Economic Essays on Adult students

by

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Sandeep Shetty
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Signed: Sandeep Shetty

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Dedication

To,

My Family

for their continuing support and love

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Abstract

Adult students are an important component of the current U.S education landscape. They account for over 40% of the degree-seeking fresh enrollees in the U.S. colleges and according to the U.S. Department of Education, their growth will soon outpace that of traditional students. Adult students have also received considerable attention in higher education policy circles as an important resource to meet the future skills demand in U.S. industries. The focus on adult students is integral to sustaining the health of the U.S economy. Chapters in this dissertation aim to understand and quantify issues surrounding adult students.

Chapter 1 of this dissertation analyzes the characteristics and factors that help or inhibit the decisions to return to school of adult students. Using an endogenous switching model and data from the Survey of Income Program and Participation (SIPP) 2008, I examine the determinants of the return decision. The results show positive selection bias from observed earnings of those who return, and the probability of returning to school hinges significantly on family size, family income, and the presence of children under 18. Chapter 2 analyzes the pecuniary returns to returning adults using the National Longitudinal Youth Survey of 1979 (NLSY79). I find 10-20% returns to returning adults across different education degrees. I also find that the post-return experience premium is higher for returners relative to non-returners. Chapter 3 analyzes the degree of persistence or state dependence in enrollment behavior of adult students using NLSY data from 1989-1994 and dynamic panel estimation methods. The results suggest that state dependence effects exist with respect to the previous enrollment incidence for men and women. For men I find that about 20% of the observed persistence in the enrollment probability is accounted for by state dependence, as compared with roughly 36% for women.

CHAPTER 1

Coming Back to School: Return to School Decisions of Adult Students

1.1 Introduction

Adult students (age 25 and above) constitute over more than a third of incoming undergraduate students in the U.S. The U.S. Department of Education expects their growth to outstrip that of traditional students.[1,2] When viewed through the lens of Human Capital theory, the growth in the number of adult students is puzzling, as the theory predicts that individuals invest in formal schooling early in life. However, the average age of adult returners in many U.S. universities is around 36 years for the undergraduate degree and has increased over the last decade (see Figure A.1).[3] Further, as indicated by surveys in the education literature, many adults return to school with the expectations of higher earnings growth or better career opportunities rather than for satisfaction of degree attainment (Chao and Good, 2004).

Adult Education has also received a lot of attention in education policy circles as a means to close the rising skills gap in U.S. manufacturing and other industries. By 2030, only 65% of the projected demand for skilled labor is predicted to be filled by traditional students.[4,5] A skilled older workforce is the source to meet this future shortage of skill demand, however, only 41% of the current adult workforce (25-64 years) have a high school degree.[6] The need for a concerted focus on adult education policy is thus imperative and significant.

[1]Traditional students are 18 years of age and enroll in college right after High School
[2]Table 21, U.S. Department of Education, National Center for Education Statistics, March 2011
[3]Report by State Council of Higher Education for Virginia
[4]Center for American Progress Report, 2012
[5]"U.S. manufacturing sees shortage of skilled factory workers", *Washington Post, 2/19/12*
"Filling the Skills Gap", *The New York Times, 7/2/12*
[6]American Consumer Survey, Five-Year Estimates: 2005-2009)

Further, adult students differ from traditional ones in some respects. Many are married with children and other dependents. Despite their dissimilarities with traditional students and their recent growth in enrollment, research in economics on adult students is limited. Most studies of education decisions either focus only on traditional students or fail to distinguish between adult students and traditional age students. And these studies have universally assumed that expectation formation across students is homogeneous (Manski, 1994). This is a strong generalization in the context of adult students. It is intuitive that adult students base the decision to return to school on information sets that are markedly different from those of the traditional students. Most of them have work experience and have possible interaction with fellow employees, which is likely to give them access to better information on schooling, wages and ability. They can observe the schooling choices, wages, and abilities of their colleagues, against which they can benchmark their own abilities to estimate their potential return to different education levels. With this information on hand, adult students can then decide whether or not to return to school.

Understanding the characteristics and forces that help or inhibit the return to school by adult students will enable better policy designs to give further impetus to increase returning adult students and meeting the future skill demand in the U.S. This paper puts the focus on adult students.

In this paper, I analyze the return to school decisions of these students and quantify the determinants of their return decision. I specify an endogenous switching model that explicitly recognizes the endogenous nature of the decision and formally accounts for the problem of self-selection (Lee, 1978).[7] The self-selection issue arises because individuals may have information on some determinants, for instance their own ability or possible career growth, that may affect the return to school decision

[7] This model has been applied to migration (Nakosteen and Zimmer, 1980), housing (Lee and Trost, 1978), self-employment (Rees and Shah, 1986), union status (Lee, 1978; Vella and Verbeek, 1998) and education (Willis, 1986)

and also potential wages, which I do not observe. Further, I observe wages for individuals in only one of the two regimes: return wages if individual returned to school or no-return if never returned. Thus, the objective is to first obtain consistent estimates for wages in the two different regimes, and then estimate the strength and statistical significance of potential wage gains and other personal and environmental factors in determining the return to school decision. This is achieved in a binary choice model framework.

The parameters of the endogenous switching model are estimated using a Generalized Method of Moments (GMM) approach (Hansen, 1982). I also estimate the model using the traditional two-stage approach as proposed in Lee (1978). GMM is the estimator of choice as it improves upon the efficiency over the two-stage approach and provides correct standard errors that are computationally easier to calculate than the two-stage approach (Lewbel, 2004).

I use cross-section data from the Survey of Income Program and Participation (SIPP) of 2008. I find positive selection bias from observed earnings of those who return in some cases, and the probability of returning to school hinges significantly on family size, family income, and the presence of children under 18.

1.2 Background

The dramatic rise of adult student enrollment in recent decades has been influenced by changes in institutional, curricular, political, economic, and social factors. Growth in the community college sector substantially contributed to the increased number of adult students, as the community colleges targeted them extensively. The declining trend in enrollment around the mid-1980s forced other higher education institutions also to target adult students to replace the loss of traditional ones (Bean and Metzner, 1985). Further, the decline in the blue-collar manufacturing sector of the economy has had a profound effect on college enrollments, forcing displaced or new workers to choose between lower wage service-sector jobs or enrolling in postsecondary education to obtain the skills necessary for technical- or professional-level jobs.[8]

Several surveys in college counseling have documented the major reasons underlying the return of adult students. Economic reasons are a strong factor. Students want to change careers or update professional credentials. For example "...As one 28 year old observes... *'I was working at a law firm. I was making nice money without a college education, but there was a lady who has been there for 20 years; she was on the track I didn't want to be in. So I decided if I want to do more on my professional work. I need to to get my degree'...*" (Chao and Good, 2004, pp:9). Some adult students continue to work while returning to school while others attend part-time. Individuals may be just starting a degree program, returning to finish a degree, seeking a second degree or an advanced degree, or taking courses for occupational or personal enrichment. Some may never have attended college or started college and then stopped because of personal, financial, or other reasons.[9]

1.3 Literature Review

Economic research on adult students is limited. Most research on schooling decisions has mainly concentrated on traditional students, and with few exceptions have rarely analyzed adult students separately. Leigh and Gill (1997) is one such study that examined the labor market returns to community college programs for returning adults. They found returns ranging from 15 to 20% for returners in different higher education degree categories. The high returns in this study are quite intuitive given that returners are generally older with a shorter work life to recoup the investments. The Leigh and Gill (1997) study is a follow up to Kane and Rouse (1995) that estimated the returns to community college for traditional students. This study found that earnings increased by 5 to 8 percent per year of college credits, whether

[8]National Center For Education Statistics,http://nces.ed.gov/pubs/web/97578d.asp
[9]http://www.back2college.com/library/faq.htm

or not a degree is earned. Seftor and Turner (2002) is another study that focused on adult students. They analyzed the effects of the means-tested Pell Grant program on the college enrollment rates for adult returners. They found sizeable effects of the Pell program on enrollment.

However, in the education literature and college counseling literature there has been a keen interest in nontraditional students and there are several papers that have studied issues concerning adult students, but these are mostly descriptive. The major preoccupation for much of the early literature on nontraditional students was with the high attrition rates among adult students. Bean and Metzner (1985) developed a conceptual model of the dropout process for the nontraditional undergraduate student. Mostly qualitative, it describes the mechanism and the various factors affecting attrition. It documented the forces behind the increase of nontraditional students in the educational landscape of the US. I adopt some variables from their model as most of the negative factors affecting attrition are also likely to be negatively associated with the decision to return to school after interruption.

Chao and Good (2004) documented the college experiences of adult students with the objective of devising better counseling methods for adult students. Their survey finds a swathe of reasons that drive adult students to return to school and among all career concerns, job opportunities and better earning potential are the key factors.

The Condition of Education (CoE) reports produced by the US Department of Education in 1986 and 2002 included a special analysis of nontraditional students with a focus on the description of nontraditional undergraduates in terms of their demographic characteristics, enrollment patterns, ways of combining school and work, participation in distance education, and persistence patterns.

The endogenous switching model used here is proposed in Lee (1978) and the model is estimated using a two-step estimation technique. However, because of the generated regressors in the second-stage the resulting standard errors are difficult to compute and are likely incorrect.[10] In order to overcome this issue, I use a GMM approach to estimate the parameters. The method relies on fewer parametric assumptions and produces asymptotically efficient standard errors (Hansen, 1982; Lewbel, 2004).

Other papers relevant for the ensuing economic set up are Oaxaca and Regan (2007), Rosen and Willis (1979) and surveys by Weiss (1986), Willis (1986), Ehrenberg (2004). Rosen and Willis (1979) determined the extent to which alternative earnings prospects distinct from family background and financial constraints influenced the decision to attend college using a structural model. Again, the paper only considers traditional students. Oaxaca and Regan (2007) conducted an analysis on the impact of family background and ability on schooling demand through its impact on individual discount rates. Certain family background variables from these papers are included in the current analysis.

1.4 Model

1.4.1 Decision Mechanism

Individuals maximize the present value of life-time earnings when choosing an optimal level of schooling.

$$\max_{\{S_i\}} \int_0^T e^{-\rho t} y_{it}(S_i)\ dt \tag{1.1}$$

where ρ is the individual‘s annual discount rate, $y_{it}(S_i)$ is earnings at time, t.

The optimization problem is conditioned on the information set, Ω_{it}, that is available to the individual at time, t. Ω_{it} could hold information on the expected wage distribution at t and or net returns to different education levels for the individual (r_{iS}). This can vary across individuals. Two individuals with the same ability and other observables can make different schooling choices because of the difference in

[10] Although Lee (1978) theoretically derives the standard error estimator he uses an approximation of the standard error owing to the difficulty of calculation of the actual standard errors

their information set on returns to schooling. X_t captures the state of an individual's environment as defined by personal, family (size, dependents), and institutional setting (access to school, income, scholarship). S_i is the previous level of schooling obtained by the individual.

After attaining the above schooling, individuals join the workforce and accumulate work experience. Workplace interactions with colleagues within a firm and industry may provide better information on wages, ability, and schooling choices for a given firm or industry. An individual can benchmark his or her ability with colleagues and can observe the schooling choices and wages of colleagues. The new information set of the individual after work experience may make a new higher level of schooling optimal.

At time, $t^{'} > t$, $\{\Omega_{t'}\}$ is updated by acquisition of new information on the wage, ability, schooling distribution, a skill-biased technical change that increases the returns to acquiring certain skills or educational degrees. Individuals who earlier had to interrupt schooling due to exogenous reasons may now face an environment in which it is optimal to return and finish their originally planned level of schooling. $X_{t'}$ may be altered by personal events such as change in marital status that may bring financial support to the family or a reduction in financial dependence on the individual through separation or divorce. Among other factors, increased access to financial aid, loans and easier physical access to colleges could also play an important role in increasing the net return to adding more schooling.

Under the new environment, $\{\Omega_{t'}, X_{t'}\}$ if the optimal schooling level is S_i^* where $S^* > S$ then it is optimal for the individual to increase schooling.

1.4.2 Econometric Model

In the following set-up, adult students have already acquired a certain amount of their optimal schooling levels. So, given some level of past schooling, an individual

i elects to return if the gain in expected wages from an additional level of schooling exceeds the associated costs. Thus a person chooses to return if

$$w_{ri} - w_{ni} > C_i \tag{1.2}$$

where w_{ri} is the expected wage an individual receives after concluding the return to school and w_{ni} is the expected wage received if one does not return to school for additional education. C_i represents direct and indirect costs of an additional level of education. I use wages because I observe hourly wages for a large proportion of individuals in the dataset. This is also in line with the approach in Lee (1978).

The costs for the additional education may be represented as a function of personal characteristics, family environment and a random disturbance term:

$$C_i = g(X_i) + \epsilon_i \tag{1.3}$$

ϵ_i represents unobserved costs for the individual. It could also consist some function of ability. The impact of ability depends on the interpretation of the cost function above. If it is considered as an opportunity cost then the cost of return to schooling is likely to increase with the individual's ability. However, in this model, the cost function specifically controls for the direct and indirect cost of schooling (potential wage captures the opportunity cost). This cost is expected to have a negative relationship with ability. The higher ability individual may find it easier (cheaper) to manage coursework and other work and familial responsibilities than an individual with relatively low ability.

Expressions (1.2) and (1.3) suggest, as a general proposition, that the return to school selectivity criterion is a function of gains in wages along with environmental and personal attributes. In this study the criterion function is modeled as a linear combination of these variables which, taken together, explain an individual‘s propensity to return to school.

Individual i chooses to return to school if

$$R_i = \begin{cases} 1 \text{ if } R_i^* \geq 0 \\ 0 \text{ if } R_i^* < 0 \end{cases} \tag{1.4}$$

where

$$R_i^* = \alpha_0 + \alpha_1(ln(w_{ri}) - ln(w_{ni})) + \alpha X_i - \epsilon_i \tag{1.5}$$

$ln(w_{ri})$ is the potential wage if returned to school for a higher degree and $ln(w_{ni})$ is the wage for not returning or continuing with the past degree. X_i is a vector that represents factors that capture the costs involved in investing in human capital, direct and non direct, and family background variables which essentially proxy for the decision environmental situation (Bean and Metzner, 1985). Family characteristics like the number of own children under 18 in the household ($child < 18$), size of household ($Family\ size$), family income ($Family\ income$), and size of the firm of individual's employment ($Firm\ size$). It is difficult to predict the sign of some of these variables a priori. The effects could be either positive or negative. [11]

If for each individual, $\{ln(w_{ri}), ln(w_{ni})\}$ were observed I could easily estimate the above model using binary choice techniques. However, for individuals who have returned to school we observe only the post return wage, and for non-returners we observe only the non-return wage; i.e.,

$$w = \begin{cases} w_r \text{ if } R_i = 1 \\ w_n \text{ if } R_i = 0 \end{cases} \tag{1.6}$$

To overcome the potential wage problem, I have to predict the wages under the two regimes of "return" and "no-return" for each individual and substitute them in the above binary structural equation. Using the information on wages of returners, I have to predict the wages non-returners would have received if they had returned.

[11] For instance, presence of a spouse may bring financial support and/or motivational support for finishing schooling, moreover the presence of child in the household may have a negative effect, which can be different for men and women. Child under 18 in the house could negatively affect a woman's decision to return to school but may motivate a male to earn more. Also, family responsibilities in terms of dependents may have a negative impact on schooling decisions.

Similarly, I have to obtain wages for returners in the potential state of no-return. Under the unconfoundedness assumption for selection on observables, I could use matching estimators to obtain the wages for the return or no-return state for each individual. I could also use Ordinary least squares (OLS). But there is a hidden bias in the mechanism of return as individuals who return to school have information about themselves, for instance ability, motivation, guaranteed career growth, or the probability of wage increases from higher degree, which I do not observe and thus I cannot control for. This is likely to lead to selection bias in my estimates with OLS or matching estimators. As Lee (1978) showed I can estimate the wages in a linear framework using OLS after controlling for selectivity into return or no-return, as described below.

Concisely stated, the estimation of the model is as follows: Estimate a reduced selection equation for the binary return variable,

$$R_i = h(X_i, Z_i, \epsilon^*; \gamma) \tag{1.7}$$

where X_i is as defined above, Z_i are variables from the wage equations defined below. γ are the parameters associated with this reduced binary selection equation. The estimates from this equation give the hazard ratio for returning that is incorporated in the wage equations described below. ϵ^* is the error variable. The potential wage equation for return and no-return adjusting for self-selection as

$$lnw_{ri} = \beta_{r0} + \beta_1 Z_i + \sigma_{r\epsilon}[-f(X_i'\gamma)/F(X_i'\gamma)] + \eta_{ri} \tag{1.8}$$

$$lnw_{ni} = \beta_{n0} + \beta_2 Z_i + \sigma_{n\epsilon}[f(X_i'\gamma)/(1 - F(X_i'\gamma))] + \eta_{ni} \tag{1.9}$$

where,

$$E(\eta_{ri}|R_i = 1) = 0$$

$$E(\eta_{ni}|R_i = 0) = 0$$

Z consists of exogenous variables and also has some elements of X. Z has individual characteristics such as age, age^2, $marital\ status$, $firm\ size$. $\sigma_{r\epsilon}$, and $f(.)$ and

$F(.)$ are the standard normal density and distribution functions, respectively. The parameters $\sigma_{r\epsilon}$, $\sigma_{n\epsilon}$ are elements of the covariance matrix of the disturbances from the selection equation, and income equations.

$$cov(\sigma_{r\epsilon}\sigma_{n\epsilon}\epsilon^*) = \begin{pmatrix} \sigma_r^2 & \sigma_{rn} & \sigma_{r\epsilon^*} \\ & \sigma^2 & \sigma_{n\epsilon^*} \\ & & 1 \end{pmatrix}$$

The wage equations (1.8) and (1.9) can be estimated by Ordinary Least Squares (OLS) and the resulting fitted values of log wage can be inserted into (1.5) to obtain consistent estimates of the decision equation.

The parametric procedure exploits the relationship between the disturbances in the model operating through the distributional assumptions. Bivariate normality dictates that the relationship between the disturbances is linear. Thus, the above approach is very restrictive with respect to the functional form of the relationship as well as the joint normality of the error distributions (see Goldberger (1983)).[12]

Two stage estimators, as described in Lee (1978) and Heckman (1979), are easy to implement but computation of standard errors is not straightforward. Also, if the errors of the selection equation, the regression equation or both are heteroscedastic, the usual two-step estimators and maximum likelihood estimators are inconsistent(Hill et al., 2003).[13] Applying Generalized Method of Moments (GMM) yields estimators that have correct standard errors and are at least as efficient as two-stage estimators (Lewbel, 2004; Hill et al., 2003; Greene, 2011).[14] The General Method of

[12]Earlier instances of relaxing the joint normality assumption while remaining in the maximum likelihood framework were suggested by Lee (1982, 1983). The direction away from parametric and towards semi/non-parametric methods has produced many estimation methods (see Vella (1998) for an earlier survey). However, the limited nature of my dataset does not allow for feasible and reliable estimation using semi or nonparametric methods

[13]This problem was studied by Donald (1995) who has suggested a semiparametric estimator that is consistent in heteroscedastic selection model

[14] Lewbel (2004) has proposed a simple alternative that is both easy to implement and robust to heteroscedastic misspecification of unknown form

Moments estimator minimizes the following quadratic function:

$$\underset{\theta}{\operatorname{argmin}} \quad \sum_{i=1}^{n} m(Z_i, X_i; \theta)' \Omega_n \sum_{i=1}^{n} m(Z_i, X_i; \theta)$$

where $m(Z_i, X_i; \theta)$ are the moment conditions and Ω_n is a weighting matrix. (See Greene (2011); Wooldridge (2004)

$$E(m(X, Z; \theta)) = E \begin{bmatrix} \partial L(X, \gamma)/\partial \gamma \\ (ln(w_n) - Z'\beta_1 - \sigma_{r\epsilon}\lambda(X'\gamma))R(X \ \ \lambda(X'\gamma))' \\ (ln(w_r) - Z'\beta_0 - \sigma_{n\epsilon}(1 - \lambda(X'\gamma)))R(X \ \ (1 - \lambda(X'\gamma)))' \end{bmatrix} = 0 \tag{1.10}$$

Where, $\partial L(X, \gamma)/\partial \gamma$ is the score of the likelihood of the selection model. $\lambda(X'\gamma))$ is the inverse mills ratio, and R is the return indicator ($R = 1$) or no-return ($R = 0$). The above estimation is applied to white men and women separately. Additionally, the return to school for an Associate degree is separately estimated from the return for a Bachelor's Degree.

1.4.3 Identification

To obtain credible estimates, "natural" experiments as instruments for exogenous return shifts are favored, which enables the identification of an exogenous return event without any assumptions about the population distribution of preferences. However, in the case of return to school by adults with dependents and family responsibilities it is difficult to find such natural experiments. An alternative approach pursued here is to maintain some exogeneity assumption, that is, to look for variables for which a case can be made for excluding them from the participation equation and which have as much explanatory power as possible (French and Taber, 2011; Lee, 2001).Variables like family size, number of dependents and the presence of children under 18 are assumed to have an impact on the return to school decision through their impact on the indirect costs of returning to school. I assume that family size, children under 18 and family income are exogenous or excluded variables that determine the selection equation and have no bearing on wage equations These assumptions on the excluded variables provide me with the necessary identification premise.

1.5 Data Description

The data for the analysis come from Wave 2 of the Survey of Income and Program Participation (SIPP) from 2008. I used Wave 2 of the survey because in this wave SIPP administered a specific set of questions (topical modules) on enrollment and educational achievement along with the usual "core" questions on labor force activity, program participation, and income. Other topics covered in these modules during different waves or periods include personal history, child care, wealth, program eligibility, child support, utilization and cost of health care, disability, taxes, and annual income.

SIPP is designed as a continuous series of panels, with a sample size from approximately 14,000 to 37,000 households. Each panel lasts from 2 to 4 years. The SIPP sample is a multistage-stratified sample of the U.S. civilian non-institutionalized population. The respondents are all household members 15 years or older. The survey uses a 4-month recall period, with approximately the same number of interviews being conducted in each month of the 4-month period for each wave. Interviews are conducted by personal visit and by telephone.

Although there are several different definitions for a non-traditional or adult student in the education literature, I focus on students in the age-group of 25-45 years. I exclude students over 50 years of age because many surveys in education indicate that they are markedly different from the younger age group. Students above 45 return to school mainly for fulfillment rather than economic reasons, as typically is the case for individuals in the early stages of their career. I also exclude individuals who served in the military or were attached to the military because the decision process of veterans is likely different from the civilian population. Army veterans can access the GI Bill (or post 9/11 GI Bill) to finance their schooling, this is not available to non-veterans and some veterans may serve in the army mainly to fund future education through the GI bill.

Table 1.1 and 1.2 summarize the the key variables of the dataset. Of the 7,128 individuals around 6% men and 17% women returned to school for an Associate Degree or Bachelor Degree. About 57 percent are married with spouse present, the others are categorized as single even if they were separated or divorced. Since there are very few observations among non-whites across return states, I conduct my analysis only on whites.

Table 1.3 and 1.4 summarizes data across returners and non-returners for Associate Degrees and Bachelor's Degrees for men and women separately. For men and women wages, family income, and firm size increase with education whereas family size and dependents decrease with education. My dataset concurs with the general understanding about the relationship of these variables with education.

Table 1.5 in the appendix reports percentage returned across different industries. Since Public Administration and the Health Industry are the major industries with the most returnees for men and women, returners are more likely to originate from prominent sectors like education, health and finance. The across-industry variation in the dataset is very small so I ignore the industry variable[15]

1.6 Empirical Results

Column 1 of Tables 1.7 and 1.9 report the estimated coefficients from the selection equation for men and women separately for the return to associate degree. Similarly, *Column* 1 of Tables 1.6, 1.10 reports the estimated coefficients from the selection equation for the Bachelor Degree treatment group. It includes marital status, family

[15]Pooling observations could have increased the sample size. However, augmenting data from 2004 and 2008 - two different business cycles - it is risky to assume that the relationship I am after is the same across the two periods.

size and child under 18 as the explanatory variables. Holding everything constant, family size is statistically significant in distributing individuals into the category of returners and non-returners. *Family size* works as an instrument in the selection equation that is excluded from the income equations and helps with the identification of the wage equations. The *Family income* coefficient is statistically significant in the selection equation for females and males at the 1 percent level. Higher family income provides more support to return to schooling. Further, metro residence has a strong positive effect on selection. A larger family size discourages return to school. Age has a positive effect for men and women. This is also evident from Figure A.1 where the age of return for men and women has been increasing over the years with the increasing access to 2-year colleges and online course.

Columns $2-3$ of Tables 1.7 report the estimation results for the wage equation for returners and non-returners with respect to Associate Degree for men and Table 1.9 reports the same for women. *Columns* $2-3$ of Tables 1.6 report the estimation results for the wage equation for returners and non-returners with respect to Bachelor Degree for men and similarly for Table 1.10 for women.The wage equations control for human capital and productivity variables like experience, and marital status along with controlling for selection bias that are calculated from the selection and explained in the section on empirical model. The coefficients on the inverse mills ratio (selection term) in all the equations are statistically significant, and is negative for return to Bachelor Degree for males. A negative parameter indicates no comparative advantage in the endogenously chosen sector. Thus, men returning for a bachelor degree do not have a comparative advantage in getting the bachelor degree. However, this does not hold for men returning for an associate degree and also for women returning for any degrees. Marital status has a positive effect on wages and the estimate ranges from 8 to 10 percent which is close to other studies (Korenman and Neumark, 1991). Firm size has the expected positive effect as in the literature on wage dispersion and firm size. However, the coefficient on metro residence is positive as expected (compensating differential in wages).

Column (4) reports the coefficients on the main binary regression (equation (1.5)).[16] Most of the individual and family background variables have the expected signs as predicted in the literature survey and in the qualitative studies on nontraditional students in education and college counseling.

Age has a negative effect on return probability, indicating an increasing cost of returning to school as one grows older. Increasing family responsibility (measured by family income, family size and children under 18) has differential effects on men and women. Family income increases the return probability for men and women, and family size has a negative effect. Children under 18 surprisingly has a positive effect. This may be because the dataset has more younger individuals in the age group most likely to have a child under 18, so the coefficient on this variable is not reliable and has much less economic significance in this analysis. Our variable of interest,$ln(w_r/w_n)$, is positive for both men and women for associate and bachelor degree but not strongly significant. This is likely because of a small sample that is affecting precision.

Tables 1.8 & 1.11 reports the marginal effects for the structural probit estimation results. In probit models, the coefficients cannot be directly interpreted as marginal effects. The marginal effect of a change in an independent variable is the product of the partial derivative of the cumulative standard normal density and the coefficient on the variable of interest, and all the other variables are set at their sample values. The marginal effects are evaluated for each observation and averaged to get a single number (average partial effect).

The potential wage gain, $ln(w_r/w_n)$, has a positive impact on the probability of returning to school however it is weakly estimated because of the sample size.[17] A

[16]The standard errors on these coefficients are corrected for heterosckedasticity using the Huber-White robust estimator

[17]Pooled observations could have increased the sample size. However, augmenting data from 2004 and 2008 - two different business cycles - it is risky to assume that the relationship I am after is the same across the two periods.

smaller effect of wages on returning could also be interpreted as the return to school decisions are based on career moves that pay in the future with higher wages or status.

Age impacts the probability of returning to school differently across degrees. For an associate degree, *age* increases the probability of return by 0.03% for women but it is small and statistically insignificant in its impact for return to a bachelor degree. Age has similar effects on return probability for men. The impact of age as obtained and described above is quite intuitive, as an associate degree is only 2 years compared to 3 to 4 years for bachelor degree. That is the time cost of an associate degree is lower and permits one to return to workforce quickly. So, as one age ages an associate degree is more favorable choice than a bachelor's degree.

Family income has a positive marginal effect for men and women across both degrees. Family size has a sizeable negative marginal effect for men and women. Finally, the presence of children under 18 has a positive effect for women's probability of returning to school. This is driven by the age composition of the dataset leaning towards a younger populace, thus the estimate for children under 18 can not be fully relied on. Although, the directions of the effects of many of the variables in the estimation are as expected and found in some of the earlier literature, the precision of the estimates could be improved with more observations.

1.7 Conclusion

This paper develops a model of schooling decisions of adult students in order to understand and quantify the main factors that facilitate or inhibit return to school. This paper quantifies the different forces working on schooling decisions and also looks at the return to school choice of a unique set of individuals who are quite different from the traditional students and are increasingly changing the U.S education landscape.

The analysis provides evidence on the hypothesis that individuals with higher potential wage gain are most likely to return to school. Also, those returning have a higher comparative advantage in doing so. This is captured in the selectivity variable in the wage equations. A smaller impact of potential wages in some cases in the above analysis could be because of the decision being based on future career opportunities or growth which are not captured in the current dataset. The issue of statistical significance is due to a small dataset. There is a serious paucity of data in this important area of adult higher education. This sentiment is also echoed by a leading non-profit organization that is involved in higher education.[18] For more research in this area the shortage of data should be overcome at the earliest.

Future research in the area of adult higher education is estimating the pecuniary returns to returning adults given the increasing costs of tuition in the U.S colleges. Moreover, there is a considerable gap in knowledge regarding the sources and process of how adult students fund and finance their degrees. There is a need to further understand the issues concerning attrition, persistence and degree attainment among adult students, which is still considered a problem.[19] With prominence of Internet and distance learning courses, there is a strong need to understand the above issues and pecuniary returns in context of these new platforms of education delivery technology.

[18] "...The nation faces significant gaps in available data about adult participation in many areas...", Council for Adult and Experential Learning(CAEL) in "State Policies to Bring Adult Learning into Focus"

[19] U.S. Department of Labor Report, "Adult Learners in Higher Education: Barriers to Success and Strategies to Improve Results"

1.8 Summary Tables

Table 1.1: Summary of Observations across Gender, Education

	High School Degree ($Treatment = 0$)	Associate Degree ($Treatment = 1$)	Bachelor Degree ($Treatment = 1$)	N
Female	2918	382	255	3555
Male	3192	216	165	3573
N	6110	598	420	**7128**

Table 1.2: Overall Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
ln(wage)	2.585	0.427	1.792	3.605
Age	37.460	7.440	25.0	50.0
High School	0.857	0.350	0.0	1.0
Associate Degree	0.084	0.277	0.0	1.0
44 Bachelor Degree	0.059	0.235	0.0	1.0
Male	0.501	0.500	0.0	1.0
Married	0.577	0.494	0.0	1.0
$Child < 18$	0.987	1.186	0.0	7.0
Family size	3.156	1.647	1.0	15.0
Family income	4.653	3.388	0.0	11.0
Firm size	2.036	0.871	1.0	3.0
Metro	0.737	0.440	0.0	1.0

Table 1.3: Averages for Male across Return groups (Degree)

Variable	High School	Associate	Bachelor
ln(wage)	2.6751	2.8570	2.9073
Age	37.0470	37.4213	36.9091
Married	0.5959	0.5741	0.5758
$Child < 18$	0.9392	0.9352	0.7758
Family size	3.1009	2.9028	2.7030
Family Income	4.5983	5.4310	6.3055
Firm size	0.3690	0.4907	0.4909
Metro	0.7149	0.8750	0.8545

Table 1.4: Averages for Female across Return groups (Degree)

Variable	High School	Associate	Bachelor
ln(wage)	2.4241	2.6860	2.7083
Age	37.8876	38.0262	37.2824
Married	0.5524	0.5916	0.6039
$Child < 18$	1.0432	1.1518	0.8627
Family size	3.2598	3.2461	3.0275
Family Income	4.3015	5.6969	6.0555
Firm size	0.3962	0.4293	0.4784
Metro	0.7320	0.7382	0.8824

Table 1.5: Percentage Adult Returners across Industries

Industry	Non-returners	Returners	Total	% returners
Agriculture	76	1	77	1.3
Mining	32	3	35	9.4
Utilities	64	9	73	14.1
Construction	674	43	717	6.4
Manufacturing	1,208	99	1,307	8.2
Wholesale Trade	220	23	243	10.5
Retail Trade	840	97	937	11.5
Transportation	294	34	328	11.6
Information	82	15	97	18.3
Finance and Insurance	158	44	202	27.8
Real Estate	84	10	94	11.9
Professional Services	450	94	544	20.9
Educational Services	226	71	297	31.4
Health care	704	314	1,018	44.6
Arts	618	64	682	10.4
Other services	228	30	258	13.2
Public Administration	152	67	219	44.1

[1] Source: Wave 2 of SIPP 2008

1.9 Empirical Tables

Table 1.6: GMM Estimates: Returned for Bachelor Degree (Male)

	Selection Equation *(1)*	$ln(Wage)_{R=1}$ *(2)*	$ln(Wage)_{R=0}$ *(3)*	Structural Equation *(4)*
$ln(w_r/w_n)$				0.76699
				(1.21896)
Age	-0.0141*	0.01582*	0.01305	0.03003
	(0.0063)	(0.06057)	(0.01572)	(0.06837)
Age^2		-0.00006	0.00000	-0.00048
		(0.00081)	(0.00021)	(0.00092)
Family size	-0.0996*			-0.157244*
	(0.0333)			(0.03520)
Family income	0.0815*			0.08268*
	(0.0129)			(0.01261)
Married	-0.2437*	0.15364*	0.32695	0.24930*
	(0.1052)	(0.08160)	(0.02513)	(0.23723)
Metro		0.11642	-0.00539	0.35991*
		(0.12822)	(0.02053)	(0.18409)
Firm size		0.22659*	0.08142	0.07018
		(0.07744)	(0.02057)	(0.11710)
Selectivity		-0.31534*	1.59441	
		(0.18606)	(0.29671)	
Constant	-0.7778*	2.63791*	2.07742*	-3.14315*
	(0.2428)	(1.09693)	(0.22093)	(1.6705))

Note: *Column* (1) are probit estimates from the selection equation of returning to school or not returning. From this estimation, Selectivity is calculated as $\frac{\phi(X\hat{\gamma})}{\Phi(X\hat{\gamma})}$ for returners and $\frac{\phi(X\hat{\gamma})}{1-\Phi(X\hat{\gamma})}$ for non-returners. *Columns* (2) & (3) are wage equation estimates for returners and non-returners, respectively. *Column* (4) is the structural probit equation of interest.

Table 1.7: GMM Estimates: Returned for Associate Degree (Male)

Variables	Selection Equation *(1)*	$ln(Wage)_{R=1}$ *(2)*	$ln(Wage)_{R=0}$ *(3)*	Structural Equation *(4)*
$ln(w_r/w_n)$				3.53284*
				(2.04424)
Age	-0.01721	0.01731*	0.01428	0.17343*
	(0.00829)	(0.06088)	(0.02172)	(0.06579)
Age^2		-0.00005	0.00013	-0.00183*
		(0.00073)	(0.00024)	(0.00095)
Family size	-0.01181			-0.08411*
	(0.05260)			(0.03079)
Family income	0.00321			0.05547*
	(0.06913)			(0.01308)
Married	-0.35875*	0.06752	0.49885*	1.50967*
	(0.10647)	(0.80415)	(0.14543)	(0.88666)
Metro		0.13371*	0.00585	0.10242
		(0.08697)	(0.02225)	(0.27808)
Firm size		0.17411*	0.08142*	-0.04096
		(0.06148)	(0.02057)	(0.10776)
Selectivity		0.51933	2.82495*	
		(2.64617)	(1.15785)	
Constant	-0.30457*	1.16033	0.96381*	-5.65488*
	(0.27005)	(2.89431)	(0.78799)	(1.22702)

Note: *Column* (1) are probit estimates from the selection equation of returning to school or not returning. From this estimation, Selectivity is calculated as $\frac{\phi(X\hat{\gamma})}{\Phi(X\hat{\gamma})}$ for returners and $\frac{\phi(X\hat{\gamma})}{1-\Phi(X\hat{\gamma})}$ for non-returners. *Columns* (2) & (3) are wage equation estimates for returners and non-returners, respectively. *Column* (4) is the structural probit equation of interest.

Table 1.8: Average Marginal Effects For Male: Returning for Associate or Bachelor Degree

	Bachelor Degree *(1)*	Associate Degree *(2)*
$ln(w_r/w_n)$	0.1192	0.6675*
	(0.1894)	(0.3860)
Age	0.0046	0.0327*
	(0.0106)	(0.0124)
Age^2	-0.00008	-0.0003
	(0.0001)	(0.0001)
Family size	-0.0244*	-0.0159*
	(0.0055)	(0.0058)
Family income	0.0128*	0.0105*
	(0.0019)	(0.0025)
Married	0.0387*	0.2853*
	(0.0368)	(0.1674)
Metro	0.0559*	0.0193
	(0.0286)	(0.0525)
Firm size	0.0109	-0.0077
	(0.0182)	(0.0204)

Note: Average Partial effects calculated from the main probit equations (*Column (4)* of Table 1.6, 1.7).

Table 1.9: GMM Estimates: Returned for Associate Degree (Female)

	Selection Equation *(1)*	$ln(Wage)_{R=1}$ *(2)*	$ln(Wage)_{R=0}$ *(3)*	Structural Equation *(4)*
$ln(w_r/w_n)$				0.29888
				(0.85103)
Age	-0.01097	0.00748	0.01430	0.13673**
	(0.00542)	(0.04016)	(0.01429)	(0.05591)
Age^2		-0.00007	0.00000	-0.00178**
		(0.00055)	(0.00019)	(0.00075)
Married	0.00214	0.10687	0.04735	-0.06163
	(0.11209)	(0.05125)	(0.01754)	(0.09492)
Family size	-0.06757			-0.13100**
	(0.06097)			(0.03647)
Child¡18	0.06858			0.14984**
	(0.07355)			(0.04475)
Family income	0.02654			0.07226**
	(0.03584)			(0.01626)
Firmsize	0.02287	0.26798	0.08002	0.00548
	(0.07949)	(0.05848)	(0.01753)	(0.09028)
Metro		0.12154	0.07193	0.00109
		(0.06161)	(0.01939)	(0.08639)
Selectivity		1.12949*	2.25095*	
		(0.80829)	(0.26905)	
Constant	-0.43216	0.61100	1.00245	-3.23363*
	(0.21747)	(1.26186)	(0.29528)	(1.09243)

Note: Note: *Column* (1) are probit estimates from the selection equation of returning to school. From this estimation, selectivity is calculated as $\frac{\phi(X\hat{\gamma})}{\Phi(X\hat{\gamma})}$ for returners and $\frac{\phi(X\hat{\gamma})}{1-\Phi(X\hat{\gamma})}$ for non-returners. *Columns* (2) & (3) are wage equation estimates for returners and non-returners, respectively. *Column* (4) is the structural probit equation of interest.

Table 1.10: GMM Estimates: Returned for Bachelor Degree (Female)

	Selection Equation *(1)*	$ln(Wage)_{R=1}$ *(2)*	$ln(Wage)_{R=0}$ *(3)*	Structural Equation *(4)*
$ln(w_r/w_n)$				6.85217
				(4.98564)
Age	-0.01580	0.01577	0.00960	0.03624
	(0.00592)	(0.05975)	(0.01496)	(0.07018)
Age^2		-0.00011	0.00015	0.00055
		(0.00079)	(0.00020)	(0.00155)
Married	-0.02201	0.03845	0.12711	0.69974
	(0.09470)	(0.07310)	(0.01786)	(0.45507)
Family size	-0.03015			-0.12401
	(0.03622)			(0.03933)
Child<18	-0.03612			0.00064
	(0.05027)			(0.05075)
Family income	0.02254			0.07107
	(0.01707)			(0.01631)
Firm size	0.05154	0.11666	0.07910	-0.03274
	(0.08648)	(0.07341)	(0.01852)	(0.10607)
Metro		0.88884	0.12502	-4.71224
		(0.20393)	(0.01984)	(3.80103)
Selectivity		0.21284	3.03020	
		(0.43724)	(0.27566)	
Constant	-0.42776	0.92587	0.81735	-3.43080
	(0.24350)	(1.07118)	(0.31082)	(1.20404)

Note: *Column* (1) are probit estimates from the selection equation of returning to school. From this estimation, selectivity is calculated as $\frac{\phi(X\hat{\gamma})}{\Phi(X\hat{\gamma})}$ for returners and $\frac{\phi(X\hat{\gamma})}{1-\Phi(X\hat{\gamma})}$ for non-returners. *Columns* (2) & (3) are wage equation estimates for returners and non-returners, respectively. *Column* (4) is the structural probit equation of interest.

Table 1.11: Average Marginal Effects For Female: Returning for Associate or Bachelor Degree

	Bachelor Degree *(1)*	Associate Degree *(2)*
$ln(w_r/w_n)$	1.4773	0.0824
	(1.0741)	(0.2344)
Age	0.00781	0.0377*
	(0.0151)	(0.0153)
Age^2	0.00012	-0.0005*
	(0.0003)	(0.0002)
Married	0.1509*	-0.0169
	(0.0980)	(0.0261)
Family size	-0.0267*	-0.0361*
	(0.0084)	(0.0099)
Child<18	0.00014	0.0413*
	(0.0109)	(0.0122)
Family Income	0.01532*	0.0199*
	(0.0034)	(0.0043)
Firm size	-0.0071	0.0015
	(0.0228)	(0.0248)
Metro	-1.0159	0.0003
	(0.8189)	(0.0238)

Note: Average Partial effects calculated from the main probit equations (*Column (4)* of Table 1.10, 1.9)

CHAPTER 2
Estimating Returns to Returning Adult Students

2.1 Introduction

Over 40 percent of incoming undergraduate students in the U.S are adult students (age 25 and above). From 1970 to 2009, their size in enrollment has increased from 28 to 42 percent.[1] The U.S. Department of Education expects their growth to outstrip that of traditional students in the coming years.[2]

Also, according to the U.S. Department of Labor data, 90 percent of the fastest growing jobs will require some form of post-secondary education and by 2030, only 65% of this projected demand for skilled labor is predicted to be filled by traditional students.[3,4] Thus, the focus on adult students as a resource to meet the skills gap is integral to sustaining the health of the U.S economy.

The growth of adult students is also theoretically interesting as the Human Capital theory predicts that individuals invest in formal schooling early on, however, in recent decades, the average age of returning adults has been rising consistently (see Figure A.1).[5] Currently, the average age of adult students is around 32-36 years

Despite this importance, research on adult students in economics is limited. Leigh and Gill (1997) estimate the returns for adult students to community college and find sizable returns. Their study can be looked as an extension of a seminal higher education paper by Kane and Rouse (1995) which for the first time estimated the

[1] Table 199, Digest of Education Statistics 2009, National Center for Education Statistics)

[2] Traditional students are 18 years of age and enroll in college right after High School

[3] Center for American Progress Report, 2012

[4] "U.S. manufacturing sees shortage of skilled factory workers", *Washington Post, 2/19/12* "Filling the Skills Gap", *The New York Times, 7/2/12*

[5] Report by State Council of Higher Education for Virginia

returns to community college but failed to distinguish between returning adults and traditional students. Kane and Rouse (1995) find that community college education raises an individual's earnings in the marketplace, even in the absence of an associate's degree. However, in recent years, the increase in college tuition costs and possible change in premiums and demand for skills raises the need to revisit some of these parameters. Along with returns to returning, this paper sets itself apart from the other studies as it also considers the impact of the gap of interruption on schooling returns, the returns to enrollment and the post-return experience which were not covered in the literature stated above.

Adult students differ from traditional students in many respects, they are married with children, hold jobs and have other dependents. Despite their dissimilarities with traditional students, research in economics on adult students is limited and most studies fail to distinguish between adult students and traditional age students. Also the information sets of adult students can be expected to be markedly different from the traditional students. Workplace interaction may give adult workers better information on schooling, wages and ability. They can observe the schooling choices, wages, and abilities of their colleagues, against which they can benchmark their own abilities to estimate their potential return to different education levels, and base their to return decision on such sharp information sets.

In this paper, I estimate the return to returning adult students for different higher educational degrees, the impact of the gap in years in returning to school on wages and the trajectory of the post-return experience using the panel data from the National Longitudinal Youth Survey (NLSY) 1979-2008. I estimate the above for white men and women separately.

The results showed that after controlling for individual heterogeneity (ability), the wage premium for returning men is 10% for a bachelor's degree, 20.8% for masters degree (MA, MBA) and the return to returning to the PhD degree is 12%. The returns for women are positive but relatively small. Returning males are catapulted into a higher post-return experience trajectory. For men, this is about 2.4% annually but the estimates for women are not conclusive. I also find that the longer one waits the lesser is the return to returning. Additionally, the return to enrolling (and not completing a degree) is neither economically nor statistically significant, indicating the market rewards finishers significantly more than non-finishers. The returns to enrollment are estimated to gain some insight into the high attrition before completion among adult students, which is a significant policy concern.

My findings also indicate the possibility of negative ability bias when estimating simple models that do not control for time-invariant features of the individuals, like IQ. The pooled OLS estimates are negative for higher levels of schooling but after controlling for individual fixed effects (FE), the returns become positive. This suggests that people with lower ability or lower comparative advantage are returning to school. Graphs (B.1, B.2) in the appendix lend some weak evidence to such a possibility. The wage profiles of returners are lower before returning than the non-returners and increases after return. There are two possible interesting explanations. Firstly, individuals, for some reason, may receive wages that are mismatched with their abilities so they return to push themselves to a higher earning path.[6] Secondly, individuals have low ability or outdated skills and they return to school and earn high post-return wages or wage-growth. This growth in earnings is open to interpretation. It could be the result of a *sheepskin effect* of the degree obtained or the possible accumulation of general skills while in school that holds a premium in the market and increases earnings irrespective of ability. In such a scenario, there is scope for policy implications to encourage adults to return to school.

[6]In this case, past wages can be thought to be exogenous to ability

2.2 Literature Review

The literature on estimating returns to education is massive. However, most research in economics studying the returns to school does not distinguish between traditional[7] and adult students. Adults students are different from traditional students on many observable characteristics, as well as motivation, ability (Cross, 1980). Further, the research in schooling choices has universally assumed that expectation formation among students is homogeneous (Manski, 1994). This is a strong generalization in the context of adult students, whose expectation formation in return to school decisions are conditioned on a much sharper information set than that of traditional students.

Even the most widely cited and seminal paper by Kane and Rouse (1995) on labor market returns to community college failed to distinguish between returning adults and the traditional 18 year old students continuing education. Kane and Rouse (1995) find that an additional year of community college corresponds with an increase of 4 to 7% in annual earnings, whereas an additional year at a four-year institution produces a 6 to 9% increase in annual earnings. They also find that receiving a college degree raises earnings even when compared to having completed an equivalent amount of schooling (such as four-years) without completing a degree.[8] Using dummies for degrees, they found that an associate's degree is associated with earnings increases of 24% for men and 31% for women.

Using data on adult students from NLSY 79, Leigh and Gill (1997) find similar returns, and they find that the returns are similar between continuing students and returning students. They find that the average return for a bachelor's degree is 42% for men and 51% for women. In the studies stated above, the comparison group in all cases is a high school graduate.

[7] Traditional students are 18 years of age and enroll in college right after high school

[8] Marcotte et al. (2005) obtain similar results for community colleges from a more recent cohort of students. They find that community college education raises an individual's earnings in the marketplace, even in the absence of an associate's degree.

Jacobson et al. (2005) look only at the returns for community college students for adult workers who have been "'displaced"' because their employers have closed down or moved out of the state. Their data is administrative data specific to the state of Washington. They find that an additional year of community college increases long-term earnings by approximately 9% for men and 13% for women, with slightly lower returns for workers age 35 or older. They also show that workers derived more benefits from technical courses and math/science courses and fewer benefits from less technical courses. Most of the increase in annual earnings came from additional hours of work rather than from higher hourly wages. However, I consider a slightly different sub-population of adult workers, mainly those returning to formal schooling, most likely to gain general skills, as opposed to (firm) specific training programs.

In the higher education literature, an initial group of studies found that the return to a 2-year college is equivalent to that of a 4-year institution (Grubb, 1993; Jaeger and Page, 1996). There were some studies that estimated the quality of the institution on student outcomes without controlling for selection bias issues and found positive effects (Loury and Garman, 1995; James et al., 1989). More recent studies that attempted to control for selection found mixed results or results favoring certain subgroups of population only (Ehrenberg and Brewer, 1994; Monks, 2000; Dale and Krueger, 2011). For a more extensive survey on higher education covering aspects on supply of education, endowment fund management and allocation see the detailed survey by Ehrenberg (2004).

Goldin and Katz (1998) provide an explanation of the historical evolution of American higher education during the 1890-1940 period. In addition, Bean and Metzner (1985) neatly place the growth of adult students in the context of the changing historical, political and cultural climate in the US over the last 40 years.

2.3 Data Description

The data used for this analysis come from the National Longitudinal Survey of Youth 1979 (NLSY), a nationally representative panel collected annually between 1979 and 1994 and biennially thereafter by the Bureau of Labor Statistics (BLS). The sample for this study is comprised of white men and women between the ages of 25 to 50 years and at least two years of survey information were chosen so as to show some variation in human capital accumulation (returners included), labor force experience, and other personal characteristics. I use the entire dataset up to 2008 and make necessary adjustments while calculating growth rates.[9]

Broadly, any individual returning to college for an associate degree or higher with a gap of more than 2 years after receiving a high school diploma is considered a returner. Non-returners are individuals who have never returned for the degree. This will include individuals who never experienced a break in education. Individuals without a gap in schooling are included as non-returners.

There are 3,026 individuals in my dataset with an average of 13 years of data per individual. The total number of observations (N) is 47,452. There are 1,443 males and 1,583 females with 301 and 486 returners, respectively.

Table 2.1: Short Summary of Observations

	Observations	Individuals	Returners
Female	24,459	1,583	486
Male	22,793	1,443	301
Total	47,452	3,026	787

Tables 2.2 shows summary statistics for the variables used in the following analysis for both returners and non-returners. Returners are individuals who have a positive gap of 2 years or more before returning to school for a higher degree. The average gap in years for returners is 10 years. Hourly earnings, the key dependent variables,

[9] I use compounded annual growth rate whenever there are jumps in years.

are normalized to 2000 dollars and values less than 5 and more than 100 are dropped from the analysis. The average hourly wage ($) is 15.43 for non-returner and 17.42 for returners. Also, the average wage growth for returners is higher than for non-returners. This difference in wage-growth is mostly driven by years after obtaining the return-degree.[10] The average age of individuals is 35 years across both categories. Further, returners are more likely to have smaller families and fewer dependents than non-returners. The distribution of returners and non-returners across the different sizes of firms is roughly the same. There are more female returners and returners are predominantly white. So, the analysis is restricted to white men and women.

Table 2.3 summarizes over time variation of some key variables for only returners in periods before they returned to college and over periods after they finished their degrees. Post return, returners witness an increase in wages of about 20%, from $13.52 to $17.61. They also see a jump in wage-growth in the post-return phase, and are likely to continue working for the same size of firms post return.

In response to some curiosity about the recent concerns over the attrition rates among adult students, Table 2.4 compares returners who completed the degree versus returners who never completed the degree for which they returned or individuals who dropped out (I call them non-finishers). About 22% of all students enrolled in 2-year colleges in 2005 had completed associate degrees by 2008. About 54 percent of students completed bachelor's degrees at a four-year public institution in that same year.[11]

Compared to non-returners, individuals who return to college but do not finish the degree, i.e. non-finishers, receive a higher wage ($12.42 vs $11.35), but it is still lower relative to those who have finished the degree ($15.33). Interestingly, they do

[10] Graphical exploration of the data gives some support to the above premise.

[11] `http://bit.ly/12a9Stz`. Also, from a U.S advisory committee report, "only 31% of nontraditional undergraduates with a bachelor's degree objective attained a degree within five years as opposed to 54% of traditional undergraduates (Horn and Carroll, 1996). In addition, 38% of adult undergraduates left school in their first year as opposed to 16% of traditional undergraduates (Horn and Carroll, 1996)."'`http://1.usa.gov/ywr1sZ`

enjoy a higher wage and better wage growth compared to those who never returned but compared to completers they experience a much lower wage-growth rate. Non-finishers experience an average wage growth of 5% versus 7% for completers and 3.88% for non-returners. Further, the non-finishers are very similar to finishers across many observable aspects such as: marital status, family size, distribution across firm sizes, number of dependents and children, work experience and ages.

Table 2.5 compares individuals before and after enrollment. A quick look into whether enrolling has any impacts on individuals. Since this table includes finishers and non-finishers, the numbers do not lend very reliable insight into the observable differences across the two categories. Hourly wages are higher ($2.57) after enrollment compared to before enrollment ($2.28) and the wage growth rate also appears to increase after enrollment into college (4.2% vs 9%). Since these numbers are averages across time, they are largely driven by finishers in the after-enrollment category.

2.4 Model

Much of the discussion on returns to school has focused on the potential correlation between individual specific latent ability and schooling (Griliches, 1977). The benefit of using panel data is the ability to control for such individual-specific effects, which may be correlated with other included variables in the specification of an economic relationship. Analysis of cross-section data alone can neither identify nor control for such individual effects.

Consider a linear regression model,

$$Y_{it} = X_{it}\beta + Z_i\gamma + \alpha_i + \eta_{it}, \quad i = 1, \ldots, N; t = 1, \ldots, T$$

where β and γ are k and g vectors of coefficients associated with time-varying and time-invariant observable variables respectively. The dependent variable is $ln(wage)$ which is a log-transformation of the hourly wages normalized to 2000 dollars. The wage equation in this application is the traditional earnings equation prevalent in the literature where $X_{i.}$ and Z are productivity controls and includes the key variables of interest (such as return to different degrees, gap (years), enrollment).

The individual effect, α_i, captures time-invariant unobservables particular to any individual in the population (innate ability or motivation). The disturbance η_{it} is assumed uncorrelated with the columns of (X_{it}, Z_i, α_i) and has zero mean and constant variance σ^2_η conditional on X_{it}, and Z_i. The latent individual effect α_i is assumed to be a time-invariant random variable, distributed independently across individuals, with variance σ^2_α. Our primary focus is the potential correlation of α_i, with the columns of X and Z. In the presence of such correlations, least squares (OLS) and generalized least squares (GLS) yield biased and inconsistent estimates of the parameters (β,γ,σ^2_α, σ^2_η).

$\{X_{it}$,$Z_i\}$ contains *actual experience* (calculated using weeks worked per calendar year and accumulated over the time-period an individual is observed in the dataset), *marital status*, *firm size*[12], *industry*[13], time dummies and independent variables of interest explained below.

Various assumptions are made about the correlation of unobserved individual fixed effects, such as ability or motivation, α_i, and variables of interest, and the resulting estimates are reported in Tables 2.6–2.10.

It is not clear in which direction the return or schooling coefficient will be biased. While a simple story of positive correlation between ability and schooling leads to an upward bias in the OLS estimate, a model in which the choice of the amount of schooling is made endogenous can lead to a negative correlation between the chosen amount of schooling and ability Griliches (1977).

[12]dummies for different sizes of firm: less than 100 employees, 100–499 employees, 500–999 and more than 1000 employees

[13]2-digit Census industry codes

Independent Variables of interest

Return is a dummy variable that records one if the individual returned for any college degree (Associate degree, Bachelor's, Master's or PhD) with an interruption or gap where in the interim the individual accumulated work experience. *Return* takes value zero if the individual did not return for any college degree (including those who completed their schooling without an interruption or a break). All the empirical results for these variable are obtained in interaction with different degrees because the coefficient on the dummy *Return* by itself is hard to interpret.

gap (*years*) measures the gap in years before the return to school for an educational degree. *gap* is also interacted with all the different educational degrees because the cost of gap is likely to be different across degrees.

enrollment captures the enrollment status in order to test if there is any pecuniary return to enrollment. Attrition among adult students is pretty high therefore it is interesting to know if enrollment alone gives them good returns that makes finishing college unoptimal.

post exp is experience in years gained after earning the return degree. Since many adults are entering school around the peak of their earnings growth, it is interesting to know whether returning puts them on a higher earning trajectory over the life-time.

2.5 Empirical Results

2.5.1 Estimates for Returns to Returning Adults

Table 2.6 shows the return estimates for men across different educational degrees. Columns of this table represent estimates under different assumptions between the errors, correlates and the intercept terms.

Column (1) represents pooled OLS estimates for returning to school. All the controls are statistically significant and shows high returns for *marital status*, *urban* residence, and firm size. The OLS estimates for returns to being married is 16.4% and for residence in urban centers is 13.7%. A 4.1% return is estimated to every year of experience and a significant quadratic relationship is found that falls at a very slow rate. The signs and strength of the above variables are aligned with the earnings relationships estimated in most other studies.

However, the OLS estimates on returns to returning are of mixed signs and significantly negative for bachelor's degree. Interestingly, some of these estimates turn positive with inclusion of individual fixed effects. The reversal of signs can be interpreted as a negative relationship between return to school decisions and individual fixed effects. This implies, if ability is interpreted as some proportion of individual fixed effects, then individuals returning are lower ability individuals.

Returning to a Bachelor's Degree has a negative return of 6.9%, however, returning for a Master's degree is positive at 6.9%. Also, returning for professional degrees are statistically negative. Further, individuals working for large firms enjoy a sizable and statistically significant wage premium. The gap in wages for working in firms with 100 to 500 employees over small firms is 14%, and 18% for firms with more than 500 employees but it dips slightly for firms larger than 1000 employees.

Columns (2) & (3) show estimates under random effects and fixed effect estimation of the data. Under fixed effects estimation (Column (3) Table 2.6), the return to returning for degrees are positive and statistically significant for men. The return to returning for a Bachelor degree is 10.4% and returning for a Master's degree increases wages by 20.8%. Also, the returns to professional degree becomes economically significant at 12% however this is not statistically significant. These returns are compared to the benchmark returner who has returned for an Associate degree.

Under fixed effects, the returns to *marital status*, *urban* and different $firm\ sizes$ are relatively lower compared to OLS estimates but are still statistically significant. the returns to *marital status* is 5.8%, *urban* is 0.9% and insignificant. The returns to $firm\ sizes$ are positive and significant at 7.8%, 9.7% and 4.6%. The returns to *actual experience* are relatively higher at 7.9% per year of experience and then declines at rate of 0.2% every year.

Table 2.7 shows the estimates for women. There are no significant returns to *marital status* as it is for men. For women, it does not appear very promising. The returns to $marital - status$ is a mere 2% and becomes almost zero under random and fixed effect estimators.

Returning for a bachelor degree has a positive return to women however it is not statistically significant. Returning to master's degree continues to remain small and close to negative. However, returns to professional degree is significantly high at 17%. The trend in returns to size of firm is similar to that of men. Working for a large firm guarantees a higher wage premium. Fixed effect returns to schooling in years is 5%.

2.5.2 Impact of gap in years on returns to Returning

Tables 2.8, 2.9 shows estimates for the impact of gap in years to return to schooling for men and women, respectively. The model gives estimates on the cost of waiting until returning to different degrees.

Column (1) shows the pooled OLS estimates for the cost of waiting to return to college. For men, a wait of one additional year reduces log wages by 0.4% . The cost increases with the length of the degree pursued. Waiting for an Associate degree decreases wages by 1.0% while a one year increase in the gap decreases wages by 1.2%. The estimates are all statistically significant except for a master's degree where impact of gap is only 0.6%. Degrees like MA and MBA have higher returns regardless of the size of the gap in returning. For professional degrees (PhD, LLD) the gap is detrimental to earnings. This may be because of the long duration of degrees (for instance 4 to 5 years). Here, the negative impact of the gap is significantly higher at -6%.

However, under fixed effects and random effects estimates the coefficients on gap in degrees change signs and also are no longer significant. Waiting for a Master degree (MBA) has a positive return of 2.4%. It maybe because gaining experience is more valuable for an MBA or master's degree so waiting before returning gives a higher return. It is likely that past experience can be leveraged better with these degrees compared to the BA or PhD where it also seems that there is also the possibility of a change in careers.

Table 2.9 shows the estimates for women. The pooled OLS estimates show that an increase in gap by a year has no impact on returning for an associate degree but reduces the return to a bachelor's or master's degree by 0.9% and 0.1%. For women, gap in returning for a professional degree has a positive impact. However, these coefficients turn negative and insignificant under random and fixed effects. There is positive ability bias in returns for women that is swept away by the fixed effects. Among women, as opposed to men, the higher ability ones come back to school.

2.5.3 Impact of re-entry on post-return experience

Table 2.10 shows the fixed-effects estimates for the post-return experience premium for men and women separately.

After completing the return degree men are pushed on a higher trajectory of earning growth with accumulated experience. Holding constant before-return experience, every year of experience with the new degree is associated with wage leads to an additional 2.4% increase in wages (over 7.4% before-return). However, for women, the post-return experience is ambiguous. The signs are positive but not statistically significant.

2.5.4 Are there returns to enrolling?

Table 2.11 & 2.12 report the estimates on whether there are returns to only enrolling and not completing the degree. As attrition among adult students is pretty high, it is interesting to know if enrollment alone gives returners good returns.

For men, the OLS estimates of returns to enrolling are statistically significant and negative. However, the fixed effects estimates are statistically insignificant and is nearly zero. This is in the opposite direction of returns to finishing the degree (see Table 2.6) which had strong positive returns after controlling for individual fixed effects.

For women, the return to enrolling is not significant and strong in either OLS estimates or fixed effect estimators. The returns to firm size and schooling (years) is similar to previous estimates. It is likely that women are more likely to complete the return-degree than men. OLS estimates for bachelor's degree is significantly negative but with individual fixed effects it reverses sign. One can interpret that enrolling in college is as costly (indirect) as finishing degrees. Individuals with low ability could be enrolling and then finding it difficult to keep up and possibly dropout.

2.6 Conclusion

Adult students are an important component of the U.S educational landscape. They make over 40 percent of incoming undergraduate students and their growth is expected to outstrip that of traditional students in the coming years.

Further, on the background of an increasing skills gap in the U.S manufacturing and other industries, adult students are an untapped resource that can be trained and educated to meet the demand and fuel economic growth going forward. Thus, the focus on adult students is important and integral to sustaining the health of the U.S economy.

Despite this importance, research on adult students in economics is limited. This paper brings the focus on adult students. Given the need of a skilled adult workforce to sustain the U.S economy and the increasing college tuition costs it make it necessary to know the pecuniary returns associated to returning to college. So adult returners can base their decision on a stronger footing. Along with estimating returns to returning, this paper also considers the impact of gap of interruption on schooling returns, analyzes the returns to enrollment, if any, and the post-return experience premium gained which were previously unattended in the literature on adult students.

My findings showed that after controlling for individual heterogeneity (ability), the wage premium for returning men is 10% for a bachelor's degree, 20.8% for masters degree (MA, MBA). And the return to returning to PhD degrees is 12%. The returns for women is positive but relatively small. Returning males are catapulted into a higher post-return experience trajectory. For men, this is an added growth rate of about 2.4% annually but it is not very strong for women. I also find that the longer one waits, the lesser are the returns to returning. The returns to enrolling (and not completing a degree) are not economically or statistically significant, indicating the market rewards finishers significantly more than non-finishers. It is good to finish what you started.

The results in the paper can be thought as causal under the assumption that the endogeneity is driven by unobserved time-unvarying components and are fully controlled for with fixed individual effects. If the timing of the return decisions is endogenous to any time-varying unobserved effects in the above analysis then the results cannot be interpreted causally. In such a scenario, a future direction would be to find instruments with variation across time and individuals in order to control for the timing of the return decision and allowing causal interpretation to the resulting estimates.

A general and important concern about research in this area is the paucity of data. This sentiment is also echoed by a leading non-profit organization that is involved in higher education.[14] For better future studies, there needs a more concerted and better

[14] "...The nation faces significant gaps in available data about adult participation in many areas..", The Council for Adult and Experiential Learning(CAEL) in their report "State Policies to Bring Adult Learning into Focus"

data collection efforts. There is room for adult student-centered surveys and possibly, experiments to better answer concerns and issues relating to this economically relevant and important group of the American future.

2.7 Summary Tables

Table 2.2: Summary of Key Variables: Returners vs Non-Returners

	Non-Returners	Returners	Total
ln(wage)	2.522	2.664	2.560
	(0.643)	(0.670)	(0.654)
wage-growth	0.0388	0.0677	0.0464
	(0.427)	(0.692)	(0.511)
hourly wage (2000 dollars)	15.43	17.42	15.95
	(14.00)	(12.81)	(13.73)
age	35.54	35.49	35.53
	(6.566)	(6.527)	(6.556)
actual experience	13.47	13.21	13.40
	(4.403)	(4.425)	(4.410)
family size	3.113	2.887	3.053
	(1.494)	(1.390)	(1.471)
married	0.639	0.622	0.635
	(0.480)	(0.485)	(0.481)
education (yrs)	13.09	15.21	13.65
	(2.202)	(2.300)	(2.416)
urban	0.689	0.770	0.711
	(0.463)	(0.421)	(0.453)
female	0.522	0.386	0.486
	(0.500)	(0.487)	(0.500)
firmsize <100	0.617	0.562	0.603
	(0.486)	(0.496)	(0.489)
firmsize 100-499	0.162	0.174	0.166
	(0.369)	(0.379)	(0.372)
firmsize 500-999	0.0442	0.0536	0.0466
	(0.205)	(0.225)	(0.211)
firmsize >1000	0.176	0.210	0.185
	(0.381)	(0.407)	(0.388)
children	0.310	0.418	0.338
	(2.379)	(2.103)	(2.310)
dependents	1.639	1.537	1.612
	(2.835)	(2.769)	(2.818)
N	34901	12351	47252

Table 2.3: Summary of Key Variables Returners: Before vs. After Completion

	Before Completion	After Completion	Total
ln(wage)	2.430	2.686	2.522
	(0.607)	(0.723)	(0.662)
wage-growth	0.0475	0.140	0.0807
	(0.509)	(1.144)	(0.798)
hourly wage (2000 dollars)	13.53	17.61	15.00
	(9.714)	(10.58)	(10.22)
actual experience	12.91	15.76	13.94
	(3.886)	(3.806)	(4.091)
post-return experience	-	6.376	2.291
	-	(3.829)	(3.825)
firmsize <100	0.593	0.573	0.586
	(0.491)	(0.495)	(0.493)
firmsize 100-499	0.158	0.177	0.165
	(0.365)	(0.382)	(0.371)
firmsize 500-999	0.0452	0.0665	0.0529
	(0.208)	(0.249)	(0.224)
firmsize >1000	0.203	0.184	0.196
	(0.403)	(0.388)	(0.397)
education (yrs)	13.63	15.94	14.46
	(1.721)	(1.899)	(2.102)
family size	2.400	1.986	2.251
	(1.284)	(1.092)	(1.234)
children	0.859	0.522	0.738
	(1.861)	(2.138)	(1.971)
dependents	0.973	1.054	1.003
	(2.696)	(2.187)	(2.525)
urban	0.803	0.744	0.782
	(0.398)	(0.437)	(0.413)
female	0.244	0.235	0.240
	(0.429)	(0.424)	(0.427)
N	7358	4993	12351

Table 2.4: Summary of Key Variables for Returners: Finishers vs Non-Finishers

	Non-Finisher	Finisher	Total
ln(wage)	2.570	2.745	2.670
	(0.668)	(0.680)	(0.680)
wage-growth	0.0594	0.0744	0.0679
	(0.742)	(0.706)	(0.722)
hourly wage (2000 dollars)	15.79	18.95	17.59
	(10.93)	(14.37)	(13.09)
age	35.86	35.70	35.77
	(6.721)	(6.647)	(6.679)
actual experience	13.07	13.57	13.35
	(4.521)	(4.365)	(4.440)
family size	2.951	2.842	2.889
	(1.421)	(1.361)	(1.388)
married	0.607	0.636	0.624
	(0.488)	(0.481)	(0.484)
education (yrs)	14.28	15.95	15.23
	(2.217)	(2.089)	(2.300)
urban	0.747	0.779	0.766
	(0.435)	(0.415)	(0.424)
female	0.375	0.396	0.387
	(0.484)	(0.489)	(0.487)
firmsize <100	0.641	0.610	0.623
	(0.480)	(0.488)	(0.485)
firmsize 100-499	0.196	0.191	0.193
	(0.397)	(0.393)	(0.395)
firmsize 500-999	0.0459	0.0695	0.0593
	(0.209)	(0.254)	(0.236)
firmsize >1000	0.117	0.130	0.124
	(0.322)	(0.336)	(0.330)
white	0.903	0.937	0.922
	(0.296)	(0.243)	(0.268)
dependents	1.541	1.547	1.544
	(2.795)	(2.728)	(2.757)
N	5388	6963	12351

Table 2.5: Summary of Key Variables Returners: Before vs After enrollment

	Before Enrollment	After Enrollment	Total
ln(wage)	2.289	2.579	2.522
	(0.540)	(0.677)	(0.662)
wage-growth	0.0424	0.0902	0.0807
	(0.390)	(0.870)	(0.798)
hourly wage (2000 dollars)	11.25	15.92	15.00
	(5.887)	(10.84)	(10.22)
actual experience	10.95	14.68	13.94
	(2.906)	(4.006)	(4.091)
education (yrs)	12.78	14.88	14.46
	(1.435)	(2.033)	(2.102)
firmsize <100	0.575	0.589	0.586
	(0.495)	(0.492)	(0.493)
firmsize 100-499	0.175	0.162	0.165
	(0.380)	(0.369)	(0.371)
firmsize 500-999	0.0349	0.0573	0.0529
	(0.184)	(0.233)	(0.224)
firmsize >1000	0.216	0.192	0.196
	(0.412)	(0.394)	(0.397)
family size	2.483	2.194	2.251
	(1.360)	(1.195)	(1.234)
children	1.117	0.644	0.738
	(1.399)	(2.079)	(1.971)
divorce	0.771	0.836	0.823
	(0.421)	(0.370)	(0.382)
dependents	1.156	0.965	1.003
	(2.764)	(2.462)	(2.525)
urban	0.813	0.774	0.782
	(0.391)	(0.418)	(0.413)
N	2907	9444	12351

2.8 Empirical Tables

Table 2.6: Estimates on Returns to Returning: Male

	Pooled OLS	Random Effects	Fixed Effects
married	0.164***	0.081***	0.058***
	(0.008)	(0.012)	(0.013)
urban	0.137***	0.036***	0.009
	(0.008)	(0.012)	(0.013)
actual experience	0.041***	0.068***	0.079***
	(0.004)	(0.006)	(0.006)
actual experienc^2	-3.75x10^{-4}**	-1.28x10^{-3}***	-1.61x10^{-3}***
	(1.64x10^{-4})	(0.21x10^{-3})	(0.22x10^{-3})
Past schooling (yrs)	0.096***	0.086***	0.025*
	(0.002)	(0.005)	(0.013)
Return*BA	-0.069***	0.020	0.104**
	(0.016)	(0.034)	(0.042)
Return*MA	0.069***	0.142**	0.208**
	(0.026)	(0.062)	(0.095)
Return*Prof	-0.046	0.040	0.122
	(0.034)	(0.060)	(0.078)
Firmsize 100-499	0.140***	0.090***	0.078***
	(0.010)	(0.012)	(0.012)
Firmsize 500-999	0.184***	0.115***	0.097***
	(0.015)	(0.017)	(0.017)
Firmsize >1000	0.131***	0.060***	0.046***
	(0.010)	(0.010)	(0.010)
constant	0.721***	0.830***	1.605***
	(0.043)	(0.084)	(0.168)
Industry	Yes	Yes	Yes
N	19198	19198	19198
$\bar{R}^2_{adj}$	0.257		0.157

Note: The intercept includes: returner to Associate Degree, firm with less than 100 employees, unmarried indivdual and non-metro residence. $Return{*}BA$ is a dummy representing returners for a Bachelor Degree (BA or Bsc), $Return{*}MA$ represents individuals returning for Master's Degree (MA, MS, MBA) and $Return * Prof$ captures returners for professional degrees like a PhD, Law and other professional degrees categorized as *"other degrees"* in NLSY 79.

Table 2.7: Estimates on Returns to Returning: Female

	Pooled OLS	Random Effects	Fixed Effects
married	0.018**	-0.010	-0.018
	(0.008)	(0.012)	(0.013)
urban	0.132***	0.055***	0.021
	(0.009)	(0.013)	(0.015)
actual experience	0.040***	0.049***	0.055***
	(0.004)	(0.005)	(0.006)
actual experience^2	-0.50x10^{-4}	-5.47x10^{-3}***	-7.65x10^{-4}***
	(1.69x10^{-4})	(0.20x10^{-3})	(2.12x10^{-4})
Past schooling (yrs)	0.111***	0.094***	0.050***
	(0.002)	(0.005)	(0.010)
Return*BA	-0.075***	-0.011	0.026
	(0.018)	(0.033)	(0.039)
Return*MA	-0.044	-0.015	-0.008
	(0.027)	(0.054)	(0.066)
Return*Prof	0.103***	0.146**	0.164**
	(0.035)	(0.070)	(0.082)
Firmsize 100-499	0.174***	0.132***	0.120***
	(0.009)	(0.011)	(0.011)
Firmsize 500-999	0.254***	0.165***	0.141***
	(0.016)	(0.018)	(0.019)
Firmsize >1000	0.174***	0.091***	0.071***
	(0.010)	(0.011)	(0.011)
constant	0.312***	0.587***	1.190***
	(0.046)	(0.080)	(0.130)
Industry	Yes	Yes	Yes
N	20193	20193	20193
$\bar{R}^2_{adj}$	0.249		0.095

Note: The intercept includes: returner to Associate Degree, firm with less than 100 employees, unmarried indivdual and non-metro residence. $Return * BA$ is a dummy representing returners for a Bachelor Degree (BA or Bsc), $Return * MA$ represents individuals returning for Master's Degree (MA, MS, MBA) and $Return*Prof$ captures returners for professional degrees like a PhD, Law and other professional degrees categorized as *"other degrees"* in NLSY 79.

Table 2.8: Effect of Gap (years) on Returns to Returning: Male

	Pooled OLS	Random Effects	Fixed Effects
married	0.163***	0.081***	0.060***
	(0.008)	(0.012)	(0.013)
urban	0.141***	0.043***	0.009
	(0.008)	(0.012)	(0.013)
actual experience	0.041***	0.084***	0.080***
	(0.004)	(0.008)	(0.006)
actual experience^2	-3.61x10^{-4}**	-1.80x10^{-3}***	-1.62x10^{-3}***
	(1.63x10^{-4})	(0.25x10^{-3})	(0.21x10^{-3})
gap(yrs)	-0.004***	-0.004*	
	(0.001)	(0.002)	
Past schooling (yrs)	0.096***	0.092***	0.030**
	(0.002)	(0.005)	(0.014)
gap*AD	-0.006***	-0.005	-0.000
	(0.002)	(0.004)	(0.004)
gap*BA	-0.008***	-0.005	0.003
	(0.003)	(0.005)	(0.006)
gap*MA	0.006	0.014	0.027*
	(0.004)	(0.009)	(0.016)
gap*Professional	-0.055***	-0.019**	0.002
	(0.016)	(0.008)	(0.003)
Firmsize 100-499	0.142***	0.093***	0.079***
	(0.010)	(0.012)	(0.012)
Firmsize 500-999	0.188***	0.123***	0.097***
	(0.015)	(0.017)	(0.018)
Firmsize >1000	0.130***	0.110***	0.048***
	(0.010)	(0.018)	(0.010)
constant	0.725***	0.608***	1.533***
	(0.041)	(0.109)	(0.180)
Industry	Yes	Yes	Yes
Year	No	Yes	No
N	19198	19198	19198
$\bar{R}^2_{adj}$	0.258		0.156

Note: The intercept includes: non-returners, firm with less than 100 employees, unmarried indivdual and non-metro residence. $gap * BA$ is a gap in years before returning for a Bachelor Degree (BA or Bsc), $gap*MA$ represents gap in returning for Master's Degree (MA, MS, MBA) and $gap * Prof$ captures gap for professional degrees like a PhD, Law and other professional degrees categorized as *"other degrees"* in NLSY 79.

Table 2.9: Effect of Gap (years) on Returns to Returning: Female

	Pooled OLS	Random Effects	Fixed Effects
married	0.019**	-0.007	-0.018
	(0.008)	(0.012)	(0.013)
urban	0.133***	0.060***	0.021
	(0.009)	(0.013)	(0.015)
actual experience	0.037***	0.070***	0.056***
	(0.004)	(0.007)	(0.006)
actual experience^2	2.21x10^{-4}	-9.81x10^{-4}***	-7.91x10^{-4}***
	(1.67x10^{-4})	(2.35x10^{-4})	(2.11x10^{-4})
gap(yrs)	-0.000	0.000***	
	(0.000)	(0.000)	
Past schooling (yrs)	0.109***	0.099***	0.051***
	(0.002)	(0.005)	(0.010)
gap*AD	-0.000	-0.001	0.001
	(0.001)	(0.003)	(0.003)
gap*BA	-0.009***	-0.006	-0.000
	(0.003)	(0.005)	(0.005)
gap*MA	-0.001***	-0.001***	-0.007
	(0.000)	(0.000)	(0.007)
gap*Professional	0.082***	0.065	
	(0.014)	(0.043)	
Firmsize 100-499	0.173***	0.134***	0.119***
	(0.009)	(0.011)	(0.011)
Firmsize 500-999	0.252***	0.174***	0.140***
	(0.016)	(0.018)	(0.019)
Firmsize >1000	0.173***	0.176***	0.072***
	(0.010)	(0.018)	(0.011)
constant	0.354***	0.357***	1.167***
	(0.043)	(0.106)	(0.133)
Industry	Yes	Yes	Yes
Year	No	Yes	No
N	20193	20193	20193
$\bar{R}^2_{adj}$	0.250		0.095

Note: The intercept includes: non-returners, firm with less than 100 employees, unmarried indivdual and non-metro residence. $gap * BA$ is a gap in years before returning for a Bachelor Degree (BA or Bsc), $gap{*}MA$ represents gap in returning for Master's Degree (MA, MS, MBA) and $gap * Prof$ captures gap for professional degrees like a PhD, Law and other professional degrees categorized as *"other degrees"* in NLSY 79.

Table 2.10: Effect of Returning on Post-return Experience

	Male (FE)	Female (FE)
married	0.055***	-0.020**
	(0.009)	(0.010)
urban	0.011	0.021*
	(0.010)	(0.011)
actual experience	0.075***	0.054***
	(0.004)	(0.004)
actual experience^2	-1.55x10^{-3}***	-7.62x10^{-4}***
	(0.12x10^{-3})	(1.53x10^{-4})
Education (yrs)	0.004	0.049***
	(0.007)	(0.006)
after-return exp	0.024***	0.006
	(0.005)	(0.006)
after-return exp (2)	-0.000	-0.000
	(0.000)	(0.000)
Firmsize 100-499	0.076***	0.120***
	(0.011)	(0.011)
Firmsize 500-999	0.093***	0.141***
	(0.017)	(0.019)
Firmsize >1000	0.039***	0.070***
	(0.009)	(0.010)
constant	1.929***	1.213***
	(0.100)	(0.084)
Industry	Yes	Yes
N	19198	20193
F	97.398	57.163
$\bar{R}^2_{adj}$	0.101	0.022

Table 2.11: Estimates on Returns to Enrollment: Male

	Pooled OLS	Random Effects	Fixed Effects
married	0.162***	0.081***	0.059***
	(0.008)	(0.012)	(0.013)
urban	0.141***	0.037***	0.010
	(0.008)	(0.012)	(0.014)
actual experience	0.041***	0.069***	0.081***
	(0.004)	(0.006)	(0.006)
actual experience^2	-6.46x10^{-4}**	-1.80x10^{-3}***	-1.66x10^{-3}***
	(1.82x10^{-4})	(0.25x10^{-3})	(0.22x10^{-3})
Past schooling (yrs)	0.103***	0.096***	0.036***
	(0.002)	(0.005)	(0.013)
Enroll*BA	-0.109***	-0.049	0.022
	(0.014)	(0.030)	(0.038)
Enroll*MA	-0.029	-0.004	-0.033
	(0.023)	(0.048)	(0.065)
Enroll*Prof	-0.183***	-0.108	-0.063
	(0.034)	(0.086)	(0.202)
Firmsize 100-499	0.139***	0.090***	0.079***
	(0.010)	(0.012)	(0.012)
Firmsize 500-999	0.181***	0.114***	0.097***
	(0.014)	(0.017)	(0.018)
Firmsize >1000	0.131***	0.060***	0.047***
	(0.010)	(0.010)	(0.010)
constant	0.640***	0.695***	1.458***
	(0.042)	(0.083)	(0.167)
Industry	Yes	Yes	Yes
N	19198	19198	19198
$\bar{R}^2_{adj}$	0.261		0.156

Table 2.12: Estimates on Returns to Enrollment: Female

	Pooled OLS	Random Effects	Fixed Effects
married	0.015*	-0.011	-0.019
	(0.008)	(0.012)	(0.013)
urban	0.131***	0.055***	0.021
	(0.009)	(0.013)	(0.015)
actual experience	0.038***	0.048***	0.055***
	(0.004)	(0.005)	(0.006)
actual experience^2	-5.27x10^{-6}	-9.69x10^{-4}**	-7.68x10^{-4}***
	(1.85x10^{-4})	(2.36x10^{-4})	(2.14x10^{-4})
Past schooling (yrs)	0.109***	0.093***	0.050***
	(0.002)	(0.005)	(0.010)
Enroll*BA	-0.056***	-0.013	0.008
	(0.014)	(0.025)	(0.029)
Enroll*MA	-0.008	0.018	-0.003
	(0.022)	(0.042)	(0.057)
Return*Prof	0.038	0.045	-0.009
	(0.030)	(0.048)	(0.050)
Firmsize 100-499	0.175***	0.133***	0.120***
	(0.009)	(0.011)	(0.011)
Firmsize 500-999	0.256***	0.166***	0.141***
	(0.016)	(0.018)	(0.019)
Firmsize >1000	0.175***	0.092***	0.072***
	(0.010)	(0.011)	(0.011)
constant	0.344***	0.603***	1.184***
	(0.044)	(0.082)	(0.134)
Industry	Yes	Yes	Yes
N	20193	20193	20193
$\bar{R}^2_{adj}$	0.249		0.095

CHAPTER 3

Enrollment persistence of Adult Students: A Dynamic Random Effects Approach

3.1 Introduction

According to the U.S. Department of Labor data, 90 percent of the fastest growing jobs will require some form of post-secondary education and by 2030, only 65% of this projected demand for skilled labor is predicted to be filled by traditional students.[1] Adult students (25 years and above) are an important resource to meet the skills gap. Although adult students are a large proportion of fresh enrollees in U.S colleges, as of now only 7% of the adult population with 12 or less years of schooling have returned to college.[2]

The relationship between persistence and learning is supported by several studies (Sticht, 1988; Darkenwald, 1986). Although enrollment of adult students has risen considerably in the last two decades, persistence (or staying enrolled) and degree completion among these students is not very strong. According to Horn and Carroll (1996)[3] adult students (or nontraditional students) were much less likely to earn a degree within 5 years of beginning their postsecondary education, and far more likely to have left school without returning than were their traditional counterparts. For example, among undergraduates with a bachelor's degree objective, about one-third (31 percent) of nontraditional students had attained a degree within 5 years, compared with more than half (54 percent) of traditional students. Thus understanding the mechanism of enrollment decisions and persistence among adult students is integral to sustaining the future health of the U.S economy.

[1] Center for American Progress Report, 2012
[2] U.S census data
[3] U.S. Department of Education study on non-traditional students (1996)

This paper studies enrollment persistence among adult students. [4] Identification of the extent of true state dependence or individual heterogeneity in persistence among adult students will be helpful in designing effective policies for degree attainment. Existence of state dependence would mean a policy with strong short-term incentives to enroll will increase enrollment and degree achievement among returning adults. If there is no state dependence in enrollment persistence at the micro level, then short run policies will have no effect in increasing attainment. Thus it is crucial to know whether there is state dependence or if it is individual heterogeneity that causes individuals to be continuously enrolled.

It is difficult to distinguish between unobservable heterogeneity and state dependence. There is also the 'initial conditions' problem that must be dealt with in order to disentangle further the effects of state dependence and unobserved heterogeneity. The initial conditions problem arises when the start of the observation period does not coincide with the start of the stochastic process of interest.

I use panel data from the National Longitudinal Survey of Youth (NLSY) 1979 spanning six years from 1989 to 1994 and follow the methods described in Wooldridge (2005) and Heckman (1981a,b) to estimate and overcome the issues mentioned above.

My results suggest that state dependence effects exist with respect to previous enrollment incidence for men and women. For men, I find that about 20% of the observed persistence in the unemployment probability is accounted for by state dependence, as compared with roughly 36% for women. This finding has important implications for policy. It indicates that short-term incentives to first-time enrollment will have a greater impact on increasing enrollment, especially in terms of their effect on women's level of human capital.

[4] As of now, this analysis disregards the type of degree adult students have enrolled. Persistence is likely to vary with duration and rigor of coursework involved in a completing degree. Such an analysis is reserved for future research.

3.2 Data

The data used in the paper are from the six continuous waves (1989-1994) of the National Longitudinal Survey of Youth (NLSY) of 1979. NLSY is a nationally representative panel collected annually between 1979 and 1994 and biennially thereafter by the Bureau of Labor Statistics (BLS). The sample for this study is comprised of white men and women between the ages of 25 to 50 years and with continuous six years (1989-1994) of survey information were chosen so as to show some variation in human capital accumulation (enrollment behavior), labor force experience, and other personal characteristics.

There are 2,321 individuals (n) in my dataset with 6 years of data per individual. The total number of observations (N) is 13,926. About 1,192 are males and 1,129 are females, with 426 individuals observed to have enrolled at least once and 1,895 never enrolled in the observation period.

The enrollment indicator is based on the *enrollmntrev* variable in the dataset indicating whether enrolled in any college degree. As of now, this analysis disregards the type of college degree adult students have enrolled in. Persistence is likely to vary with duration and rigor of coursework involved in a completing degree. Such an analysis is reserved for future research.

Table 3.2 displays the probabilities of enrollment, unconditional and conditional on status at $t-1$, over 1989-1994 for various groups. The raw unconditional probability of being enrolled at a point in time in this sample is 6%. Columns 2 and 3 of the table give conditional probabilities by status at $t-1$ in the past year. The first row of the table shows that there is considerable state dependence in enrollment in the raw data: the probability of being enrolled at t is much higher for those enrolled at $t-1$. In other words, an individual enrolled at $t-1$ is more likely to be enrolled at t than an individual not enrolled at $t-1$.

Enrollment persistence among women is similar to those of men. Also, it is similar for individuals across firm sizes. However it is higher for those enrolled for professional degrees given previous college degrees. Unemployed individuals who return to school are equally persistent than employed individuals. Further, individuals with flexible working hours have a marginally higher enrollment persistence relative to those in inflexible jobs.

Table 3.3 summarizes enrollment probabilities across different wage categories. If those enrolled at $t-1$ are partitioned into different wage buckets, the conditional probability of being enrolled at t is 0.58 for the low-wage group and the probability is slightly lower for higher wages. Also, first-time enrollment probability is slightly higher for individuals in the higher range of wages. However, there does not appear to be a perceptible relationship between wages and enrollment persistence relationship in the dataset. Table 3.4 presents summary statistics for men and women separately.

3.3 Model

The observed dependent variable is binary, taking the value of one if the individual is enrolled at the time of the interview, and zero otherwise. This variable is observed at most at 6 separate interview dates. I specify the model for individual i at the interview date at time t as

$$y_{it}^* = x_{it}'\boldsymbol{\beta} + \gamma y_{i,t-1} + \nu_{it}, \quad i = 1, 2, \ldots, n \text{ and } t = 2, \ldots, T \tag{3.1}$$

where y^* denotes the unobservable individual propensity to be enrolled, x is a vector of observable characteristics affecting y^*, $\boldsymbol{\beta}$ is the vector of coefficients associated with x, and ν is the unobservable error term. Since the sample is balanced panel, the total number of observations per individual is T.

An individual is observed to be enrolled when his propensity to be enrolled crosses a threshold (zero in this case), that is,

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^* \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

3.3.1 Modelling state dependence

In equation (3.1) y_{it}^* is a function of the observed enrollment status of the individual in the previous period $y_{i,t-1}$; that is, it is the actual enrollment in a period, rather than the propensity to be enrolled, that affects the persistence into the next period. The inclusion of the lagged dependent variable on the right hand side of (3.1) allows us to test for the presence of genuine state dependence in enrollment persistence. However, a positive sign on the coefficient of lagged enrollment can arise from spurious correlation resulting from inadequate controls for individual characteristics correlated with individuals' propensities to stay in school (Heckman, 1981a,b). To deal with this, I control for observable and unobservable individual characteristics.

3.3.2 Modelling unobserved heterogeneity

Assuming the unobservable individual-specific heterogeneity is time-invariant, the error term ν_{it} in (3.1) is decomposed as

$$\nu_{it} = \epsilon_i + u_{it} \tag{3.3}$$

where ϵ_i denotes the individual-specific unobservable effect and u_{it} is a random error. I treat the ϵ_i as random, and use the random effects probit models estimated under the common assumption that $u_{it} \sim N(0, \sigma_u^2)$ and the u_{it} are independent of the x_{it} for all i and t.

In order to marginalize the likelihood, as in the literature, I also assume that $\epsilon_i \sim N(0, \sigma_\epsilon^2)$ and is independent of the u_{it}. Under the assumption that the ϵ_i is independent of x_{it} for all i and t, and if this assumption is violated, maximum likelihood estimates will be inconsistent. That is, the estimated $\boldsymbol{\beta}$ coefficients will pick up some of the effects of the unobservable ϵ. As an example, suppose that ϵ represents individual commitment or motivation, which makes the individual both more likely to be able to stay enrolled and more likely to be keeping a job. Thus any model which does not allow for the correlation between employment and ϵ will suffer from omitted variable bias. To avoid this problem, I relax the assumption that ϵ is independent of the observable time-varying characteristics in X_{it}. Following Chamberlain (1984), I model the dependence between ϵ and x by assuming that the regression function of ϵ is linear in the means of all the time-varying ccovariates and therefore I can write this as

$$\epsilon_i = a_0 + \boldsymbol{a_1'}\boldsymbol{\bar{x}_i} + \alpha_i \tag{3.4}$$

where I also assume that $\alpha_i \sim N(0, \sigma_\alpha^2)$ and is independent of the x_{it} and the u_{it} for all i and t, a_0 is the intercept, and $\boldsymbol{\bar{x}_i}$ refers to the vector of means of the time-varying o-ovariates for individual i over time. Note, the coefficients in a_1 corresponding to the time-invariant variables in eq. (3.1) are set equal to zero. Thus eq. (3.1) becomes

$$y_{it}^* = x_{it}'\boldsymbol{\beta} + \gamma y_{i,t-1} + \boldsymbol{a_1'}\boldsymbol{\bar{x}_i} + \epsilon_i + u_{it}, \quad i = 1, 2, \ldots, n \text{ and } t = 2, \ldots, T \tag{3.5}$$

where the intercept a_0 is absorbed into the $\boldsymbol{\beta}$. This is equivalent to the random effects probit model with additional regressors, $\boldsymbol{\bar{x}_i}$.

In the above specification the correlation between two successive error terms is equi-correlated for the same individual, given by

$$r = corr(\nu_{it}, \nu_{it-1}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2}, \quad t = 2, \ldots, T \tag{3.6}$$

3.3.3 Initial conditions problem

If the initial observation y_{i1} is correlated with the unobservable α_i then the estimation problem is called the initial conditions problem. This problem arises because the start of the observation period does not coincide with the actual start of the stochastic process generating individuals' enrollment experiences. In the sample, I have few individuals who have entered college prior to the starting period in the sample. Thus an individual observed in the state of enrollment in the first period may be there because of an earlier return to college (state dependence) or because of some observed and/or unobserved characteristics affecting his enrollment propensity. There are several suggested methods - varying in complexity of implementation - that account for the initial condition problem (Heckman, 1981b; Orme, 2001; Wooldridge, 2005). I follow Heckman (1981b) to account for the problem (and also the Wooldridge method) by first specifying a reduced form equation for the initial observation as follows

$$y^*_{i1} = \boldsymbol{\lambda' z_i} + \eta_i \tag{3.7}$$

where $\boldsymbol{z_i}$ is a vector of strictly exogenous instruments, $var(\eta_i) = \sigma^2_\eta$ and $corr(\alpha_i, \eta_i) = \rho$. The vector $\boldsymbol{z}$ includes variables relevant in period 1, some sample information affecting the probability of enrollment in period 1 and $\boldsymbol{\bar{x}_i}$. The vector of means is included to pick up possible correlation between the time-varying regressors and any unobservable heterogeneity. The next step involves a linear specification, in terms of orthogonal error components, to account for the possibility of non-zero ρ

$$\eta_i = \theta\alpha_i + u_{i1} \tag{3.8}$$

By construction, α_i and u_{i1} in 3.8 are orthogonal to one another, $\theta = \rho\sigma_\eta/\sigma_\alpha$ and $var(u_{i1}) = \sigma^2_\eta(1 - \rho^2)$. I assume that the initial observation y_{i1} is uncorrelated with u_{it} and also that u_{i1} is uncorrelated with the x_{it} for all i and t. From the above equations

$$y^*_{it} = x'_{it}\boldsymbol{\beta} + \gamma y_{i,t-1} + \boldsymbol{a'_1 \bar{x}_i} + \alpha_i + u_{it} \quad i = 1, 2, \ldots, n \text{ and } t = 2, \ldots, T \tag{3.9a}$$

$$y^*_{i1} = \boldsymbol{\lambda' z_i} + \theta\alpha_i + u_{i1} \quad i = 1, 2, \ldots, n \text{ and } t = 1 \tag{3.9b}$$

Equations (3.9a) and (3.9b) specify a complete model for the enrollment persistence process.

As shown in Heckman (1981a, 1981b), this model is easily estimated by noting that the distribution of y_{it} conditional on α_i is independent normal. One can then marginalize the likelihood with respect to the α to obtain the appropriate likelihood function for the maximization. Orme (2001) suggests a two-step method of estimation, in the spirit of Heckman's standard sample selection correction method which is an approximation in the case of small values of ρ. To account for the correlation between the initial condition and the unobserved heterogeneity α, a correction term is added to the conditional model which is then easily estimated using standard software packages that enable estimation of random effects models (Arulampalam, 2000). Wooldridge's model is bit simpler than Heckman's, he suggests a models for the random effect conditioned on the initial value (Wooldridge, 2005; Greene, 2011).

3.3.4 Heckman's estimator

According to Heckman (1981b), since y_{it} is binary the outcome probabilities and likelihood for a random sample are as follows (along with a normalization of $\sigma_u^2 = 1$),

$$P_{it}(\alpha^*) = \begin{cases} \Phi[(x_{it}'\boldsymbol{\beta} + \gamma y_{i,t-1} + \boldsymbol{a_1'}\boldsymbol{\bar{x}_i} + \alpha^*)(2y_{it} - 1)] & \text{for } t \geq 2 \\ \Phi[(\boldsymbol{\lambda' z_i} + \theta\alpha^*)(2y_{i1} - 1)] & \text{for } t = 1 \end{cases} \tag{3.10}$$

$$\mathrm{L} = \prod_{i=1}^{N} \int_{\alpha^*} \left\{ \prod_{t=1}^{T} P_{it}(\alpha^*) \right\} \mathrm{d}F(\alpha^*) \tag{3.11}$$

where F is the distribution function of $\alpha^* = \alpha/\sigma_\alpha$ and $\sigma_\alpha = \sqrt{r/(1-r)}$. If α is taken to be normally distributed, the integral over α^* can be evaluated using Gaussian-Hermite quadrature(Butler and Moffitt, 1982; Stewart, 2006).

3.3.5 Wooldridge's CML estimator

Wooldridge (2005) has proposed an alternative Conditional Maximum Likelihood (CML) estimator that considers the distribution conditional on the initial period value (and exogenous variables). Wooldridge suggests modelling the density of $y_{i2}, \ldots, y_{iT}$ conditional on $\{y_{i1}, x_{i1}\}$.[5] Specifying a model for y_{i1} given x_i and α_i is replaced by

[5] This produces a very simple estimation method which has the advantage that it can be implemented with standard random-effects probit software. Heckman estimation is computed using `-redprob-` package. See Stewart (2006) for more details.

specifying one α_i given y_{i1} and x_i leading to:

$$y^*_{it} = x'_{it}\boldsymbol{\beta} + \gamma y_{i,t-1} + \boldsymbol{a'_1}\boldsymbol{\bar{x}_i} + \alpha_0 + \varrho y_{i1} + \kappa_i + u_{it} \tag{3.12}$$

3.4 Empirical results

Tables 3.5, 3.6 show the estimates of the random effects probit model for the probability of enrollment using the Heckman and Wooldridge estimators for men and women separately. All the models include year dummies. As explained in the section above, the models also contain means over time for each time-varying variable. The corresponding pooled probit model (without random effects) estimated on the same sample is given in the last column for comparison.

The dynamic random effects probit model estimates and the pooled probit model cannot be readily compared as they involve different normalizations. As shown in Arulampalam (1999), the random effects probit estimates are normalized on $\sigma^2_u = 1$ while the pooled probit estimates are normalized on the composite error, $\sigma^2_v = 1$. Thus random effects probit models provide an estimate of γ/σ_u while pooled probit models an estimate of γ/σ_v . For comparison, the random effects model has to be multiplied by an estimate of $\sigma_u/\sigma_v = \sqrt{1-r}$. The above tables do not represent scaled coefficient estimates.

The absence of the initial conditions problem in the random effects model can be tested by a simple significance test under the null of $\theta = 0$ for the Heckman estimator and $y_1 = 0$ for the Wooldridge estimator. It is clear that the in this model, the data strongly rejects both indicating that the initial conditions are not exogenous.

The estimates from the two estimators are quite similar on key variables. The coefficient of the lagged dependent variable is positive and highly significant indicating strong persistence effects in the incidence of enrollment. Assuming the initial conditions as exogenous overstates the effect of state dependence only a little. This is evident in the scaled pooled probit model (without random effects) estimates.

For the Heckman estimator, personal variables and pre-sample variables related to educational characteristics, and employment status are used as instruments. These include spouse's education, economic class, presence of a child under 5, and whether or not unemployed. These are some of the variables that are considered to be important to influence the start of the process.

Both estimators provide strong support to the proposition of state dependence in the incident of enrollment. With exogenous initial conditions, the random effects variance is restricted to zero, implying that there is no unobserved heterogeneity in participation probabilities. The estimate of state dependence in this case is $\gamma = 1.86$ from the pooled estimates for men and 1.715 for women.

This estimate will overstate state dependence if the unobserved individual specific effect influences the sample initial conditions. As explained in the above section, Heckman and Wooldridge allow endogenous initial conditions and the results change and the state dependence estimates now for men are 1.302 and 1.213, respectively. For women, under endogenous initial conditions, the estimates change considerably to 1.228 and 1.201 for Heckman and Wooldridge estimators, respectively. Also the estimate of σ_{α}^2 implies that approximately 40% of the total error variance is attributable to unobserved heterogeneity.

Tables 3.5, 3.6 also provides estimates of the predicted probabilities together with the average partial effects (APE), $\hat{p}_1 - \hat{p}_0$, and the predicted probability ratios (PPR), $\hat{p}_1/\hat{p}_0$. The interest is in the partial effect of y_{t-1} on the $Prob(y_{it} = 1)$ and is calculated as prescribed in Stewart (2007). It is based on the calculation of a counter-factual outcome probability assuming y_{t-1} fixed at the two alternate states (1 and 0) evaluated at $x_{it} = \bar{x}$.

$$\hat{p}_1 = \frac{1}{N} \sum_{i=1}^{N} \Phi\{(\bar{x}'\hat{\beta} + \hat{\gamma} + \bar{x}_i'\hat{a})(1 - \hat{\lambda})^{1/2}\}$$

$$\hat{p}_0 = \frac{1}{N}\sum_{i=1}^{N}\Phi\{(\bar{x}'\hat{\beta} + \bar{x}_i'\hat{a})(1-\hat{\lambda})^{1/2}\}$$

Table 3.1 summarizes the predicted probabilities for enrollment. The pooled probit model gives an average partial effect (APE) of enrollment at $t-1$ of 0.39 for men and 0.36 for women. The Heckman estimator of the random-effects model reduces this APE to 0.11 for men (0.18 for women) and the Wooldridge estimators are higher at 0.20 for men and 0.18 for women. The degree of persistence exhibited considerably, but it remains significant. Thus, an individual with a given set of characteristics (observed and unobserved) is considerably more likely to continue enrolling at t if they had been enrolled at $t-1$. For men, I find that about 20% of the observed persistence in the enrollment probability is accounted for by state dependence, as compared with roughly 36% for women. This finding has important implications for policy. It indicates that short-term incentives to first-time enrollment will have greater impact to increase enrollment.

Table 3.1: Predicted Probabilities

	Men			Women		
	Heckman	Wooldridge	Pooled	Heckman	Wooldridge	Pooled
$\hat{p}_1$	0.132	0.273	0.417	0.230	0.234	0.389
$\hat{p}_0$	0.018	0.073	0.023	0.045	0.052	0.023
APE: $\hat{p}_1 - \hat{p}_1$	0.114	0.200	0.393	0.185	0.182	0.366
PPE: $\hat{p}_1 / \hat{p}_1$	7.4	3.7	17.9	5.2	4.5	17.0

3.5 Conclusion

This paper presented evidence on state dependence of enrollment persistence among adult students using two different estimators for the dynamic random effects probit model proposed in the literature, namely, the Heckman (1981b) and Wooldridge (2005) estimators. This was achieved by estimating a model for the determinants of enrollment participation amongst adult students using panel data from the National Longitudinal Survey.

Adult students are an important component of the U.S educational landscape. Adult students with better human capital skills will be an important resource to meet the increasing demand for higher skills in U.S. industries. Presently, they account for 40 percent of incoming undergraduate students in the U.S, however, only 7% of the adult workforce is enrolled. The focus on adult students is thus important and integral for the health of the U.S economy.

Knowledge of the extent of true state dependence or individual heterogeneity in enrollment persistence among adult students will be helpful in designing effective intervention policies for increasing the number of adults with higher education. If there is strong state dependence among adult returners then a policy designed with strong short-term incentives to encourage first time enrollment will have the desired effect of increasing the number of returners and also degree achievement among the returning adults. However, the absence of state dependence would mean that short run policies will have no effect in increasing enrollment and attainment. Thus it is crucial to know whether there is state dependence or if it is individual heterogeneity that causes individuals to be enrolled and persist.

My results suggest that state dependence effects exist with respect to previous enrollment incidence for men and women. For men, I find that about 20% of the observed persistence in the enrollment probability is accounted for by state dependence, as compared with roughly 36% for women. This finding has important implications for policy. It indicates that short-term incentives to first-time enrollment will have greater impact to increase enrollment with major benefits centering on women's level of human capital.

3.6 Summary Tables

Table 3.2: Unconditional and conditional probabilities of Enrollment

	Unconditional	Enrolled at $t-1$	Not Enrolled at $t-1$
Age (yrs)			
< 30	0.053	0.519	0.024
> 30	0.078	0.521	0.036
Age of young child (yrs)			
> 5	0.063	0.539	0.031
< 5	0.066	0.516	0.029
Hours			
Inflexible	0.061	0.517	0.028
Flexible	0.071	0.523	0.030
Gender			
Female	0.080	0.520	0.037
Male	0.052	0.520	0.021
Firm size			
< 1000	0.063	0.513	0.028
> 1000	0.089	0.556	0.038
Race			
White	0.041	0.462	0.017
Non-white	0.069	0.526	0.031
Past Education (yrs)			
< 16	0.061	0.513	0.027
> 16	0.107	0.562	0.049
Unemployed	0.084	0.520	0.039
Employed	0.065	0.521	0.029
Non-metro	0.056	0.564	0.027
Metro	0.069	0.509	0.030
All	0.066	0.520	0.029

[1] Pooled data for NLSY (1990-1994).
[2] Sample size is 13,926.

Table 3.3: Wages and Enrollment persistence

wages($)	Unconditional	Enrolled at $t-1$	Not Enrolled at $t-1$
< 10	0.066	0.585	0.026
$10-30$	0.066	0.493	0.031
$30-50$	0.043	0.474	0.015
$50 <$	0.045	0.667	0.048

[1] Entire sample. Inflation-adjusted hourly wages.

Table 3.4: Summary of Key Variables

	Female		Male		Total	
ln(wage)	2.435	(0.546)	2.624	(0.520)	2.532	(0.541)
hourly wage	13.16	(8.270)	15.76	(10.13)	14.50	(9.363)
wage-growth	0.0248	(0.405)	0.0281	(0.391)	0.0265	(0.398)
age	31.03	(2.542)	30.96	(2.568)	31.00	(2.556)
actual experience	11.36	(2.752)	11.68	(2.847)	11.52	(2.806)
family size	2.945	(1.407)	2.863	(1.465)	2.903	(1.437)
married	0.617	(0.486)	0.631	(0.483)	0.624	(0.484)
education (yrs)	13.78	(2.283)	13.49	(2.440)	13.63	(2.369)
metro	0.761	(0.427)	0.738	(0.440)	0.749	(0.433)
firm<100	0.628	(0.483)	0.656	(0.475)	0.643	(0.479)
firm 100-499	0.198	(0.398)	0.176	(0.381)	0.187	(0.390)
firm 500-999	0.0576	(0.233)	0.0576	(0.233)	0.0576	(0.233)
firm>1000	0.116	(0.321)	0.110	(0.313)	0.113	(0.317)
white	0.892	(0.311)	0.902	(0.298)	0.897	(0.304)
children	1.111	(1.132)	0.972	(1.133)	1.039	(1.135)
dependents	2.416	(1.792)	2.253	(1.994)	2.332	(1.901)

[1] Hourly wage normalized at 2000 dollars.
[2] Pooled data for NLSY (1990-1994).
[3] Sample size is 13,926.
[4] Standard deviation in parenthesis.

3.7 Empirical Tables

Table 3.5: Dynamic Random Effects Models for Enrollment Probability: Male

	Heckman estimator				Wooldridge estimator		Pooled probit	
	y_t		$y(t=1)$		y_t		y_t	
y_{t-1}	1.302***	(0.152)			1.213***	(0.139)	1.860***	(0.085)
married	-0.058	(0.187)	-0.337	(0.176)	0.051	(0.189)	0.080	(0.169)
$age > 30$	0.220*	(0.099)	0.247	(0.233)	0.068	(0.107)	0.080	(0.076)
metro	-0.399	(0.245)	0.549*	(0.232)	-0.433	(0.241)	-0.339	(0.242)
flexible hours	-0.121	(0.098)	0.202	(0.152)	-0.131	(0.094)	-0.110	(0.072)
large firm	0.269*	(0.128)	0.166	(0.189)	0.212	(0.125)	0.159	(0.087)
a(wage)	-0.379*	(0.152)			-0.317*	(0.143)	-0.222**	(0.085)
a(edu)	0.179***	(0.030)			0.176***	(0.029)	0.121***	(0.015)
a(mar)	0.074	(0.239)			-0.042	(0.235)	-0.071	(0.196)
a(emp)	1.054	(0.735)			1.117	(0.638)	0.760*	(0.328)
a(metro)	0.478	(0.293)			0.356	(0.288)	0.306	(0.261)
$y(t=1)$					0.776***	(0.204)		
$childage < 5$			-0.418	(0.369)				
previous education			0.161***	(0.044)				
white			0.712	(0.399)				
spouse education			0.055	(0.039)				
unemployed			0.146	(0.483)				
family size			-0.041	(0.068)				
$ln(wage)$			-0.313*	(0.147)				
constant	-4.131***	(0.532)	-4.701***	(0.891)	-4.408***	(0.508)	-3.239***	(0.235)
θ	0.729***	(0.215)						
r	0.355***	(0.080)						
σ_u					0.832***	(0.115)		
LL	-839.58				-747.12		-766.79	
Pred. prob. $\hat{p}_1$	0.132				0.273		0.417	
Pred. prob. $\hat{p}_0$	0.020				0.070		0.023	
APE:$\hat{p}_1 - \hat{p}_0$	0.114				0.203		0.393	
PPR: $\hat{p}_1/\hat{p}_0$	7.3				3.7		17.9	

[1] All models include time dummies
[2] Variable $a(x)$ is the mean over time of the variable x
[3] $\hat{p}_1$, $\hat{p}_0$: predicted probabilities of enrollment at t given enrollment, unenrollment at $t-1$ respectively.
[4] APE, average partial effect; PPR, predicted probability ratio.

Table 3.6: Dynamic Random Effects Models for Enrollment Probability: Female

	Heckman estimator				Wooldridge estimator		Pooled probit	
	y_t		$y(t=1)$		y_t		y_t	
y_{t-1}	1.228***	(0.125)			1.201***	(0.112)	1.715***	(0.069)
married	-0.271	(0.153)	-0.106	(0.161)	-0.305*	(0.148)	-0.209	(0.122)
$age > 30$	0.164*	(0.083)	-0.127	(0.187)	0.157	(0.082)	0.104	(0.063)
metro	-0.225	(0.244)	0.220	(0.183)	-0.152	(0.226)	-0.149	(0.200)
flexible hours	0.047	(0.082)	-0.114	(0.140)	0.105	(0.073)	0.092	(0.058)
large firm	0.137	(0.108)	0.032	(0.186)	0.134	(0.097)	0.126	(0.074)
a(wage)	-0.265*	(0.128)			-0.234*	(0.114)	-0.170*	(0.074)
a(edu)	0.142***	(0.026)			0.137***	(0.023)	0.105***	(0.014)
a(mar)	0.084	(0.198)			0.192	(0.180)	0.131	(0.139)
a(emp)	0.209	(0.657)			0.536	(0.555)	0.392	(0.397)
a(metro)	0.194	(0.277)			0.100	(0.253)	0.109	(0.216)
$y(t=1)$					0.604***	(0.143)		
$childage < 5$			-0.089	(0.226)				
previous education			0.133***	(0.037)				
white			-0.179	(0.253)				
spouse education			0.005	(0.013)				
unemployed			-0.114	(0.435)				
family size			-0.063	(0.065)				
$ln(wage)$			-0.262	(0.150)				
constant	-3.414***	(0.401)	-2.429***	(0.688)	-3.564***	(0.357)	-2.920***	(0.200)
θ	0.841***	(0.213)						
r	0.345***	(.067)						
σ_u					0.661***	(0.089)		
LL	-1154.72				-1095.06		-1113.29	
Pred. prob. $\hat{p}_1$	0.230				0.234		0.389	
Pred. prob. $\hat{p}_0$	0.045				0.053		0.023	
APE:$\hat{p}_1 - \hat{p}_0$	0.185				0.182		0.366	
PPR: $\hat{p}_1/\hat{p}_0$	5.2				4.5		17.0	

[1] All models include time dummies
[2] Variable $a(x)$ is the mean over time of the variable x
[3] $\hat{p}_1$, $\hat{p}_0$: predicted probabilities of enrollment at t given enrollment, unenrollment at $t-1$ respectively.
[4] APE, average partial effect; PPR, predicted probability ratio.

APPENDIX A

Figure A.1: Average Age of Returners since 1990

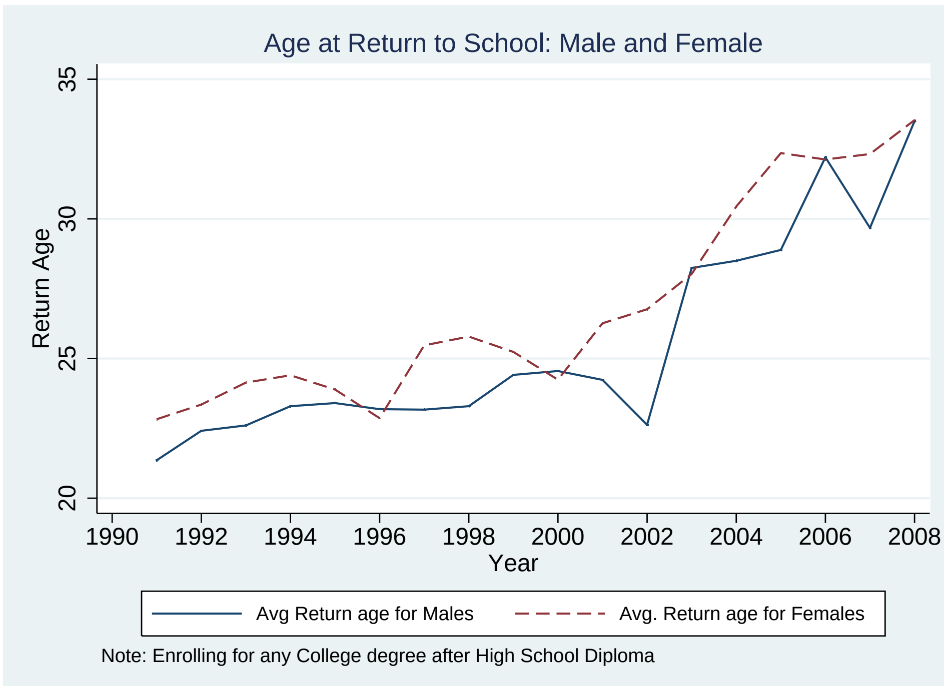


Figure A.2: Predicted return and non-return wages for Associate Degree: Women

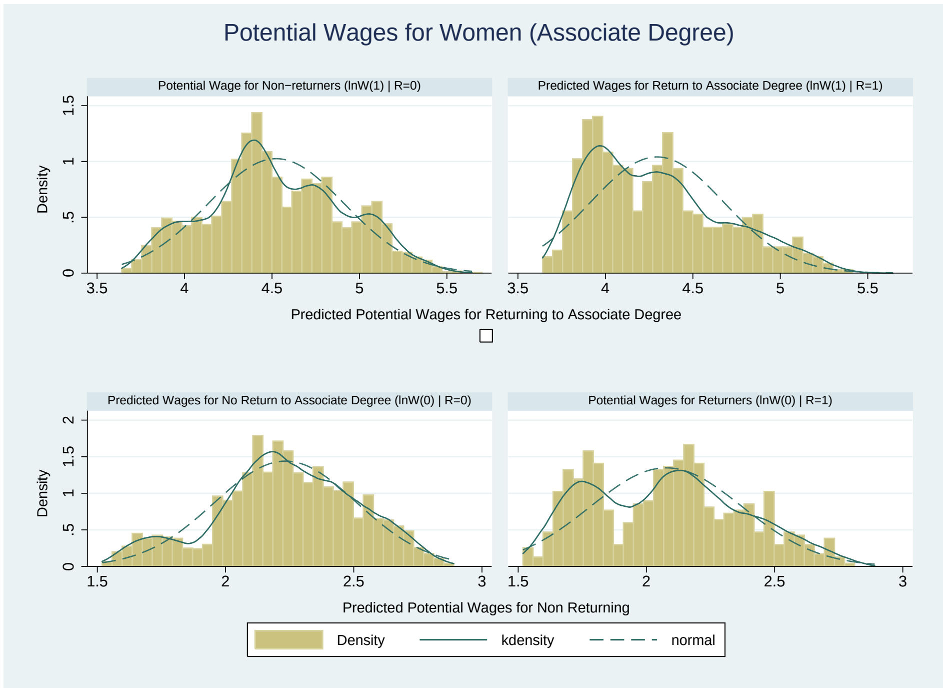


Figure A.3: Predicted return and non-return wages for Associate Degree: Men

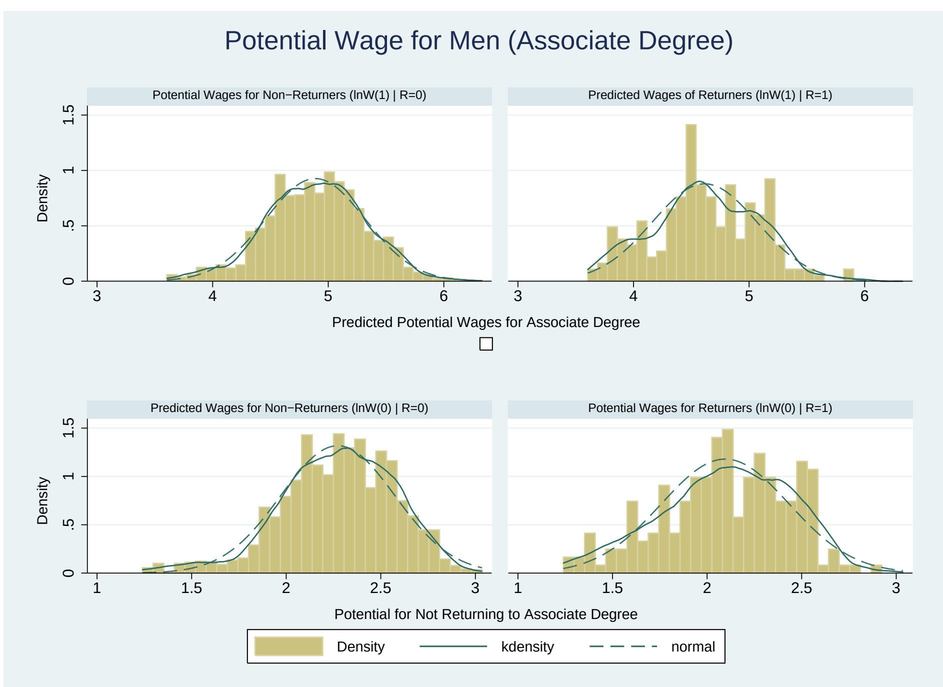


Figure A.4: Predicted return and non-return wages for Bachelor Degree: Men

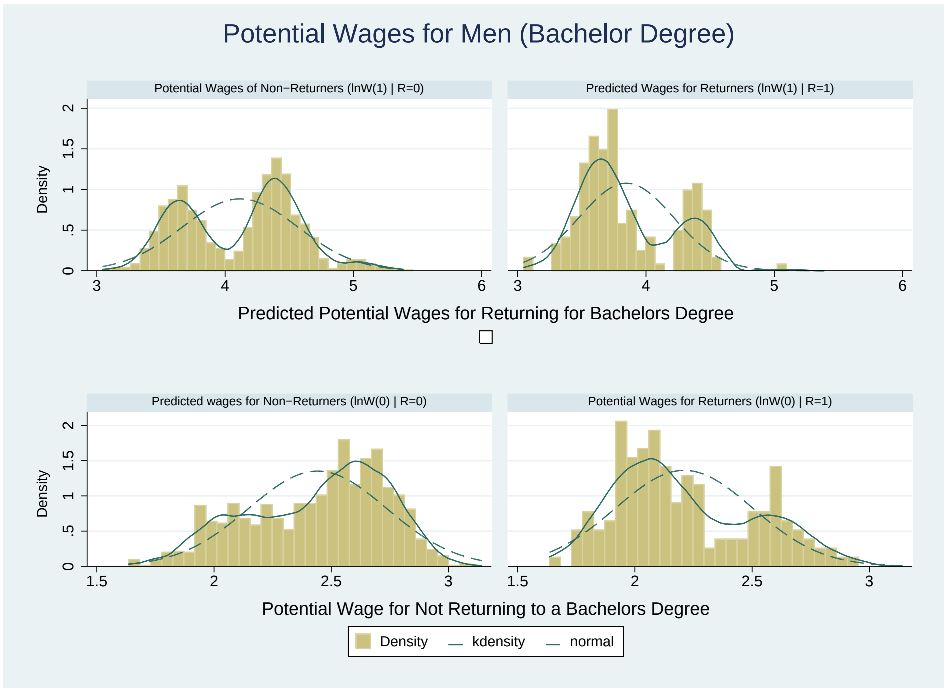
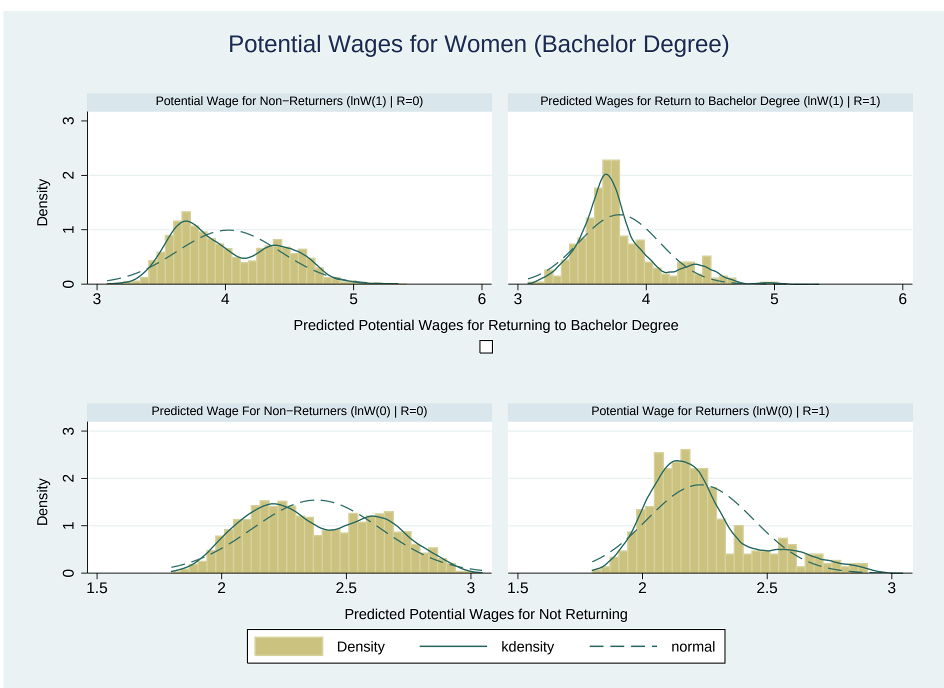


Figure A.5: Predicted return and non-return wages for Bachelor Degree: Women



APPENDIX B

Figure B.1: Earnings Profile: Female Returners for Associate Degree vs. Non-returners with HSD

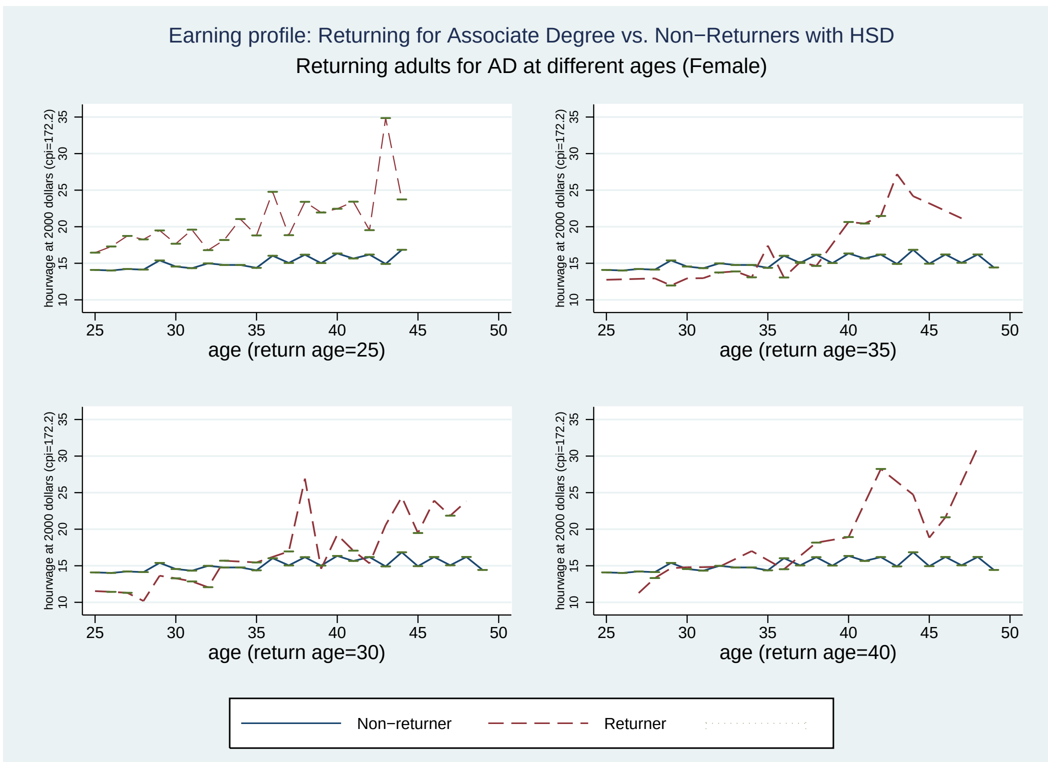
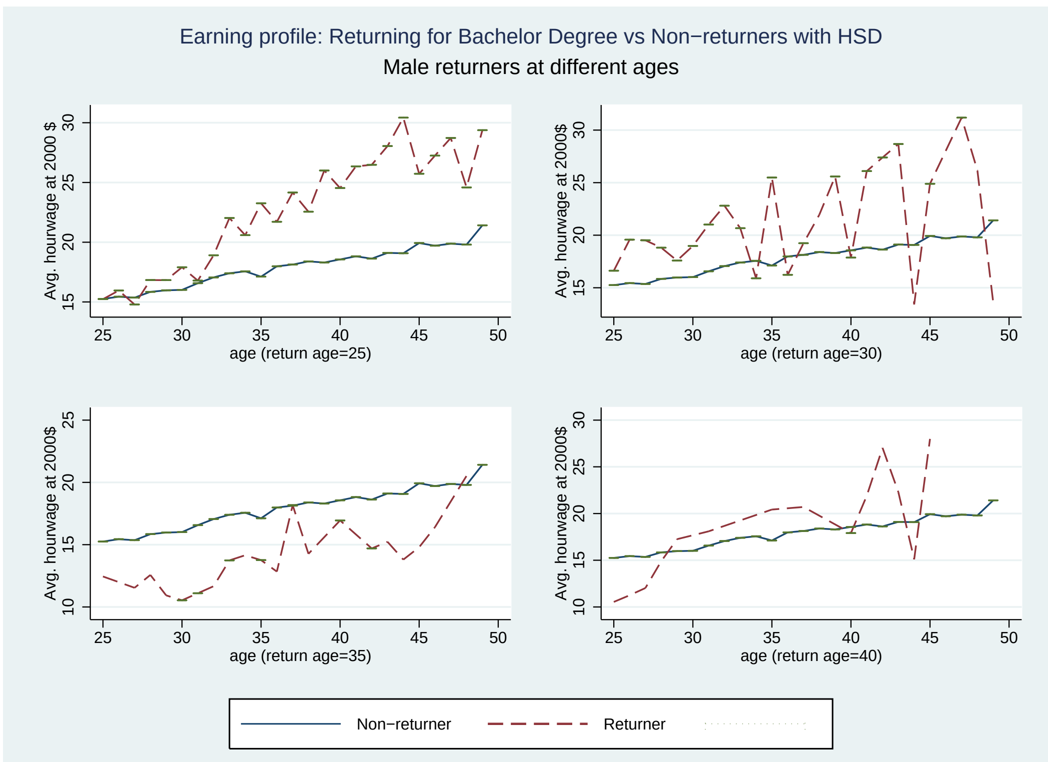


Figure B.2: Earnings Profile: Male Returners for Bachelor's Degree vs. Non-returners with HSD



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