  .010658   3.36689
   age16*|  -.1526199      .01227   -12.44   0.000  -.176659 -.128581   .231785
   age17*|  -.1557998      .01506   -10.34   0.000  -.185322 -.126278   .354987
   age18*|  -.0972046      .01302    -7.46   0.000  -.122728 -.071681   .250648
   black*|  -.0612566      .01138    -5.39   0.000  -.083552 -.038961   .253596
hispanic*|   .0009004       .0136     0.07   0.947  -.025752  .027553   .192643
    male*|  -.0544733      .01243    -4.38   0.000  -.078829 -.030117   .533836
    SE_1*|  -.0306459      .01435    -2.14   0.033  -.058779 -.002513   .231078
   NSE_1*|   .2476082      .03558     6.96   0.000   .177875  .317341   .092903
  NSNE_1*|   .5066256      .03242    15.63   0.000   .443084  .570167   .129804
   faminc |  -5.53e-06      .00000    -8.99   0.000  -6.7e-06 -4.3e-06   18048.6
  famsize |  -.0054205      .00294    -1.84   0.065  -.011188  .000347   4.76598
---------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Table 7:

```
. mfx c, at(mean SE_1=0 NSE_1=0 NSNE_1=0) predict(outcome(1));
```

Marginal effects after mlogit
y = Pr(ACT==1) (predict, outcome(1))
= .67152166

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
RMW_1	.2548439	.12175	2.09	0.036	.016226	.493462	.437112
GPA	.0433123	.01048	4.13	0.000	.022765	.06386	1.50972
zeroGPA*	.0543147	.02942	1.85	0.065	-.003349	.111978	.255129
unempr~e	.0302893	.00744	4.07	0.000	.015701	.044877	3.36689
age16*	.1258584	.03673	3.43	0.001	.053873	.197844	.231785
age17*	.0888728	.03662	2.43	0.015	.017094	.160652	.354987
age18*	.0082538	.03911	0.21	0.833	-.068409	.084917	.250648
black*	.1479394	.01624	9.11	0.000	.116119	.179759	.253596
hispanic*	.0478528	.01805	2.65	0.008	.012473	.083233	.192643
male*	.004466	.01495	0.30	0.765	-.024837	.033769	.533836
SE_1*	-.3607218	.01635	-22.06	0.000	-.392765	-.328678	0.00000
NSE_1*	-.6215166	.0245	-25.37	0.000	-.669537	-.573497	0.00000
NSNE_1*	-.5660085	.02159	-26.22	0.000	-.608322	-.523695	0.00000
faminc	1.29e-06	.00000	2.34	0.019	2.1e-07	2.4e-06	18048.6
famsize	.0049766	.004	1.24	0.214	-.002871	.012824	4.76598

(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=0 NSNE_1=0) predict(outcome(2));

Marginal effects after mlogit
y = Pr(ACT==2) (predict, outcome(2))
= .24215274

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
RMW_1	-.3182281	.10803	-2.95	0.003	-.529959	-.106497	.437112
GPA	.0559427	.00892	6.27	0.000	.038458	.073427	1.50972
zeroGPA*	.0479964	.02824	1.70	0.089	-.007349	.103342	.255129
unempr~e	-.022367	.00653	-3.43	0.001	-.035164	-.00957	3.36689
age16*	.0077265	.03575	0.22	0.829	-.062342	.077795	.231785
age17*	.0508574	.03498	1.45	0.146	-.017708	.119422	.354987
age18*	.071018	.03846	1.85	0.065	-.004372	.146408	.250648
black*	-.083516	.01443	-5.79	0.000	-.111796	-.055236	.253596
hispanic*	-.0507637	.01521	-3.34	0.001	-.080577	-.020951	.192643
male*	.0106274	.01301	0.82	0.414	-.014874	.036129	.533836
SE_1*	.361298	.01628	22.20	0.000	.329398	.393198	0.00000
NSE_1*	-.1588196	.02734	-5.81	0.000	-.212401	-.105238	0.00000
NSNE_1*	-.21012	.01488	-14.12	0.000	-.239294	-.180946	0.00000
faminc	1.94e-06	.00000	4.32	0.000	1.1e-06	2.8e-06	18048.6
famsize	.0039607	.00354	1.12	0.263	-.002976	.010897	4.76598

(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=0 NSNE_1=0) predict(outcome(3));

Marginal effects after mlogit
y = Pr(ACT==3) (predict, outcome(3))
= .03118841

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
RMW_1	.0786958	.03002	2.62	0.009	.019854	.137537	.437112
GPA	-.035726	.00383	-9.32	0.000	-.043242	-.02821	1.50972
zeroGPA*	-.037748	.00479	-7.87	0.000	-.047146	-.02835	.255129

```
unempr~e |  -.0065095      .00184   -3.53   0.000  -.010123 -.002896   3.36689
   age16*|  -.0547128      .00648   -8.45   0.000   -.06741 -.042016   .231785
   age17*|  -.0564226      .00745   -7.58   0.000  -.071015  -.04183   .354987
   age18*|  -.0307839      .00484   -6.36   0.000  -.040274 -.021294   .250648
   black*|  -.0299257      .00416   -7.20   0.000  -.038076 -.021776   .253596
hispanic*|   .0035564      .00441    0.81   0.419  -.005078  .012191   .192643
    male*|   .0105758      .00383    2.76   0.006   .003069  .018083   .533836
    SE_1*|   .0115632      .00616    1.88   0.061  -.000513  .023639   0.00000
   NSE_1*|   .4947111      .03529   14.02   0.000   .425539  .563883   0.00000
  NSNE_1*|   .2356222      .02531    9.31   0.000    .18602  .285225   0.00000
  faminc |  -4.72e-07      .00000   -2.65   0.008  -8.2e-07 -1.2e-07   18048.6
 famsize |   -.005706      .00114   -5.00   0.000  -.007945 -.003467   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=0 NSNE_1=0) predict(outcome(4));

Marginal effects after mlogit
      y  = Pr(ACT==4) (predict, outcome(4))
         =   .0551372
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |  -.0153116      .04677   -0.33   0.743  -.106987  .076364   .437112
     GPA |  -.0635291      .00547  -11.61   0.000   -.07425 -.052808   1.50972
zeroGPA*|  -.0645631      .00675   -9.56   0.000  -.077798 -.051329   .255129
unempr~e |  -.0014128      .00279   -0.51   0.613  -.006881  .004056   3.36689
   age16*|  -.0788721      .00785  -10.05   0.000  -.094261 -.063484   .231785
   age17*|  -.0833077      .00987   -8.44   0.000  -.102644 -.063971   .354987
   age18*|  -.0484879      .00693   -6.99   0.000  -.062077 -.034899   .250648
   black*|  -.0344978      .00589   -5.85   0.000  -.046048 -.022948   .253596
hispanic*|  -.0006456      .00692   -0.09   0.926  -.014205  .012914   .192643
    male*|  -.0256692      .00641   -4.00   0.000  -.038238   -.0131   .533836
    SE_1*|  -.0121394      .00709   -1.71   0.087  -.026029   .00175   0.00000
   NSE_1*|   .2856251       .0334    8.55   0.000   .220158  .351092   0.00000
  NSNE_1*|   .5405062      .02903   18.62   0.000     .4836  .597413   0.00000
  faminc |  -2.75e-06      .00000   -8.67   0.000  -3.4e-06 -2.1e-06   18048.6
 famsize |  -.0032313      .00152   -2.12   0.034  -.006216 -.000247   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=1 NSE_1=0 NSNE_1=0) predict(outcome(1));

Marginal effects after mlogit
      y  = Pr(ACT==1) (predict, outcome(1))
         =  .31079988
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |   .2979493      .12227    2.44   0.015   .058312  .537586   .437112
     GPA |    .001105      .01065    0.10   0.917  -.019773  .021983   1.50972
zeroGPA*|   .0118725      .03081    0.39   0.700  -.048511  .072256   .255129
unempr~e |   .0301011      .00747    4.03   0.000    .01546  .044742   3.36689
   age16*|   .0784604       .0427    1.84   0.066  -.005235  .162155   .231785
   age17*|   .0331384      .03836    0.86   0.388  -.042049  .108326   .354987
   age18*|  -.0257406      .03936   -0.65   0.513  -.102886  .051405   .250648
   black*|   .1479842      .01987    7.45   0.000   .109037  .186931   .253596
hispanic*|   .0566611      .01988    2.85   0.004   .017696  .095627   .192643
    male*|  -.0050861      .01482   -0.34   0.732  -.034139  .023967   .533836
    SE_1*|  -.3607218      .01635  -22.06   0.000  -.392765 -.328678   1.00000
   NSE_1*|  -.2917895      .01584  -18.42   0.000  -.322842 -.260737   0.00000
  NSNE_1*|  -.2598719       .0161  -16.14   0.000   -.29142 -.228324   0.00000
```

```
   faminc |  -2.22e-07      .00000    -0.42   0.675  -1.3e-06  8.2e-07   18048.6
  famsize |   .0017339        .004     0.43   0.665  -.006111  .009578   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=1 NSE_1=0 NSNE_1=0) predict(outcome(2));

Marginal effects after mlogit
      y  = Pr(ACT==2) (predict, outcome(2))
         =  .60345073
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |  -.4435432      .14047   -3.16   0.002   -.71886 -.168227   .437112
     GPA |   .1026344      .01233    8.32   0.000   .078465  .126804   1.50972
 zeroGPA*|   .0922753      .03313    2.78   0.005   .027332  .157219   .255129
unempr~e |  -.0245135      .00848   -2.89   0.004  -.041132 -.007895   3.36689
   age16*|   .0553411      .04678    1.18   0.237  -.036348  .147031   .231785
   age17*|    .110721      .04445    2.49   0.013   .023598  .197844   .354987
   age18*|   .1108787      .04408    2.52   0.012    .02449  .197267   .250648
   black*|   -.093218      .02149   -4.34   0.000  -.135344 -.051092   .253596
hhspanic*|  -.0704412      .02197   -3.21   0.001  -.113499 -.027384   .192643
    male*|   .0126314      .01712    0.74   0.461   -.02093  .046193   .533836
    SE_1*|    .361298      .01628   22.20   0.000   .329398  .393198   1.00000
   NSE_1*|  -.4328712      .05177   -8.36   0.000  -.534334 -.331408   0.00000
  NSNE_1*|  -.5202023      .03247  -16.02   0.000   -.58384 -.456565   0.00000
  faminc |   3.24e-06      .00000    5.14   0.000   2.0e-06  4.5e-06   18048.6
 famsize |   .0087647      .00464    1.89   0.059  -.000331  .017861   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=1 NSE_1=0 NSNE_1=0) predict(outcome(3));

Marginal effects after mlogit
      y  = Pr(ACT==3) (predict, outcome(3))
         =  .04275161
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |   .1326321      .04244    3.12   0.002   .049444   .21582   .437112
     GPA |  -.0515769      .00681   -7.57   0.000  -.064925 -.038229   1.50972
 zeroGPA*|  -.0527637      .00753   -7.01   0.000  -.067526 -.038001   .255129
unempr~e |  -.0067107      .00254   -2.65   0.008  -.011682 -.001739   3.36689
   age16*|  -.0736403      .00985   -7.47   0.000  -.092952 -.054329   .231785
   age17*|  -.0781249      .01208   -6.47   0.000  -.101808 -.054442   .354987
   age18*|  -.0447021      .00778   -5.74   0.000  -.059953 -.029451   .250648
   black*|  -.0349451      .00563   -6.21   0.000  -.045981 -.023909   .253596
hispanic*|   .0097455      .00651    1.50   0.135  -.003019   .02251   .192643
    male*|   .0135236      .00521    2.59   0.009   .003304  .023743   .533836
    SE_1*|   .0115632      .00616    1.88   0.061  -.000513  .023639   1.00000
   NSE_1*|   .5493807        .058    9.47   0.000   .435707  .663055   0.00000
  NSNE_1*|   .3386579      .05312    6.38   0.000   .234545  .442771   0.00000
  faminc |  -7.60e-07      .00000   -3.04   0.002  -1.2e-06 -2.7e-07   18048.6
 famsize |  -.0078999      .00166   -4.75   0.000  -.011157 -.004643   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=1 NSE_1=0 NSNE_1=0) predict(outcome(4));

Marginal effects after mlogit
      y  = Pr(ACT==4) (predict, outcome(4))
         =  .04299778
```

```
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |   .0129617      .03738    0.35   0.729   -.0603  .086223   .437112
     GPA |  -.0521625      .00708   -7.37   0.000 -.066038 -.038287   1.50972
 zeroGPA*|  -.0513841      .00794   -6.47   0.000 -.066947 -.035821   .255129
unempr~e |   .0011232      .00221    0.51   0.612 -.003218  .005464   3.36689
   age16*|  -.0601612      .00891   -6.75   0.000 -.077624 -.042699   .231785
   age17*|  -.0657345      .01013   -6.49   0.000 -.085588 -.045881   .354987
   age18*|  -.0404359      .00725   -5.58   0.000 -.054638 -.026234   .250648
   black*|  -.0198211      .00508   -3.90   0.000 -.029782  -.00986   .253596
hispanic*|   .0040346      .00581    0.69   0.487 -.007346  .015415   .192643
    male*|  -.0210689      .00578   -3.65   0.000 -.032395 -.009743   .533836
    SE_1*|  -.0121394      .00709   -1.71   0.087 -.026029   .00175   1.00000
   NSE_1*|     .17528      .03893    4.50   0.000  .098974  .251586   0.00000
  NSNE_1*|   .4414163      .05378    8.21   0.000  .336019  .546814   0.00000
  faminc |  -2.26e-06      .00000   -6.09   0.000 -3.0e-06 -1.5e-06   18048.6
 famsize |  -.0025987      .00124   -2.10   0.036 -.005027  -.00017   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=1 NSNE_1=0) predict(outcome(1));

Marginal effects after mlogit
      y  = Pr(ACT==1) (predict, outcome(1))
         =  .05000505
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |  -.0381189      .04419   -0.86   0.388 -.124724  .048487   .437112
     GPA |   .0518582       .0214    2.42   0.015   .00992  .093797   1.50972
 zeroGPA*|   .0964165      .03942    2.45   0.014  .019164  .173669   .255129
unempr~e |   .0084529      .00419    2.02   0.043  .000248  .016658   3.36689
   age16*|   .1891908      .07308    2.59   0.010  .045962   .33242   .231785
   age17*|   .1139355      .04659    2.45   0.014  .022617  .205254   .354987
   age18*|   .0624391      .02745    2.27   0.023  .008643  .116235   .250648
   black*|   .0740677      .03052    2.43   0.015  .014254  .133881   .253596
hispanic*|   .0014246       .0059    0.24   0.809  -.01013  .012979   .192643
    male*|  -.0008216      .00519   -0.16   0.874 -.010997  .009354   .533836
    SE_1*|  -.0309946      .01357   -2.28   0.022   -.0576 -.004389   0.00000
   NSE_1*|  -.6215166       .0245  -25.37   0.000 -.669537 -.573497   1.00000
  NSNE_1*|  -.0490468      .02159   -2.27   0.023 -.091356 -.006737   0.00000
  faminc |   1.31e-06      .00000    2.32   0.020  2.0e-07  2.4e-06   18048.6
 famsize |   .0060937      .00289    2.11   0.035   .00043  .011758   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=1 NSNE_1=0) predict(outcome(2));

Marginal effects after mlogit
      y  = Pr(ACT==2) (predict, outcome(2))
         =  .08333313
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |  -.2046633       .0873   -2.34   0.019 -.375761 -.033566   .437112
     GPA |   .1002984      .02801    3.58   0.000  .045394  .155203   1.50972
 zeroGPA*|   .1810977      .04838    3.74   0.000  .086284  .275912   .255129
unempr~e |   .0026308      .00425    0.62   0.536 -.005704  .010966   3.36689
   age16*|   .2737994      .07465    3.67   0.000  .127485  .420114   .231785
   age17*|   .2026908      .05758    3.52   0.000  .089831  .315551   .354987
   age18*|   .1447663      .04706    3.08   0.002  .052538  .236995   .250648
```

```
    black*|   .0470037       .01839     2.56    0.011     .01096  .083048    .253596
 hispanic*|  -.0204692       .01064    -1.92    0.054   -.041332  .000393    .192643
     male*|   .0016941       .00885     0.19    0.848   -.015655  .019044    .533836
     SE_1*|   .0872464       .02946     2.96    0.003    .029506  .144987    0.00000
    NSE_1*|  -.1588196       .02734    -5.81    0.000   -.212401 -.105238    1.00000
   NSNE_1*|  -.0819886        .0248    -3.31    0.001   -.130602 -.033375    0.00000
    faminc |   2.68e-06       .00000     3.26    0.001    1.1e-06  4.3e-06    18048.6
   famsize |   .0109006       .00369     2.95    0.003    .003665  .018137    4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=1 NSNE_1=0) predict(outcome(3));

Marginal effects after mlogit
      y  = Pr(ACT==3) (predict, outcome(3))
         =  .52589952
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |   .7264955      .21107     3.44   0.001    .312802  1.14019   .437112
     GPA |  -.0909424      .02763    -3.29   0.001   -.145101 -.036783   1.50972
zeroGPA* |  -.1795007      .04478    -4.01   0.000   -.267271  -.09173   .255129
unempr~e |  -.0445849      .01288    -3.46   0.001   -.069828 -.019342   3.36689
  age16* |   -.368278      .05007    -7.36   0.000   -.466414 -.270142   .231785
  age17* |  -.2524919       .0448    -5.64   0.000   -.340297 -.164687   .354987
  age18* |  -.1560865      .03948    -3.95   0.000   -.233471 -.078702   .250648
  black* |  -.1692821      .03398    -4.98   0.000   -.235877 -.102687   .253596
hispanic*|   .0369087       .0288     1.28   0.200   -.019537  .093354   .192643
   male* |   .1638013      .02739     5.98   0.000    .110122  .217481   .533836
   SE_1* |   .0662328       .0473     1.40   0.161   -.026471  .158937   0.00000
  NSE_1* |   .4947111      .03529    14.02   0.000    .425539  .563883   1.00000
 NSNE_1* |   .0228165      .04784     0.48   0.633    -.07095  .116583   0.00000
  faminc |   4.76e-06      .00000     3.27   0.001    1.9e-06  7.6e-06   18048.6
 famsize |  -.0360249      .00716    -5.03   0.000   -.050058 -.021992   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=1 NSNE_1=0) predict(outcome(4));

Marginal effects after mlogit
      y  = Pr(ACT==4) (predict, outcome(4))
         =  .3407623
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |  -.4837132      .19213    -2.52   0.012   -.860287 -.107139   .437112
     GPA |  -.0612142      .02241    -2.73   0.006   -.105136 -.017293   1.50972
zeroGPA* |  -.0980135      .03506    -2.80   0.005   -.166734 -.029293   .255129
unempr~e |   .0335012      .01152     2.91   0.004    .010916  .056086   3.36689
  age16* |  -.0947123      .04753    -1.99   0.046   -.187864 -.001561   .231785
  age17* |  -.0641345      .03807    -1.68   0.092   -.138746  .010477   .354987
  age18* |  -.0511189      .03129    -1.63   0.102   -.112444  .010206   .250648
  black* |   .0482107      .03261     1.48   0.139   -.015708  .112129   .253596
hispanic*|  -.0178641      .02585    -0.69   0.490   -.068529  .032801   .192643
   male* |  -.1646738      .02508    -6.57   0.000   -.213832 -.115516   .533836
   SE_1* |  -.1224845      .03418    -3.58   0.000   -.189478 -.055491   0.00000
  NSE_1* |   .2856251       .0334     8.55   0.000    .220158  .351092   1.00000
 NSNE_1* |   .1082189      .04419     2.45   0.014    .021609  .194829   0.00000
  faminc |  -8.75e-06      .00000    -7.06   0.000   -.000011 -6.3e-06   18048.6
 famsize |   .0190305       .0063     3.02   0.003    .006692  .031369   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

```
. mfx c, at(mean SE_1=0 NSE_1=0 NSNE_1=1) predict(outcome(1));

Marginal effects after mlogit
      y  = Pr(ACT==1) (predict, outcome(1))
         =  .10551316
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |  -.0133221      .07983   -0.17   0.867  -.169792  .143148   .437112
     GPA |   .1099681      .01996    5.51   0.000   .070845  .149091   1.50972
zeroGPA* |   .2015552      .03955    5.10   0.000    .12403   .27908   .255129
unempr~e |   .0120554      .00508    2.37   0.018   .002096  .022015   3.36689
  age16* |   .3514108      .05796    6.06   0.000   .237819  .465002   .231785
  age17* |    .226351      .04361    5.19   0.000   .140874  .311828   .354987
  age18* |    .129061      .03174    4.07   0.000   .066848  .191274   .250648
  black* |   .1254585      .02719    4.61   0.000   .072173  .178744   .253596
hispanic*|   .0048912      .01233    0.40   0.692  -.019273  .029056   .192643
   male* |   .0194005      .01116    1.74   0.082   -.00248  .041281   .533836
   SE_1* |  -.0545852      .01139   -4.79   0.000  -.076915 -.032255   0.00000
  NSE_1* |  -.1045549      .01954   -5.35   0.000  -.142843 -.066267   0.00000
 NSNE_1* |  -.5660085      .02159  -26.22   0.000  -.608322 -.523695   1.00000
  faminc |   3.71e-06      .00000    4.79   0.000   2.2e-06  5.2e-06   18048.6
 famsize |   .0094779      .00306    3.10   0.002   .003486  .015469   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=0 NSNE_1=1) predict(outcome(2));

Marginal effects after mlogit
      y  = Pr(ACT==2) (predict, outcome(2))
         =  .03203278
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |  -.0582973       .0353   -1.65   0.099  -.127488  .010893   .437112
     GPA |   .0387195      .01415    2.74   0.006   .010978  .066461   1.50972
zeroGPA* |   .0690028      .02616    2.64   0.008   .017739  .120266   .255129
unempr~e |  -.0007437      .00161   -0.46   0.643   -.00389  .002402   3.36689
  age16* |   .0922177      .03477    2.65   0.008   .024061  .160375   .231785
  age17* |   .0734755      .02675    2.75   0.006   .021048  .125903   .354987
  age18* |   .0547222      .02113    2.59   0.010   .013305   .09614   .250648
  black* |   .0115382      .00631    1.83   0.067  -.000825  .023902   .253596
hispanic*|  -.0073909      .00425   -1.74   0.082  -.015716  .000934   .192643
   male* |   .0070587      .00419    1.68   0.092  -.001153   .01527   .533836
   SE_1* |   .0512157      .01996    2.57   0.010    .01209  .090342   0.00000
  NSE_1* |  -.0306883      .01148   -2.67   0.008  -.053193 -.008184   0.00000
 NSNE_1* |    -.21012      .01488  -14.12   0.000  -.239294 -.180946   1.00000
  faminc |   1.32e-06      .00000    2.58   0.010   3.2e-07  2.3e-06   18048.6
 famsize |   .0031639      .00139    2.27   0.023   .000431  .005897   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=0 NSNE_1=1) predict(outcome(3));

Marginal effects after mlogit
      y  = Pr(ACT==3) (predict, outcome(3))
         =  .26681064
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |   .5382837      .16986    3.17   0.002    .20536  .871208   .437112
```

```
      GPA |  -.0447616      .01756    -2.55   0.011  -.079182 -.010341   1.50972
 zeroGPA*|    -.093574        .028    -3.34   0.001  -.148451 -.038697   .255129
unempr~e |  -.0372375      .01055    -3.53   0.000  -.057914 -.016561   3.36689
   age16*|  -.2114655      .02701    -7.83   0.000  -.264396 -.158535   .231785
   age17*|  -.1461879      .02607    -5.61   0.000  -.197279 -.095097   .354987
   age18*|   -.083817      .02337    -3.59   0.000  -.129629 -.038005   .250648
   black*|  -.1214652      .02247    -5.40   0.000  -.165514 -.077416   .253596
hispanic*|   .0236182      .02396     0.99   0.324  -.023341  .070577   .192643
    male*|   .1365644      .02371     5.76   0.000    .09009  .183039   .533836
    SE_1*|   .1145988      .04709     2.43   0.015   .022298    .2069   0.00000
   NSE_1*|   .2819054      .04627     6.09   0.000   .191221   .37259   0.00000
  NSNE_1*|   .2356222      .02531     9.31   0.000    .18602  .285225   1.00000
  faminc |   4.84e-06      .00000     4.29   0.000   2.6e-06  7.0e-06   18048.6
 famsize |  -.0268245      .00567    -4.73   0.000  -.037946 -.015703   4.76598
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx c, at(mean SE_1=0 NSE_1=0 NSNE_1=1) predict(outcome(4));

Marginal effects after mlogit
      y  = Pr(ACT==4) (predict, outcome(4))
         =  .59564342
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   RMW_1 |  -.4666643      .19243    -2.43   0.015  -.843812 -.089516   .437112
     GPA |  -.1039261      .02369    -4.39   0.000  -.150354 -.057498   1.50972
 zeroGPA*|    -.176984     .04214    -4.20   0.000  -.259573 -.094395   .255129
unempr~e |   .0259258      .01153     2.25   0.025   .003324  .048527   3.36689
   age16*|   -.232163      .05367    -4.33   0.000  -.337354 -.126972   .231785
   age17*|  -.1536386      .04268    -3.60   0.000  -.237284 -.069993   .354987
   age18*|  -.0999661      .03481    -2.87   0.004  -.168196 -.031736   .250648
   black*|  -.0155315      .03334    -0.47   0.641  -.080881  .049818   .253596
hispanic*|  -.0211185      .02726    -0.77   0.438  -.074543  .032306   .192643
    male*|  -.1630236      .02413    -6.76   0.000  -.210324 -.115723   .533836
    SE_1*|  -.1112293      .04872    -2.28   0.022  -.206719  -.01574   0.00000
   NSE_1*|  -.1466622      .04858    -3.02   0.003  -.241879 -.051446   0.00000
  NSNE_1*|   .5405062      .02903    18.62   0.000     .4836  .597413   1.00000
  faminc |  -9.87e-06      .00000    -7.42   0.000  -.000012 -7.3e-06   18048.6
 famsize |   .0141827       .0061     2.32   0.020   .002223  .026142   4.76598
```