Back to School: An Application of Human Capital Theory for Mature Workers

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Abstract

There is a vast literature on the decision to enroll in higher education, but it focuses almost entirely on traditional students: 18 year olds graduating from high school. Yet less than half of students at degree-granting institutions are in the traditional 18-22 age range; nearly 40 percent are at least 25. This paper examines the enrollment behavior of persons 25 or older. We use data from a large-scale 1998 Department of Labor (DOL) policy demonstration in Greater Baltimore. By studying the behavior of older people we can examine such factors such as age, earnings and marital status that vary little among the much-studied traditional students. Our results conform to the (rarely tested) predictions of human capital theory that age and opportunity costs are impediments to enrollment. We also find that where you live has a substantial impact on whether you return to school.

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1. Introduction

Volumes have been written about individual decisions whether to enroll in higher education. But the vast majority of studies consider only high school seniors. This focus offers a rather narrow view of higher education because less than half of students at degree-granting institutions are younger than 22. Nearly 40 percent are at least 25 years old (U.S. Department of Education, 2008). Ignoring nontraditional students is increasingly problematic given that the return to school of mature workers appears to be a growing phenomenon. Studies by Marcus (1986) and Light (1996), for example, found that from 20 to 40 percent of men in the NLSY who leave school return within a relatively few years. Our study attempts to help fill this substantial gap in the literature by examining the enrollment in higher education of non-traditional students, persons between the ages of 25 and 65.

To examine the educational decisions of mature people, we take advantage of a unique 1998 policy experiment conducted by the U.S. Department of Labor in the Greater Baltimore area. It was called the Lifelong Learning Demonstration. The idea was to determine how mature (over 25) workers (there was an earnings criterion) would respond to an information campaign extolling the learning opportunities in the area's higher education community. The results were disappointing – the information campaign was insufficient to stimulate enrollment (Buron, Orr, and Patrabansh, 1999). But the project collected, from various sources, demographic information on more than 450,000 mature potential students. Administrative records of the Maryland Higher Education Commission revealed which of Maryland's 2-year or 4-year colleges, if any, these people attended between 1990 and 1998. A relatively small fraction, about five percent, did.

Still, we have data on several tens of thousands of students and hundreds of thousands of non-students.

Because data from administrative sources are limited, Lifelong Learning also conducted a detailed telephone survey of 3,600 of the sample members. The survey sample was weighted to heavily oversample enrollees. Our study employs both the administrative data and the survey. We know of no other data set that provides nearly such a comprehensive picture of the education behavior of mature individuals.

We model both the probability of enrolling in higher education and the number of credits taken once enrolled. Our results are consistent with the main hypotheses of human capital theory. Because older people have less time to recoup an educational investment, enrollment drops rapidly with age. Similarly, the human capital model predicts that opportunity costs of school, through lost earnings, should tend to discourage investment in schooling. We observe this effect strongly for attendance at community colleges, but less so for four-year institutions. Another discovery is that, consistent with trends observed among traditional students, mature women are about one third to one half more likely to pursue further education than their male counterparts.

Finally, we find that where you live has a substantial impact on whether you enroll. Our results show that controlling for the effects of location is important in obtaining accurate measures of the effects of demographic variables.

2. Why Study Mature Students?

As argued above, focusing on traditional students has left a sizeable hole in the economic literature on higher education. People over 25 constitute a large, and largely ignored, fraction of the student population in the U.S. Mature (potential) students are also interesting on "theoretical" grounds, however. Consider the diagram in Figure 1, showing the earnings benefit of a college education, as might appear in the human capital chapter of any labor economics text (e.g. Ehrenberg and Smith, 2006). The diagram illustrates that starting college at 22 generates lower net benefits than starting at 18 for two reasons: salary gains are lower for older students and opportunity costs are higher. But it is difficult to test the effect of age by studying students who are virtually all in their late teens -- there is little age variation to observe.[1] There is a similar problem in measuring the effect of lost wages: many high school seniors will get low-paying jobs near the minimum wage (Card, 1992). It is hard to test the impact of earnings differentials among people whose earnings do not differ very much. For these reasons, studying mature (prospective) students should deepen our understanding of the human capital model.

FIGURE 1 ABOUT HERE

Finally, consider the effect of gender observed among traditional students. In 1968, 46% of male and 25% of female high school graduates aged 18-22 enrolled in higher education. By 2008, the percentage for males had fallen slightly; the percentage for females had doubled (National Center for Educational Statistics, 2010). Older persons are likely to face greater family responsibilities than young people, and women typically bear more family responsibilities than men. How does gender influence the enrollment rates of mature people?

3. Previous Studies of the Education Decisions of Older Workers

[1] Figure 1 seems to beg the question: how could an educational opportunity, rejected at 18, *ever* become viable at 22? Remember that the standard human capital models assume that students can accurately predict earnings with and without a college education. A few years in the job market might revise their expectations. Heckman, Lochner, and Todd (2006) provide a comprehensive theoretical treatment of role of earnings uncertainty in a dynamic model of education decisions.

As stated above, the economic literature on educational choice of mature people is relatively thin. Corman (1983) compared the behavior of 18-22 year olds with that of 25-44 year olds with respect to enrollment at a college[2] or, alternatively, an occupational school. She showed that older and younger students responded similarly to the economic incentives to attend school. Papers by Leigh and Gill (1997) and Light (1995) compared the earnings effects of *returning* to school, after a spell in the workforce, with those of *continuing* in school after high school. Jacobson, LaLonde, and Sullivan (1993, 2005) looked specifically at the return-on-investment that displaced workers can expect from returning to school at a community college. In a different paper, they considered mature workers' decisions whether to return to school (Jacobson, LaLonde, and Sullivan, 2002). Their observations were limited, however, to whether a particular group of displaced workers chose to attend community college.[3] More recently, Cheng (2011) looks at the role of risk in explaining gender differences in adult enrollment decisions.

Two previous studies have looked at how earnings experiences influence the decision to return to school after first leaving. Both limited their analysis to men, and both studied enrollment in "regular" school, defined as a secondary school, or a post-secondary school (two-year or four-year) that provides credit toward an academic degree. Using National Longitudinal Survey (NLS) data, Marcus (1986) found that a man who left school between 1966 and 1970 was more likely to return to school (within a seven year period) if his earnings fell below those predicted by his IQ and socioeconomic background. Light (1996) modeled the hazard rate of re-enrolling, in a given year, for men in the National Longitudinal Survey of Youth (NLSY) who originally left school

[2] Corman's (1983) data set was unable to distinguish between a two-year and a four-year college.
[3] They also considered workers' decisions to enroll in training through the Job Training Partnership Act.

between 1978 and 1990. She found that holding a high-paying and/or full-time job made men less likely to go back to school. This result is consistent with human capital theory which suggests that the opportunity cost of forgone wages creates a disincentive to pursue further schooling.

Using the administrative data from the same demonstration, Jepsen and Montgomery (2009) look at the effect of distance on the decision of whether to enroll in community college and which school to attend. Simulation results suggest that if people had to travel an extra three miles to the nearest community college, then the likelihood of community college attendance drops by as much as 14 percent.

What does our study contribute to this literature? First, we have enough observations that even with low enrollment rates (3-5%) we can observe tens of thousands of people reenrolling in school. Second, we have a random sample of both men and women, and our sample members range in age from 25 to 65. Third, we are among the first studies of this population to have information on neighborhoods people live in, which, as we see below, has a sizeable impact on enrollment decisions. Fourth, we have not merely enrollment figures, but the number of credits taken, both for community colleges and for four-year institutions.

It is in some ways limiting that we have only one geographic area to study, Greater Baltimore. But in other ways this is advantageous because it allows us to implicitly hold constant the state of the local economy. In summary, we believe that this is the most comprehensive look at enrollment in higher education by mature individuals that has yet to appear in the economic literature.

4. Data

In 1995 the U.S. Department of Labor (DOL) contracted with Abt Associates Inc. of Cambridge Massachusetts to conduct a demonstration that "included designing and testing a targeted public information campaign promoting lifelong learning to mature incumbent workers in the Greater Baltimore area," (Buron, Orr, and Patrabansh, 1999, pp. 1-1). The study targeted persons aged 25 to 65 with quarterly earnings of at least $1,105 (half time at minimum wage) in 6 of the 8 quarters between the fourth quarter of 1993 and the third quarter of 1995. The project was structured as a classic experiment with a treatment group that received informational brochures on educational opportunities and a control group that did not. The null hypothesis was that the treatment group was statistically no more likely to go back to school than was the control group. In the final report, Abt Associates could not reject the hypothesis ─ the mailings were not enough to increase the education behavior of these older workers.

The Lifelong Learning Demonstration has provided an exceptionally rich data source for evaluating questions about the decision to return to school. The evaluation team was able to assemble an extraordinarily comprehensive set of information on mature workers at the experimental site, Greater Baltimore. In evaluating the demonstration, person-specific data were drawn from three major information sources:

1. The Maryland Department of Labor, Licensing, and Regulation provided wages and salaries (earned in Maryland) from the first quarter of 1990 through May 1996.

2. Experian Inc (a credit reporting agency) provided demographic data in May 1996.

3. The Maryland Higher Education Commission provided enrollment records, for each public post-secondary institution in the state, from the fall term of 1990 through the fall term of 1998.[4]

[4] Data on private post-secondary institutions are not available.

Data from these three sources were collected for the universe of individuals in the Greater Baltimore area who met the earnings criteria mentioned above. Because the Experian data contained addresses of residence for about half of the people in the full sample, we were able to supplement the Lifelong Learning data as follows.

4. From the U.S. Census we collected demographic characteristics of the Census tract of residence. Sample members were distributed among 410 Census tracts.

5. Using a Geographic Information System we estimated the straight-line ("as the crow flies") distance from the individual's residence to the nearest community college and public four-year school.

The demographic data in the Experian files are limited; they exclude such important factors as race and educational background. To address this problem the demonstration supplemented the Experian data with a detailed telephone survey of 5,000 of the 450,000 people in the overall sample. The survey sample was stratified to include 1,250 students, 2,500 non-students and 1,250 people who had responded to the information campaign. The survey was conducted in the summer of 1998, and the response rate was 72 percent.[5]

A schematic view of the format of the data is presented in Figure 2 below. This paper relies upon two separate data sets drawn mainly from the information provided by the Lifelong Learning Demonstration and supplemented by the authors.

1. The 201,236 persons in the Experian records for whom we can identify the census tract and other demographic information.
2. The 3,526 persons who answered the survey questionnaire.

--FIGURE 2 ABOUT HERE--

[5] For more information on the survey, sampling design, and response rates, see Buron, Orr, and Patrabansh (1999).

Because we can identify the census tract for both samples, we can explore the impact of neighborhood characteristics on enrollment behavior, as shown in Table 1. The advantage of the large Experian data set is that with so many observations we have more census tracts represented, and more sample members within a tract. The advantage of the survey, on the other hand, is that it has more complete demographic information, especially regarding race which is absent from the Experian data.

--TABLE 1 ABOUT HERE--

The means and standard deviations for the variables in Experian sample and the survey sample are also presented in Table 1. Basic demographics, age, gender, and marital status are similar between the two groups. Because the survey sample overrepresented students, all estimation, including the descriptive statistics in Table 1, are weighed to provide representative samples of mature workers in the Baltimore area.

5. Econometric Method

Equation (1) presents the linear probability model, i.e. ordinary least squares (OLS), of attending a public institution of higher education, in Greater Baltimore, in the fall semester of 1996, 1997, or 1998, for the Experian and survey samples, respectively:

$$Attend_{ij} = X'_{ij}\beta + Z'_j\alpha + \varepsilon_{ij}\,, \tag{1}$$

where $Attend_{ij}$ is a dichotomous variable equal to one for individuals who attended postsecondary education at any time between fall 1996 through 1998, based on the administrative data from the Maryland Higher Education Commission mentioned above. For subscripts, i denotes individuals and j denotes Census tracts. Note that an observation is an individual; we do not observe the same individual at different points in time or in different Census tracts. X_{ij} is a vector of individual-level demographics, and Z_j

is a vector of Census tract characteristics. We allow for within-Census-tract correlation in ε_{ij}, the unobserved term, by using the "cluster" option in Stata.

Rather than controlling for specific Census tract characteristics such as percent Black or percent high school dropout, we also consider specifications that control for the overall effects of Census tracts through the use of Census tract fixed effects.[6] Equation (2) illustrates these specifications, where θ_j are the fixed effects and everything else is defined as in equation (1).

$$Attend_{ij} = X'_{ij}\beta + \theta_j + \varepsilon_{ij}, \qquad (2)$$

Equations (1) and (2) are estimated as linear probability models rather than probits or logits for several reasons. Linear probability models are less sensitive to distributional assumptions than logit or probit models (Wooldridge, 2001). However, estimates from linear probability models are not constrained to lie within the 0 to 100 percent probability interval, and linear probability models violate the heteroskedasticity assumption. On the other hand, the nonlinear nature of logit and probit models complicates the use of logit fixed effects models and precludes the use of probit fixed effects models; see Cameron and Trivedi (2005) for further discussion of nonlinear panel data models. We wanted to use the same model for equations (1) and (2). Linear probability coefficients are easier to interpret than probit or logit coefficients, which can also be complicated in logit fixed effects models (Cameron and Trivedi, 2009). These advantages of the linear probability model outweigh the disadvantage that the estimates are not constrained to lie within the 0 to 100 percent probability interval; the concern about heteroskedasticity is mitigated by tour ability to cluster all standard errors by

[6] We also estimate random effects models. We discuss the results of these models in footnotes in the results section.

census tract. As it turns out, our results are not sensitive to choice among linear probability models, logit, and probit.

We estimate a Tobit model where the outcome is the total number of credits taken in higher education during the fall semesters of 1996 through 1998. The Tobit model accounts for the large percentage of observations with no credits earned, which are interpreted as being censored at zero. However, the Tobit model also requires strong distributional assumptions regarding homoskeasticity and normality (Cameron and Trivedi, 2005). Because, in most circumstances, it is not possible to produce a consistent fixed effects Tobit estimator, we focus on the Tobit model that contains specific Census tract characteristics. This Tobit model, which contains the same independent variables as the linear probability model for attendance in Equation (1), is presented in Equation (3):

$$
\begin{aligned}
&Credits^*_{ij} = X'_{ij}\beta + Z'_j\alpha + \varepsilon_{ij}\,, \\
&Credits_{ij} = 0 \text{ if } Credits^*_{ij} \le 0\,, \qquad (3) \\
&Credits_{ij} = Credits^*_{ij} \text{ if } Credits^*_{ij} > 0\,.
\end{aligned}
$$

In this equation $Credits_{ij}$ is the observed value of the credits variable (left censored at zero), and $Credits^*_{ij}$ is the "true" underlying credits variable. The remaining terms are defined as in equation (1).

6. Econometric Results

Tables 2 through 5 contain the estimation results. For the Experian and survey samples, respectively, Tables 2 and 3 report the results of linear probability models of the decision whether or not to attend a public postsecondary institution at any time during the fall semesters of 1996 through 1998. Tables 4 and 5 report Tobit models of total credits taken in those semesters. Tables A.1 and A.2 compare linear probability, logit, and probit results for the Experian and survey samples, respectively.

6.1 Does It Matter Where You Live?

Before discussing the key demographic variables, it is worth pausing to consider the effect of neighborhood characteristics. One of the important features of the Lifelong learning data set is the ability to identify census tract of residence for a large subsample of the Experian observations, and for all but a handful of the survey observations. We would expect location to matter more for mature students than for traditional students. The latter are likely to have non-academic demands on their time including full-time jobs and family responsibilities, and Jepsen and Montgomery (2009) find a strong effect of one measure of location – distance to nearest community college – on whether to attend a community college.

Our estimation exploits the location information in two alternative (and mutually exclusive) ways. In the second two columns for each outcome of Tables 2 and 3, we supplement the demographic characteristics of the individual with those of her residential neighborhood. These include how residents are distributed among ethnic groups and education levels, median household income, distance to the nearest community college and four-year school (main campuses).[7] An alternative way to address location is to subsume all the impacts of neighborhood into a tract-specific fixed effect. The inclusion of neighborhood characteristics allows estimation of structural coefficients of location effects, e.g. how living in a half-Hispanic neighborhood instead of an all-Hispanic neighborhood affects enrollment. The tract fixed effects approach obscures the structure of the neighborhood affects but permits more efficient estimation of the individual-level

[7] Omitted categories are White and High-School Educated.

parameters, e.g. how being Hispanic *oneself* affects enrollment conditional on living in a given Census tract.

In the Experian model (left half of Table 2), several tract level variables are associated with changes in individuals' community college attendance. The percentage of college graduates and high school dropouts have negative effects on community college attendance. A 10 percentage point increase in each is associated with a 0.003 to 0.004 decrease in the likelihood of attendance. The percentage black has a negative effect on community college attendance, a result we discuss in more detail below. As in Jepsen and Montgomery (2009), distance to the nearest community college is negatively associated with community college attendance; an increase of one mile is decreases the likelihood of attendance by 0.001. Distance to nearest four-year school is positively associated with community college attendance, although the magnitude of the effect is quite small: an increase of one mile is associated with increased likelihood of attendance of 0.0002.

The right half of Table 2 contains a model predicting attendance at a public four-year institution. A 10 percent increase in log median income is associated with a 0.06 decrease in the likelihood four-year college attendance. A 10 percent point increase in fraction of black residents tends to increase the probability of enrolling in a four-year college by 0.001. The percentage college graduate and the percentage with some college are positively associated with four-year college attendance; the percentage of high school dropouts is negatively associated.[8] Distance to the nearest community college has no

[8] The effect of some college is marginally significant at the five-percent level in probit models (Appendix Table 1). The effect of percent Hispanic is marginally significant at the ten-percent level in the logit and probit models. For community college attendance, the significance level of the percent Hispanic

effect on four-year college attendance, providing no support for the argument that community colleges divert attendance from four-year institutions (Rouse, 1995; Gill and Leigh, 2003; Doyle, 2009). The distance to the nearest four-year college is negatively associated with attendance, consistent with previous research (Alm and Winters, 2009, and references cited therein).

For the survey data, (Table 3) fewer neighborhood characteristics are significant at the 90 percent level. For both outcomes, log median income has a positive effect (although the significance level varies). Distance to the nearest community college has a negative effect on the likelihood of community-college attendance, but only a small and insignificant effect on four-year college attendance. Neighborhood racial/ethnic composition and education levels have insignificant effects in the survey data.

Nevertheless, location seems to matter more than the results in the second two column(s) suggest. In the third and fourth columns, we use fixed effects in models of going to a community college or 4-year school, respectively. When we do an F test for whether the tract-specific effects improve the model, we can reject the hypothesis that the tract fixed effects are jointly zero at the one-percent level.[9] Clearly, where you live matters to whether or not you enroll.

Because, in many circumstances, detailed location information is not available, we investigate the sensitivity of the individual-level coefficients to the inclusion of either tract-level characteristics or tract fixed effects. The first two columns of results for each outcome contain the results excluding both tract-level characteristics and tract fixed

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coefficient also varies by model. Otherwise, the sign and level of significance is consistent across Census tract characteristics between linear probability, logit, and probit models.

[9] In unreported results, we also find similar results for the random effects when we estimate a random effects model.

effects. In a few cases, holding constant location has an impact on the significance of important demographic coefficients. For example, the effects of individual and household income levels are sensitive to the inclusion of location controls in the Experian sample (Table 2). In the survey sample (Table 3), individual earnings, gender, and the receipt of a brochure are sensitive to controls for location. To the extent that one's demographics are correlated with where one lives, ignoring an individual's location can bias the observed effects of demographics.

--TABLES 2 AND 3 ABOUT HERE--

6.2 Demographics: What Kind of Mature Person Returns to School?

For ease of discussion, we will focus on the fixed-effects models.[10] It is reassuring that most of demographic variables common to both samples (these are age, gender, earnings and marital status) have similar effects in the two tables. For both samples and both types of school (2-year or 4-year) a ten-percent increase in age reduces the likelihood of attending school by 0.005 to 0.007. This represents a 20 percent reduction in the probability of going to a community college and about a 25 percent reduction of going to a 4-year school. A 35 year old is approximately 60 percent less likely to enroll than an otherwise identical 25 year old. This effect is substantial. The prediction of human capital theory that age is an impediment to educational investment is strongly supported by our results.

Also as predicted by human capital theory, the probability of enrollment falls with higher opportunity cost of attendance, as measured by yearly earnings. According to the fixed effects models, a 10 percent increase in earnings in 1994-1995 reduces the

[10] Although not reported, the coefficients for the demographics are nearly identical whether we estimate a random effects model or a fixed effects model. Therefore, we only report the fixed effects results.

likelihood of attending a community college by about 0.08 (Experian sample) to 0.12 (survey sample).[11] If this result were solely for the Experian sample it might merely reflect the absence of data on previous education: people with more education earn more money, and tend to invest less in additional education due to diminishing returns.[12] But, in fact, the earnings coefficient is actually larger in magnitude in the survey sample, where prior education is held constant. Previous earnings have noticeably smaller impacts, however, on the decision to attend a four-year college.

Gender has a significant effect for both samples for both types of school attendance in the fixed effects specifications. Consistent with observations about traditional students, mature women are more likely to go to school than their male counterparts, with a coefficient of approximately 0.01. The impact is sizeable, between 35 and 50 percent. This effect is after controlling for family characteristics.

The results for marriage and presence of children differ by sample. In the Experian sample, both marriage and children are negatively associated with college attendance at either community colleges or four-year institutions. In the survey sample, the effects of marriage and children are imprecisely estimated with t-statistics below 1.5 in absolute value.

Does a mature person's race matter? Here, we focus on the survey sample in which we can directly observe race. There are no clear racial / ethnic differences in enrollment likelihoods, although being black is associated with higher likelihood of

[11] As mentioned previously, earnings are measured in the third quarter of 1994 through the second quarter of 1995 to avoid endogeneity with actual or expected enrollment starting in the fall of 1996.
[12] The previous education question asks survey respondents to report their highest level of education as of July 1, 1996, prior to the fall 1996 through fall 1998 time frame of the dependent variables for enrollment.

attendance at four-year institutions, at least in the specifications that do not include tract fixed effects.

6.3 Alternate Specifications

In our first set of alternative specifications, we consider possible joint effects between age and earnings.[13] Older students will have a shorter time horizon over which to recoup lost earnings. Thus, one might think that the effect of earnings varies across age. We estimated a specification where we allowed the age effect to vary by earnings quartile, as well as a specification where we allowed the earnings effect to vary by age quartile. In these models, we found few if any differences in the coefficients for different quartiles. In other words, the effect of age varied little across the earnings distribution, and the effect of earnings varied little across the age distribution.

The results in Tables 2 and 3, above, are from a linear probability model. Because the model does not fully capture the binary nature of the outcomes studied (community college and four-year college attendance), Tables A.1 and A.2 contain the results from probit and logit models in addition to linear probability models. For ease of comparison, we report the marginal effects for the logit and probit models. For brevity, none of the models contain tract fixed effects or random effects. Table A.1 contains the results from the Experian data, and Table A.2 contains the results for the survey data.

The results from each table illustrate that the results are similar between linear probability, logit, and probit models. There are slight changes in magnitudes as expected from the different functional forms. Overall, we conclude that the results from the linear probability models reported in Tables 2 and 3 are not sensitive to functional form

[13] The results are available from the authors upon request. We thank an anonymous referee for suggesting this interaction.

assumptions even though they do not constrain the predicted probability of attendance to lie within the unit interval.

The logit and probit results in Tables A.1 and A.2 are similar to results from logit and probit random effects models as well as logit fixed effects models, and the results from these random and fixed effects models are available from the authors upon request.[14]

6.4 Potential Endogeneity Problems

A limitation of these results is that they implicitly assume that earnings, previous education levels, and location are exogenous to the schooling decision. This may not be the case. For example, suppose that ability bias exists, so that people with higher levels of education prior to the enrollment decision have higher returns from additional schooling. Under this scenario, the coefficients for previous education and earnings may be biased. We attempted to mitigate the concern about potential endogeneity by running specifications where we exclude people who attended school in fall 1994 or 1995, the time period when location, earnings, and other demographics were determined. The results from these specifications were similar in significance, but smaller in magnitude, when compared to the results presented in the tables. See Jepsen and Montgomery (2009) for more discussion about our assumptions regarding the exogeneity of the location decision.

6.5 Total Credits Taken

Tables 4 and 5 look at the intensity of enrollment, as measured by the number of credits earned in the 3 fall semesters under observation (1996, 1997, and 1998).[15] We

[14] As discussed earlier, probit fixed effects models are biased and therefore not estimated.
[15] Data on spring and summer credits and enrollment are not available.

measure credits for either type of college, and report the model with specific tract characteristics rather than the tract fixed effects model due to the difficulties of estimating a fixed-effects Tobit model (Cameron and Trivedi, 2009). Table 4 contains the results from the Experian sample, and Table 5 contains the results from the survey sample. Because these credits are only fall semester credits, the coefficients almost certainly understate the impact of the independent variables on total credits earned.

The results for credits taken are consistent with those for enrollment in Tables 2 and 3. Older people who go to school take fewer credits than younger people, high earners take fewer credits than low earners, and women take more credits than men. In the Experian data, individuals who are married and individuals with children in the household take fewer credits than single individuals and individuals without children. We also find similar results for census tract characteristics. In the Experian data, the percentage black and the percentage of people with some college are positively correlated with credits, and the percentages of people who are high school dropouts or college graduates are negatively associated with the number of credits. Distance from the nearest community college is negatively associated with the number of credits, and distance from the nearest four-year school is negatively associated with the number of credits in the Experian sample.

--TABLES 4 AND 5 ABOUT HERE--

7. Caveats and Cautions

Although we consider our data set to be uniquely well suited for addressing our subject, it is not without weaknesses. First, there is the fact than the Lifelong Learning Demonstration applied an earnings test to the sample members. To qualify one needed to earn at least $1,105 (half time at minimum wage) in 6 of the 8 quarters between the fourth quarter of 1993 and the third quarter of 1995. While not a stringent test for an average worker, this restriction is likely to have eliminated some long-term unemployed and/or discouraged workers. To the extent that such people might most benefit from additional education, this limits the generality and usefulness of our results.

A second limitation is that the Experian data could identify the residence of about 200,000 of the 450,000 people in its data files. Does this exclusion bias our results for that sample? To explore this question we ran linear probability models, without location variables, on the unrestricted Experian sample and compared the estimates with those from the location-identified group. The results are reported in Table A.3. The coefficients on the primary demographic variables (age, gender, marital status, and children in the household) vary little between the samples. An exception, however, is effect of log earnings on the probability of attending a four-year college. For the unrestricted sample, the coefficient is negative and significant at one percent. In the restricted sample, the coefficient is half as large and is not statistically different from zero at ten percent. Similarly, the effects of the household income variables are often insignificant (at ten percent) in the restricted sample but are significant (at one percent) in the full sample.

We interpret this set of findings to suggest that whether a credit-reporting agency knows an individual's location (i.e. Census tract) may be related to an individual's personal or household income. Homeowners, for example, generally have higher income than renters and are less peripatetic; their addresses are more likely to be known. Although Jepsen and Montgomery (2009) find individuals with non-missing Census tract information had slightly higher earnings than individuals with missing Census tract information, the authors conclude that demographic variables are weakly correlated with the probability of having a non-missing Census tract (based on probit results). We find similar results for the survey sample, which has very little missing data on Census tract, and we also find similar, negative effects of earnings on community college attendance in both samples. However, we cannot entirely dismiss the possibility that earnings coefficients for the restricted Experian sample may suffer from selection bias.

8. Conclusions

This paper sought to bolster the thin literature on the higher-education decisions of mature individuals. Our main results reinforce some standard – but rarely tested – predictions of human capital Theory. The likelihood of pursuing additional higher education falls rapidly with age. Opportunity costs, in the form of lost wages, are also an impediment to attending community college. Earnings seem less important for attending a four-year college, but this effect may be dampened by a likely correlation between earnings and unobserved academic ability.

We found a significant difference between mature men and mature women in the probability of further education. A mature woman is about 35% to 50% more likely than her male counterpart to enroll in higher education. Thus, the relative feminization of higher education that we observe among traditional students seems also to apply to their older classmates.

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Figure 1
Age and Opportunity Cost Reduce the Net Earnings Gain from College

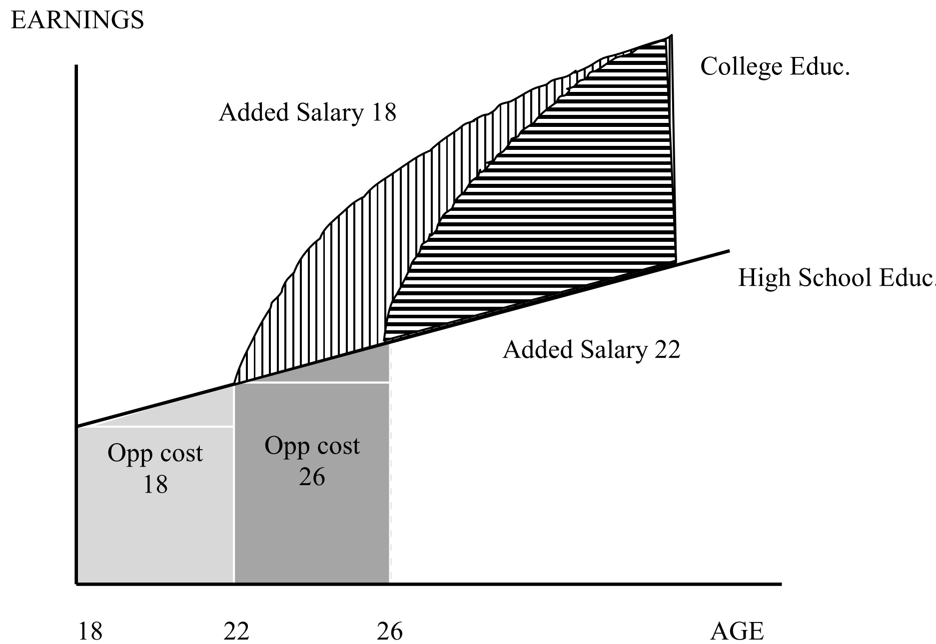

Figure 2
Structure of the Data Sets

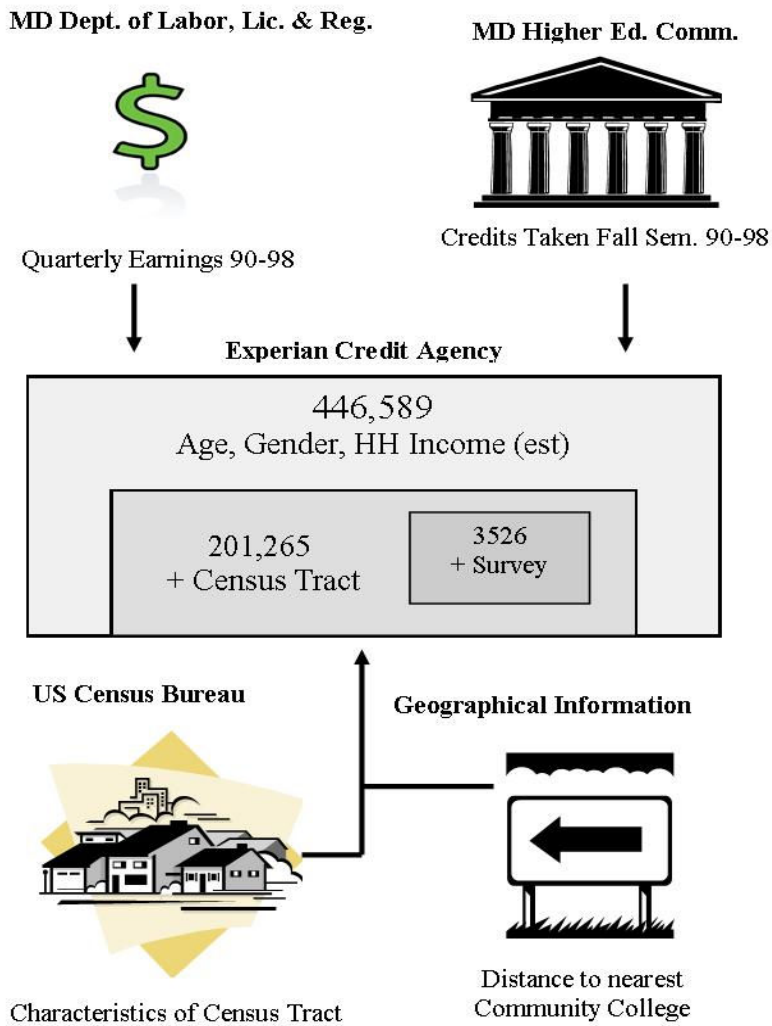

Table 1
Descriptive Statistics

	Experian Sample		Survey Sample	
	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables				
Attended community college	0.032	0.18	0.036	0.19
Attended four-year college	0.023	0.15	0.023	0.15
Number of credits attained	0.14	1.04	0.15	1.07
Demographic characteristics				
Age	42.87	10.78	42.84	11.10
Married	0.55	0.50	0.70	0.46
Had kids in household	0.33	0.47	0.32	0.47
Female	0.47	0.50	0.51	0.50
Earnings 1994-1995	36,559	27,120	36,240	25,801
Black			0.18	0.38
Hispanic			0.02	0.14
Asian			0.01	0.11
Less than high school			0.06	0.23
Some college			0.26	0.44
BA degree			0.23	0.42
Graduate degree			0.16	0.36
Household inc. 15,000-25,000	0.09	0.29		
Household income 25-35k	0.12	0.32		
Household income 35-50k	0.21	0.41		
Household income 50-75k	0.29	0.46		
Household income > 75k	0.25	0.43		
Received brochure	0.50	0.50	0.50	0.50
Census tract characteristics				
Percent black	17.57	26.88	17.41	26.46
Percent Hispanic	1.17	0.98	1.18	0.93
Percent high-school dropout	21.96	13.06	21.75	12.80
Percent some college	18.85	4.35	18.98	4.31
Percent BA degree or more	25.33	16.07	25.19	16.02
Median household income	42,162	14,056	41,810	13,138
Miles to nearest comm. coll.	5.40	3.37	5.39	3.35
Miles to nearest 4-yr school	8.64	6.74	8.54	6.85
Number of individuals per tract	1017	829	19.8	16.0
Number of observations	201,236		3,139	

Number of Census tracts	409	373

Notes: Data for survey sample are weighted. The education levels in the demographics characteristics are measured as of July 1, 1996, prior to the measurement of the schooling decisions used as dependent variables. Log earnings are from the third quarter of 1994 through the second quarter of 1995.

Table 2
Linear Probability Analysis of the Experian Data
Changes in the Probability of Attending Institutional Type in Fall of 1996, 1997, or 1998

	Attend Community College						Attend four-year school					
	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.
Log age	-0.0584	-31.39	-0.0575	-30.90	-0.0574	-35.59	-0.0579	-26.08	-0.0583	-26.41	-0.0584	-42.46
Female	0.0131	14.75	0.0134	14.85	0.0133	16.08	0.0095	12.39	0.0085	11.10	0.0084	11.87
Married	-0.0027	-3.12	-0.0034	-3.91	-0.0033	-3.83	-0.0077	-10.76	-0.0063	-9.01	-0.0062	-8.58
Had kids in household	-0.0028	-3.38	-0.0032	-3.79	-0.0031	-3.59	-0.0061	-9.01	-0.0052	-7.82	-0.0050	-6.66
Log individual earnings	-0.0087	-12.07	-0.0081	-10.50	-0.0081	-11.57	-0.0003	-0.52	-0.0015	-2.17	-0.0015	-2.50
HH income under 15,000	-0.0008	-0.35	0.0022	0.89	0.0026	1.06	-0.0030	-1.54	-0.0043	-2.01	-0.0024	-1.16
HH income 15,000-25,000	0.0006	0.37	0.0017	0.92	0.0030	1.64	-0.0011	-0.66	-0.0012	-0.73	-0.0010	-0.67
HH income 25,000-35,000	0.0027	1.66	0.0021	1.29	0.0031	1.93	-0.0017	-1.13	-0.0001	-0.10	-0.0010	-0.72
HH income 35,000-50,000	0.0048	3.44	0.0031	2.24	0.0037	2.80	-0.0020	-1.77	0.0003	0.27	-0.0006	-0.51
HH income 50,000-75,000	0.0024	2.26	0.0008	0.81	0.0013	1.17	-0.0005	-0.51	0.0012	1.17	0.0003	0.29
Received brochure	0.0001	0.19	0.0002	0.19	0.0001	0.13	0.0009	1.35	0.0009	1.38	0.0009	1.42
Log median HH income			0.0017	0.71					-0.0059	-2.55		
Pct black			-0.0001	-2.48					0.0001	6.78		
Pct Hispanic			0.0006	1.26					-0.0009	-2.01		
Pct college graduate			-0.0004	-5.04					0.0002	4.00		
Pct some college			0.0003	1.65					0.0003	2.00		
Pct high school dropout			-0.0003	-2.86					-0.0002	-2.14		
Miles to nearest comm coll			-0.0013	-7.44					0.00003	0.25		
Miles to nearest 4-yr school			0.0002	2.04					-0.0005	-7.45		
Census tract fixed effects?	No		No		Yes		No		No		Yes	

Notes: The distance measures are for public schools only. Standard errors are clustered to allow for within-census-tract correlation. N=201,236.

Table 3
Linear Probability Analysis of the Survey Data
Changes in the Probability of Attending Institutional Type in Fall of 1996, 1997, or 1998

	Attend Community College						Attend four-year school					
	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.
Log age	-0.0689	-4.74	-0.0702	-4.94	-0.0597	-3.69	-0.0502	-6.46	-0.0504	-6.45	-0.0544	-5.08
Female	0.0120	1.71	0.0114	1.60	0.0174	2.24	0.0096	2.09	0.0095	2.08	0.0119	2.17
Married	-0.0067	-0.72	-0.0087	-0.95	-0.0105	-1.21	-0.0007	-0.15	-0.0021	-0.42	-0.0016	-0.31
Had kids in household	-0.0119	-1.40	-0.0114	-1.35	-0.0118	-1.17	0.0006	0.09	0.0013	0.19	0.0008	0.11
Log individual earnings	-0.0164	-2.68	-0.0177	-2.68	-0.0118	-1.68	-0.0065	-1.87	-0.0068	-1.84	-0.0080	-1.80
HH income under 15,000	-0.0087	-0.63	-0.0060	-0.41	0.0071	0.38	-0.0081	-0.66	-0.0067	-0.54	-0.0080	-0.46
HH income 15,000-25,000	-0.0052	-0.53	0.0083	0.60	-0.0047	-0.27	0.0135	2.10	0.0195	2.08	0.0137	1.59
HH income 25,000-35,000	0.0118	0.36	0.0139	0.42	-0.0047	-0.11	-0.0110	-1.55	-0.0102	-1.41	-0.0026	-0.22
HH income 35,000-50,000	-0.0040	-0.34	-0.0046	-0.37	0.0027	0.17	0.0063	2.18	0.0072	2.21	0.0128	2.24
HH income 50,000-75,000	0.0446	4.30	0.0452	4.34	0.0511	4.43	0.0304	5.97	0.0305	6.08	0.0322	5.64
Received brochure	-0.0011	-0.13	0.0006	0.07	0.0031	0.34	0.0347	5.39	0.0351	5.19	0.0385	4.86
Log median HH income			0.0023	0.24					0.0295	4.04	0.0305	3.43
Pct black			-0.0054	-0.79					0.0071	1.45	0.0120	2.17
Pct Hispanic			0.0265	1.79					0.0216	1.99		
Pct college graduate			-0.0002	-1.08					-0.0001	-0.69		
Pct some college			-0.0015	-0.37					0.0015	0.50		
Pct high school dropout			-0.0001	-0.24					0.0001	0.24		
Miles to nearest comm coll			-0.0002	-0.13					0.0012	1.10		
Miles to nearest 4-yr school			0.0003	0.42					0.0008	0.89		
Census tract fixed effects?	No		No		Yes		No		No		Yes	

Notes: Data for survey sample are weighted. The independent variables for education levels are measured as of July 1, 1996, prior to the measurement of the schooling decisions used as dependent variables. The distance measures are for public schools only. Standard errors are clustered to allow for within-census-tract correlation. N=3,139.

Table 4
Tobit Model Results for Experian Data
Number of College Credits in Fall 1996, 1997, and 1998

	Without tract characteristics		With tract characteristics	
	Coeff.	t-ratio	Coeff.	t-ratio
Log age	-12.496	-33.87	-12.511	-33.79
Female	2.958	17.17	2.890	16.77
Married	-1.122	-6.48	-1.045	-6.01
Had kids in household	-0.415	-2.29	-0.369	-2.02
Log individual earnings	-0.858	-5.81	-0.876	-5.86
HH income under 15,000	0.886	2.10	0.555	1.15
HH income 15,000-25,000	0.786	2.48	0.449	1.23
HH income 25,000-35,000	0.641	2.16	0.462	1.43
HH income 35,000-50,000	0.567	2.26	0.438	1.63
HH income 50,000-75,000	0.240	1.02	0.165	0.69
Received brochure	0.224	1.40	0.210	1.31
Log median HH income			-0.169	-0.37
Pct black			0.017	4.35
Pct Hispanic			-0.069	-0.79
Pct college graduate			-0.027	-2.00
Pct some college			0.070	1.98
Pct high school dropout			-0.063	-2.68
Miles to nearest comm coll			-0.138	-4.84
Miles to nearest 4-yr school			-0.045	-2.97

Notes: The distance measures are for public schools only. Standard errors are clustered to allow for within-census-tract correlation. N=201,236.

Table 5
Tobit Model Results for Survey Data
Number of College Credits in Fall 1996, 1997, and 1998

	Without tract Characteristics		With tract characteristics	
	Coeff.	t-ratio	Coeff.	t-ratio
Log age	-12.945	-5.51	-13.438	-6.15
Female	3.916	3.17	3.738	3.16
Married	-1.061	-0.73	-1.442	-1.01
Had kids in household	0.836	0.59	0.919	0.67
Log individual earnings	-2.030	-2.49	-2.245	-2.77
Asian	-1.577	-0.49	-1.109	-0.33
Black	1.478	1.01	3.482	1.83
Hispanic	5.835	1.17	6.372	1.33
Less than HS	1.414	0.41	1.519	0.45
Some college	6.034	3.75	6.143	3.86
BA degree	2.433	1.37	2.684	1.46
Graduate degree	2.101	0.90	2.197	0.93
Received brochure	-1.011	-0.83	-1.037	-0.87
Log median HH income			3.384	1.13
Pct black			-0.039	-1.19
Pct Hispanic			-0.881	-1.18
Pct college graduate			-0.014	-0.14
Pct some college			0.183	0.61
Pct high school dropout			0.067	0.40
Miles to nearest comm coll			-0.303	-1.66
Miles to nearest 4-yr school			0.065	0.57

Note: Data for survey sample are weighted. The independent variables for education levels are measured as of July 1, 1996, prior to the measurement of the schooling decisions used as dependent variables. The distance measures are for public schools only. Standard errors are clustered to allow for within-census-tract correlation. N=3,139.