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How do young people choose college majors?

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Abstract

Previous studies on the determinants of the choice of college major have assumed a constant probability of success across majors or a constant earnings stream across majors. Our model disregards these two restrictive assumptions in computing an idiosyncratic expected earnings variable to explain the probability that a student will choose a specific major among four choices of concentrations. The construction of an expected earnings variable requires information on the student's perceived probability of success, the predicted earnings of graduates in all majors and the student's expected earnings if he (she) fails to complete a college program. Using data from the National Longitudinal Survey of Youth, we evaluate the chances of success in all majors for all the individuals in the sample. Second, the individuals' predicted earnings of graduates in all majors are obtained using Rumberger and Thomas's [Econ. Educ. Rev. 12 (1993) 1] regression estimates from a 1987 Survey of Recent College Graduates. Third, we obtain idiosyncratic estimates of earnings alternative of not attending college or by dropping out with a condition derived from our college major decision-making model applied to our sample of college students. Finally, with a mixed multinomial logit and probit models and an heteroscedastic extreme value model, we explain the individuals' choice of a major. The results of the paper show that the expected earnings variable is essential in the choice of a college major. There are, however, significant differences in the impact of expected earnings by gender and race.

JEL classification: J24; C35

Keywords: College majors; Expected idiosyncratic earnings; Mixed multinomial logit probit and HEV models

1. Introduction

At some point during the early stages of an undergraduate education, every college student must choose an area of concentration such as science, business, liberal arts or education. A certain proportion of these undergraduates will not finish college, and an ill-advised choice of concentration may be a contributing factor. It is generally thought, for example, that majoring in science is more difficult, and hence riskier, than majoring in education. It may be, however, that people who differ in their socioeconomic and ascriptive characteristics as well as cognitive capabilities also differ in their willingness to choose riskier areas of concentration. If it is true, for example, that students from more affluent socioeconomic backgrounds are more willing to take risks in the pursuit of their education, then, in effect, more privileged socioeconomic backgrounds enhance the educational choices of those who possess them. Similarly, insofar as men are willing to take more risks than women in the

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choice of concentration, there is an element of gender inequality in educational choice.

While many studies[1] have explored the impacts of socioeconomic background and ascriptive characteristics such as gender on the demand for education and the choice of occupation, they have not addressed the more specific question of the impacts of these variables on the choice of undergraduate concentration. There are, however, important exceptions. In Freeman (1971), individuals select the occupation or major that offers the greatest total expected (linear) utility. Blakemore and Low (1984) apply a human capital approach of occupational selection to the decision process for college majors. Their results demonstrate that young female students with higher expected fertility (obtained by direct questioning from the 1972 NLSHS and follow up surveys) tend to choose majors that are less subject to atrophy and obsolescence. Berger (1988a) shows that, in their choice of concentrations, individuals are less influenced by initial earnings levels in occupations related to different concentrations and more influenced by the stream of earnings that these occupations are expected to yield.

If the choice of college major significantly determines subsequent career progress, then, for the sake of both the efficient allocation of human resources and the elimination of discriminatory barriers, it is important to know why certain types of individuals choose certain types of college majors. Assuming that (1) the choice of college major is a significant determinant of subsequent career success, (2) riskier majors are associated with higher subsequent earnings streams, and (3) students are motivated in their choice of major by the possibilities of accessing higher earnings streams, an analysis of the impact of the perceived probability of success in a college major on the choice of college major can have important policy implications. Duru and Mingat (1979) were the first to present a model that takes into account the probability of success in selecting a major. They suggest a trade off between the economic return to education and the risk of failure. For Bamberger (1987), the individuals take into account that they may fail in a field of study (equivalent to choosing an occupation), move to another major where they may also fail, and so on. Bamberger compares the predicted first occupation to the actual first occupation chosen by each member of the NL572 panel sample and finds that the sequential model of occupational choice has statistically significant explanatory power for his sample of college students. There is an overlap between his research and ours that we shall discussed later on. Recently, Arcidiacono (1999) has extended the Bamberger model with a dynamic structural model that allows students to change their decisions over time as to what schools to attend and what majors to study. Paglin and Rufolo (1990) show that "comparative advantage influences the observed choice of college major and that quantitative ability is one of the most important factors in this choice". Turner and Bowen (1999) suggest that observed differences in choice of major between men and women reflect the effects of pre-collegiate preparation.

This paper analyzes the extent to which the choice of college major depends on the student's expected earnings in that major as opposed to other areas of concentration that could have been chosen. Previous studies on the determinants of the choice of college major have assumed a constant probability of success across majors or a constant earnings stream across majors. Our model disregards these two restrictive assumptions. Choosing a major is a decision made under uncertainty as one must successfully complete the major to gain the associated earnings. We test the hypothesis that abilities influence the perceived probability of success in a major and we explore the role of family background and family culture on the determinants of college major. We also use the model to determine whether distinct groups exhibit significant differences in their choice of college major. In the next section of the paper, we develop a model of a decision-making process in which the student's expected earnings in a major is the central determinant of the choice of a major. We also discuss some econometric issues associated with the model. In Section 3, we present the data. In Section 4, we discuss the empirical results of the students' perceived probability of success. Section 5 discusses the estimates of earnings of graduates in all majors and the students' earnings alternative if they fail to complete a college program. In Section 6, we present the empirical results on the choice of majors. Section 7 concludes.

2. Theoretical framework and econometric issues

Define p_{ij} as the perceived probability of success of individual i in major j and e_{ij} the earnings individual i expects by graduating in major j.

For given preferences, assume that the expected utility of individual i choosing major j depends on expected earnings:

$$E(u_{ij})=p_{ij}(x)e_{ij}(z)+(1-p_{ij}(x))e_{io}(z), \quad i=1,\ldots,N;\ j=1,\ldots,m, \tag{1}$$

where x and z are factors that influence the probability of success and earnings of graduates respectively. e_{io} is the earnings alternative with no success in any major.[2]

[1] See Blau and Ferber (1991) and Flyer (1997).

[2] A complete model would consider the probability of graduates finding unemployment in their specific majors.

We assume that expected earnings of graduates are always realized. Then, an individual i will choose j over the alternative k if $E(u_{ij}) \geq E(u_{ik})$, that is,

$$p_{ij}(x)(e_{ij}(z)-e_{ik}(z))+(p_{ij}(x)-p_{ik}(x))(e_{ik}(z)-e_{io}(z)) \geq 0. \quad (2)$$

If p_{ij} substantially differs from p_{ik}, it could play a major role in choosing major j with respect to smaller differences in $(e_{ij}-e_{ik})$. With $p_{ij} \simeq p_{ik}$, the main determinant of choosing a major is the earnings difference in occupations expected from the two majors. For very talented students, the probability of success is high in all majors and earnings at graduation should matter more than the probabilities of success.

Preceding the choice of college major is the decision to go to college. For at least one major, the discounted expected earnings of s years of additional schooling is equal to or greater than the discounted earning alternative, the tuition and information costs:

$$\int_{s}^{n+s} [p_{ij}(x)e_{ij}(z)+(1-p_{ij}(x))e_{io}(z)]\exp(-rt)\mathrm{d}t \quad (3)$$

$$\geq \int_{0}^{n} e_{io}(z)\exp(-rt)\mathrm{d}t+\int_{0}^{s} sc_{ij}\exp(-rt)\mathrm{d}t,$$

where n is the expected number of years in the labor force, and r the student's discount rate. The schooling costs sc_{ij} include tuition and information costs. Solving for the integrals, Eq. (3) implies:

$$p_{ij}(x) \geq \frac{\exp(rs)-1}{e_{ij}(z)-e_{io}(z)}[e_{io}(z)+sc_{ij}/(1-\exp(-rn))]=\tilde{p}_{ij} \quad (4)$$

With our sample of students, this equation will be useful in the empirical specification of the model, which is discussed next.

Define u^*_{ij} as the expected level of indirect utility for individual i in major j, expressed as a linear function of the individual's expected earnings y^*, normalized by the characteristics of the individual (w), and an unobserved random component (ε) that reflects the idiosyncrasies of this individual's preferences for major j:[3,4]

$$u^*_{ij}=\beta' y^*_{ij}+\alpha'_j w_i+\varepsilon_{ij}, \quad (5)$$

where

$$y^*_{ij}=p_{ij}(x)e_{ij}(z)+(1-p_{ij}(x))e_{io}(z).$$

u^*_{ij} is unobserved. However, the choice C_{ij} made by the individual is observed:

$C_{ij}=1$, if $u^*_{ij} \geq u^*_{ik}$ for all $k \neq j$; $C_{ij}=0$, otherwise.

From McFadden's (1973) random utility models and, if the residuals are independently and identically distributed with the Type 1 extreme-value (or Gumbell) distribution, we can derive a mixed model of the discrete choice [see Maddala (1983), and Hoffman and Duncan (1988)] of the probability P_{ij}, for individual i choosing major j:

$$P_{ij}=\mathrm{Prob}(C_{ij}=1)=\frac{\exp(\beta y^*_{ij}+\alpha'_j w_i)}{\sum_{k=1}^{m}\exp(\beta y^*_{ik}+\alpha'_k w_i)}, \quad (6)$$

where w_i is the vector of individual characteristics for individual i (age, gender, socioeconomic background, etc.). The coefficients α differ for each concentration. We also assume a different constant term for each concentration. Given a new individual with specified characteristics, we can predict the probability that the individual will choose one of the m possible concentrations. The impact of the expected earnings, y^*_{ij}, when enrolling in the concentration j for the individual i is assumed to be constant across alternatives. The coefficient β is expected positive: an individual chooses the concentration that, given his or her preferences, has the highest expected earnings.

We cannot directly estimate Eq. (6), since the components of the expected earnings variable for each concentration, y^*_{ij}, are not observable. The students' perceived probability of success, p^*_{ij}, the expected earnings after graduation, e^*_{ij}, and the earnings alternative, e^*_{io}, are ex-ante variables that must be inferred by the econometrician for all the different college majors that students consider.

The decision-making process is that the individuals evaluate their chances of success in all majors based on their differential probabilities of success. Assume that the underlying probability of success is defined by the regression:

$$p^*_{ij}=\gamma'_j x_i+\mu_{ij}, \quad i=1,\ldots,N,\ j=1,\ldots,m. \quad (7)$$

We must know the vector of parameters γ_j from a set of independent variables x, for example some ability and informational background variables, to infer for each student in our sample his (her) perceived probability of success in all majors. μ_{ij} is an error term. The latent variable p^*_{ij} is unobservable, but we observe a dummy

[3] The are no specific attitude questions or indicators of preferences for college students in the NLSY data set used in this paper.

[4] The linearity of Eq. (5) suggests that the assumption of neutrality with respect to risk should be retained. Extensions on this question along the lines proposed by Orazem and Mattila (1986) and Flyer (1997) would be worth considering in future work.

variable D with D_{ij}=1, if the individual i has completed the degree in major j, D_{ij}=0, otherwise.

In the decision-making process, earnings of graduates also influence students' choices of major. Assume that the earnings of graduates are defined by the regression:

$$e_{ij}=\lambda_j' z_i+\xi_{ij}, \quad i=1,\ldots,N, j=1,\ldots,m, \tag{8}$$

where z is a vector of the demographic, ability, family background and college education variables and ξ is an error term. Again, the parameters of the vector λ_j must be known to infer for each student in the sample his (her) expected earnings after graduation from a major.

Finally, to complete our estimates of the expected earnings for all the individuals in our sample, we need idiosyncratic estimates of earnings alternative. Let us solve Eq. (4) for e_{io}:

$$e_{io}\leq\frac{p_{i.}e_{i.}-sc_{i.}\lfloor(\exp(rs)-1)/(1-\exp(-rn))\rfloor}{p_{i.}+\exp(rs)-1}. \tag{9}$$

Given the average perceived probability of success, $p_{i.}$, and average (expected) earnings $e_{i.}$ after graduation, Eq. (9) indicates the value of the earnings alternative for an individual i not to enroll in a college program.[5] These estimates of earnings alternative are idiosyncratic and preferable to an average earnings of high school graduates.

Assuming one can write the likelihood function for the equation system (6)-(9), its estimation will remain a difficult problem. A two-step procedure will be preferred and considering the recursive nature of the system and assuming weak exogeneity for p^*_{ij} and e_{ij}, this will provide consistent estimates.[6]

This assumed independence between the error terms of the model can be seen as avoiding the usual problem of selection bias and deserves further discussion. To appreciate the difficulty of selection bias with our model, let us go back to the traditional model of occupational or major choices that assumes p^*_{ij}=1 in Eq. (1). Under this assumption, expected earnings by major is reduced to $e_{ij}(z)$. The usual procedure is to estimate a reduced form of the mixed model that included the systematic parts of $e_{ij}(z)$ from Eq. (8) for the expected variable y^*_{ij} in the utility function of Eq. (5). The estimated parameters yield a selection variable (Lee, 1983) for which a value can be calculated for each individual who chooses a particular major. Estimation of the earnings equation by college majors including the selection variables in the second step procedure provided consistent parameters of the determinants of $e_{ij}(z)$. The earnings equation can then be used to calculate predicted (unconditional) graduate earnings for each individual for each major. The last step is to replace y^*_{ij} by $\lambda' z_{ij}$ to obtain the estimates of the structural form of u^*_{ij} with the mixed model. With $p^*_{ij}\neq 1$ (the key feature of our model), this approach is basically unfeasible. The reason being that substitution of the systematic part corresponding to the expected value of p^*_{ij} (Eq. (7)) and e_{io} (Eq. (10)) leads to a highly nonlinear specification of the mixed model. If we use a linear probability model for p^*_{ij}, instead of a probit to simplify the function, we are then confronted with the problem of too many additional parameters to estimate (over 100 additional parameters to estimate corresponding to the cross terms implied by the general definition of y^*_{ij}) relative to the number of observations in some categories. With such a plethora of observed variables to explain the probability of success and graduate earnings (and indirectly earnings alternatives), the expected value of the error terms of these equations, albeit not zero when not correcting for the selection bias, are likely to be small. Clearly, by including a large number of variables that typically are associated with selection bias (the ASVAB vocational test scale score variables and grade point average are proxies for ABILITY) we will not expect a large selection bias in reported estimates. This could explain why, in the literature, "comprehensive" earnings models found little selection bias.[7]

Insofar as the selection issue must be fully comprehended, a couple of extra points are necessary. We used the Rumberger and Thomas (1993) parameter estimates as instruments for estimating graduate earnings as we did not have a sufficient range of variables to allow for plausible estimation. Rumberger and Thomas have not corrected for a selection bias in their earnings equations. This is fortunate since if they had used a correction based on the traditional model of choice of major (i.e. with p^*_{ij}=1), they would have produced a specification error if the "true" model is ours (i.e. with $p^*_{ij}\neq 1$). Finally, in the context of small samples, the real pertinence of selection bias when dealing with the choice of college majors and other related problems involving an expected variable is not that obvious: a biased OLS coefficents can also produce the smallest predictions error of the predicted value of y^*_{ij}.[8]

Before presenting the data and the empirical results, it is important to stress the value added by our model and empirical strategies over Bamberger's (1987) work. Bamberger presents a sequential model of choice of occupation taking into account that individuals, poten-

[5] This upper bound value for e_{i0} based on average (expected) earnings of college students approximates a situation where a person enters a program with the alternative of dropping out but also to a certain extent of changing fields.

[6] Weak exogeneity assumes the independence of the error terms ε_{ij}, μ_{ij} and ξ_{ij}. See Engle, Hendry, and Richard (1983).

[7] See, for example, Fallaris (1987) and Stern, Paik, Catterali, and Nakata (1989).

[8] See Judge, Hill, Griffiths, and Lee (1985).

Table 1
The determinants of college major choice: Major fields of study in college

Constructed title	Description
Business (BUSINESS)	Business and management, business technology
Liberal arts (LIBARTS)	Area studies, communications, fine and applied arts, foreign languages, letters, psychology, home economics, public affairs and services, social sciences, theology, interdisciplinary studies
Science (SCIENCE)	Agricultural and natural resources, architecture and environmental design, biological sciences, computer and information sciences, library science, mathematics, military science, physical sciences, engineering
Education (EDUC)	Education

tially at least, are able to fail in a field of study (equivalent to choosing an occupation), move to another major where they may also fail, and so forth. In our model, we compute idiosyncratic measurements of alternative income if the student fails in college. Bamberger does not do so explicitly although he computes the probability of success in a given occupation, conditional or unconditional to having the ability to complete college. With a simpler model such as ours, we are able to introduce an additional measure of uncertainty incorporated in the *monetary return* associated with *each* major. We are also able to test the robustness of our empirical results across different breakdowns. Finally, the opportunity to change majors is not ignored in our paper. A mixed multinomial probit model we use to explain the data allows for the possibility of correlated error terms across fields of study. In previous literature, the authors only referred to the mixed or conditional multinomial logit assuming the IIA hypothesis. A final complementarity between our study and Bamberger's is that Bamberger predicts the first choice of a major, while we predict the last choice.

3. The data

To estimate the model, we use a subsample drawn from the NLSY cross-sectional sample of 6111 people, ranging from the ages of 14 and 22 in 1979.[9] This subsample includes 851 people whose enrollment status on 1 May 1979 was "in college", studying in either business, liberal arts, science or education (see Table 1 for the construction of these concentrations). Unfortunately, the NLSY did not collect what type of degree had been received from 1985 to 1987, thus limiting our ability to increase the sample size. For the students who were enrolled in 1979, the year of graduation was settled to be in 1983 (i.e., 5 years later). For the others, the graduation years considered were 1982, 1981, 1980 and 1979, respectively.[10] With the elimination of the missing data, the basic sample size for this study is 562. Of these 562 individuals, 150 were in business, with 68 (45%) completing their degree in business; 189 were in liberal arts, with 87 (46%) completing their degree in liberal arts; 157 were in science, with 80 (51%) completing their degree in science and 66 were in education, with 38 (58%) completing their degree in education. The NLSY data base is supplemented by data on various measures of knowledge and skill gathered by means of the Armed Services Vocational Aptitude Battery (ASVAB) that was administered to NLSY respondents in 1980 to generate the Profile of American Youth Study mentioned earlier.[11]

In Table 2, we have divided the variables measuring individual characteristics into four categories: personal, socioeconomic, educational and regional. The personal variables measure gender, race and the ASVAB test scores. The gender variable, for example, seeks to determine whether women are (as is generally believed) less likely than men to choose science. The ASVAB variables seek to determine whether different types of cognitive capabilities affect the probability of success and expected earnings of graduates in the different concentrations. The socioeconomic variables measure family income, the education and occupational levels of parents, as well as elements of family structure such as the education of siblings. By including these variables, we want

[9] In fact, there were three independent probability samples, designed to represent the entire population of youth born in the United States between 1957 and 1964, that were drawn from the NLSY. We used the cross-sectional sample of 6111 people designed to represent noninstitutionalized civilian American youngsters aged 14-22 in 1979.

[10] Note that the results based on 4 years before graduation instead of 5 were similar to those reported in the paper. They are available upon request.

[11] For a description of the NLSY data base and the Profile of American Youth Study, see the NLS Handbook published by the Center for Human Resource Research, 1988, and NLSY documentation Attachment 4: Fields of Study in College, and NLSY Attachment 106: Profiles.

Table 2
The determinants of college major choice: symbol and variable definition

Symbol	Variable definition
Personal characteristics	
GENDER	1 if male, 0 if female
WHITE	1 if white, 0 if black or hispanic
HISPANIC	1 if hispanic, 0 if black or white
BLACK	1 if black, 0 if hispanic or white
ASVABSC1	ASVAB vocational test scale score — general science
ASVABSC2	ASVAB vocational test scale score — arithmetic reasoning
ASVABSC3	ASVAB vocational test scale score — word knowledge
ASVABSC4	ASVAB vocational test scale score — paragraph comprehension
ASVABSC8	ASVAB vocational test scale score — mathematics knowledge
ASVABS10	ASVAB vocational test scale score — electronics information
Socioeconomic factors	
FAMINC	total net family income in 1979 (in dollars)
MOMEDU	highest grade completed by mother (in years)
DADEDU	highest grade completed by father (in years)
MOMPROF	1 if mother worked as a professional, manager or in armed forces in past calendar year, 0 otherwise
DADPROF	1 if father worked as a professional, manager or in armed forces in past calendar year, 0 otherwise
MAMPROF	1 if mother professional, 0 otherwise
DADPROF	1 if father professional, 0 otherwise
MOMMAN	1 if mother manager, 0 otherwise
DADMAN	1 if father manager, 0 otherwise
NUMSIBLS	number of siblings currently attending or enrolled in school
SIBLOEDU	1 if oldest sibling completed college grade, 0 otherwise
FAMILY14	1 if mother and father were both present in household at age 14, 0 otherwise
Regional characteristics	
SMSA	1 if current residence in SMSA, 0 otherwise
SOUTH	1 if region of current residence is South, 0 otherwise
URBAN	1 if current residence urban, 0 rural
School factors	
FIELD	major field of study at current college
EDULOAN	1 if supported by an educational loan, 0 otherwise
PUBLIC12	1 if attended grades 1–12 in a public school, 0 otherwise
GPA	grade point average (0–4 scale)
Others	
XINCS	expected earnings of college students
SUCCESS	estimated probability of success
XEARNG	earnings of graduates
XEARNA	earnings alternative

to see whether there is any systematic relation between a family background that is more privileged in terms of parental income, education, role models, and stability as independent variables and the type of college concentration chosen. As already mentioned, it may be argued that a more privileged background would lead a student to be willing to risk entering a more demanding concentration in science. The parental education variables measure potential educational advantages due to family background that a student has that may influence him or her to choose a concentration with a higher risk of failure. The regional variables measure college education received in urban areas or outside the South. Depending on where an individual acquires his or her education might affect his or her ability or willingness to choose a riskier concentration. It also represents different opportunity costs.

Of the 562 individuals in the sample, 54% are male and 85% are white. As one might expect, women are over represented in liberal arts and education, and under represented in science. For all but one category of ASVAB scores, those of men are higher than those of women. Women come from families with somewhat higher incomes than those of men, while a larger proportion of men than women have fathers who are professionals. Most of the remaining socioeconomic characteristics are the same for men and women.

4. The empirical results of students' perceived probability of success

In the first step of the estimation procedure, under the assumption of the normality of the errors, we use the binary probit model for each major to estimate the determinants of the probability of success in each of the four concentrations.[12] The independent variables are those mainly affecting the perceived probability of success, notably the ability and informational background variables. The ability variables are mainly the ASVAB test scores which are key instruments for the purpose of identification and are excluded from the determinants of the choice of college major equation. These ASVAB test scores are derived from an item response curve psychometric model and are assumed to be independent of the student's race, socioeconomic background and schooling.

The variables with the most significant impact on the probability of success in the business major are the ASVAB mathematics knowledge and vocabulary (word knowledge) scores. In liberal arts, the mathematics knowledge affects the probability of success in this major positively and significantly. The SMSA variable is negative and significant. Living in the south is a significant determinant of the probability of success in education. In addition, as might be expected, the ASVAB vocabulary scores are significant in this major. Also, being a woman positively affects the probability of success in education. In science, no variable appears statistically significant, except for the constant term. A plausible explanation is the collinearity between the ability variables more important in science, where we also observe higher mean ASVAB scores with less dispersion in science than for any other majors. When tested by a block of variables, the ability variables are always significant for each major.

From the coefficients of the probit models, we then compute the perceived probability of success (SUCCESS) in each major for each of the 562 individuals in the sample. In Table 3, we present descriptive statistics for males and females on the observed and perceived probabilities of success by choice of major. As already pointed out, the observed probabilities are the actual proportions of those who enter a college major and successfully complete that major.[13] The highest observed probability of success is in education (0.64) and the lowest is in science (0.36). The perceived (or predicted) probabilities of success are based on the probabilities of success of students with particular abilities, personal and socioeconomic characteristics. We call these probabilities "perceived", because we assume that students with particular characteristics (e.g. women) and abilities recognize that, as a group or individuals, they have a different probability of success in a given major than students with other characteristics and abilities.

Table 3 shows that our model predicts that 52% (the observed probability of success is 0.52) of males who entered the business major succeed. If those same students who entered the business major had instead gone into liberal arts, 45% of them would have succeeded. Note that this percentage is greater than the observed success rate in liberal arts (42%). In contrast, if the male business majors had gone into science, only 44% would have succeeded, a figure that is less than the 57% who actually succeeded.

The probit model predicts that for those who entered liberal arts and education, the perceived probability of success in science is well below the observed probability of success. As for those who entered science, they would do very well in business and education. Table 3 also shows that the male students who actually enter education are especially suited to that major and poorly suited to other majors.

For the female students of any major, the perceived probability of success in education dominates all other probabilities by an important margin. The results of the probit model indicate that most female students, other than science majors, would have done poorly in science had they chosen that major. Women majoring in science show a better or equal predicted probability of success than the male and female observed probabilities of success in business, liberal arts and education majors. At the other end of the spectrum, female education majors would have done poorly in business and science.

5. Estimates of earnings of graduates in each major and the students' alternative

In our theoretical model, the student's expected earnings is a weighted average of earnings when graduating in major j, e_{ij} , and earnings alternative, e_{io}, if the individual has no success in any major. Berger (1988a) showed that the predicted future earnings stream significantly affects the probability of choosing one major over others, more than the predicted beginning earnings. Rumberger (1984) and others have shown that college graduates who major in engineering and business tend to have higher salaries than graduates from other majors and that these differences tend to increase over time (see also Berger, 1988a,b). Data from the NLSY database are

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[12] Results of the probit regressions are reported in Appendix A.

[13] In computing the perceived probability of success for all majors, we have considered a student to be successful in a 4-year program if he or she graduates within 5 years. Although it is possible that some students took longer than 5 years to complete their degree. However, at the time the student decides which major to choose, it is reasonable to assume that the student considers completing the program within the 5-year time period.

Table 3
Means of observed variables and the predicted probability of success

	Observed		Perceived							
			Business		Liberal arts		Science		Education	
	M	F	M	F	M	F	M	F	M	F
Business	0.52	0.38	0.52	0.37	0.45	0.47	0.44	0.21	0.48	0.63
Liberal arts	0.42	0.5	0.45	0.38	0.42	0.5	0.41	0.24	0.51	0.76
Science	0.57	0.36	0.6	0.49	0.45	0.54	0.57	0.35	0.52	0.78
Education	0.45	0.64	0.35	0.31	0.35	0.43	0.31	0.19	0.46	0.64

not suitable to provide an estimate of a future earnings stream by majors. It is also difficult to find instrumental variables that are not used in the probability of success equations or in the final determinants of the choice of major. To circumvent these difficulties, we have borrowed regression coefficient estimates from the study of Rumberger and Thomas (1993) on the economic returns to college majors. With the 1987 Survey of Recent College Graduates (SRCG), this study provided separate regression coefficients of the demographic, ability, family background and other determinants of earnings for men and women that graduated in a specific major.

We were able to link most of these determinants to our set of variables in the NLSY database[14] to compute the (expected) earnings of graduates in each major for the same 562 individuals in the sample for whom a probability of success was estimated in the previous section. The regression constants were adjusted for the unaccountable variables between the two surveys with the mean annual earnings of employed 1985-86 bachelor degree recipients available, by gender, in Rumberger and Thomas (1993).

Table 4 reports the means of the predicted earnings of graduates by major for the men and women in our sample. In every major, the table shows that the earnings of women are noticeably lower than those for men. We observe that science offers the highest earnings for both men and women, closely followed by business. The education major presents the lowest earnings for graduates. The average graduate male and female in science expect earnings better than or equal to all the other average graduates in all fields. The average male and female student entering education faces the lowest earnings after graduation across all majors. On average the business and the liberal arts majors expect marginally lower earnings from graduating in education and marginally higher earnings in science.[15]

Comparing the results of Tables 4 and 5, we note that the projected success in education is higher for an average female student in all fields, but the projected earnings of graduates in education are lower. Therefore, not every woman will choose to major in education. Relative differences in average earnings and in average perceived probabilities of success are observable across all majors in support of the expected earning variable as a major determinant to explain the choice of a major. For a majority of students in science, as for any student likely to succeed in any field, the differentials among earnings of graduates and the students' preferences should play a strong role in their choice.

We do not account for the future earnings stream as in Berger's (1988a) study for men. Estimating the future earnings stream for women will always remain a difficult problem given the many career interruptions of women for pregnancy and motherhood considerations. We have assumed a different constant term for each concentration in the determinants for major choices (Eq. (6)) to reflect, in part, the different expected permanent earnings.

To complete the specification of the expected earnings variable for each individual i in our sample of college

[14] We have considered the following set of overlapping variables between the NLSY and the SRCG databases: demographic (HISPANIC, BLACK, WHITE); family background (MOMEDU, DADEDU, MOMPROF, DADPROF, MOMMAN, DADMAN); college majors (business, liberal arts, science and engineering and education); PUBLIC12 was used as a proxy for the "Private College" variable on the assumption that an individual who has attended grades 1–12 in a public school is likely to continue in a public college; the mean of ASVABSC1, ASVABSC2, ASVABSC3, ASVABSC4, ASVABSC8, recoded to a 0-4 scale was used as a proxy for the "Grade Point Average" variable not available in the NLSY database.

[15] Betts (1996) using evidence from a survey of undegraduates found strong support of the human capital theory assumption that individuals acquire information about earnings by level of education to choose their optimal level of education. He also found that students differ significantly in their beliefs about different fields which implies that students form expectations in various fields. His survey concerned, however, estimates of average salaries not the students' own salaries.

Table 4
Means of predicted earnings of graduates

	Business		Liberal arts		Science		Education	
	M	F	M	F	M	F	M	F
Business	21,298	18,690	18,545	15,824	21,960	18,525	16,866	13,680
Liberal arts	21,369	19,106	18,619	16,192	22,040	18,949	16,902	13,987
Science	21,301	19,634	18,565	16,623	21,975	19,469	16,852	14,358
Education	21,163	18,677	18,449	15,829	21,838	18,534	16,738	13,680

students, we need an idiosyncratic estimate of earnings alternative, e_{io}. Ignoring the schooling costs, sc_{ij}, Eq. (9) simplifies to:

$$\hat{e}_{io} \leq \frac{\hat{p}_{i.}\hat{e}_{i.}}{\hat{p}_{i.}+\exp(rs)-1}. \quad (10)$$

and $\hat{e}_{i.}$ are respectively the average predicted probability of success in college and average (expected) graduate earnings of individual i. With these values, 5 years of schooling, s=5, and assuming a student's discount rate r of 3%,[16] we obtain from Eq. (10) an average earnings alternative of US$13,129 ($e_{.o}$=$13,129) representing 71% of the average earnings of graduates ($e_{..}$=$18,437). For the male sample, the average earnings alternative is US$14,017 or 71% of the average earnings of the male graduates which is US$19,680. The average female earnings alternative is US$12,083 or 71% of the US$16,973 average earnings of the female graduates.

These differences in earnings expressed in terms of high school graduates are coherent with recent statistics reported by Farrell (1999) showing that the ratio of hourly wages of high school only educated workers to college educated workers varies from 65% to 69% over the period 1985-1990. Over a 30-year period, this ratio has ranged from a peak of 74% in 1978 to a low of 63% in 1994. Finally, our earnings alternative estimates result from a decision process by which an individual decides to attend college, conditional on the parameters of that decision process. As pointed out earlier, we consider this approach an interesting way to integrate into the decision model the sample selectivity issue of dealing with a sample of college students.

6. The emirical results on the choice of majors

Table 5 reports the results of the mixed multinomial logit model estimated for all 562 individuals in the sample.

The significance of the α coefficient estimates of the mixed model in Table 6 must be interpreted with respect to major number 4, education. For example, GENDER is highly significant and positive when major number 3, science, is compared with major number 4, education. Therefore, a man is significantly more likely to choose science rather than education. Other variables are also statistically significant. The variable NUMSIBLS, the number of siblings currently attending or enrolled in school, and SIBLOEDU, the oldest sibling having completed a college grade are positive and significant in both science and business. In those sectors, prior information and family experience with college play a role in the student's choice of major. FAMILY14 is negative and SMSA is positive and significant in liberal arts which imply that students with two parents at home at age 14, are less likely to choose liberal arts than education and those living in SMSAs are more likely to choose liberal arts than education. If a student is supported by an educational loan, EDULOAN, he or she is less likely to choose business and science than education or liberal arts. This result suggests that students from less affluent families favor less risky concentrations, as intimated by the Duru-Mingat (1979) model. Although there are a relatively small number of statistically significant variables, when tested blockwise, the group of personal and regional characteristics, socioeconomic and school factors are all statistically significant.[17] The INTERCEPT variable partly captures the differences in future expected earnings of graduates that may systematically vary across majors. They are not, however, statistically significant, suggesting that differences in future earnings are partly measured by some of our quality variables retained in our estimate of the student's expected earnings variable. That last variable, XINCS, is positive and highly statistically significant. This result strongly supports the hypothesis that students choose the major with the highest expected earnings. With a p-value for XINCS at 0%, it clearly establishes that the use of the person specific measures of earnings and the probability of suc-

[16] This follows Rogers (1994) who suggested an evolutionary rate of time preference of 2% per year per generation with the young adults discounting the future more rapidly than the elders.

[17] The p-values rejecting the null hypothesis are, following the same order as in the text, 0%, 0%, 0% and 1%.

Table 5
The determinants of college major choice:mixed model analysis of the full sample

Variable	Comparison	Coefficient estimate	Standard error
Personal characteristics			
GENDER	1/4	0.5679[c]	0.3339
	2/4	0.6600[b]	0.3166
	3/4	0.8098[b]	0.3561
WHITE	1/4	0.1044	0.4846
	2/4	−0.2239	0.4587
	3/4	−0.3592	0.4848
Socioeconomic factors			
FAMINC	1/4	0.00001006	0.00001158
	2/4	0.00001283	0.00001103
	3/4	0.00000743	0.00001148
MOMEDU	1/4	−0.04022	0.08623
	2/4	0.01195	0.08489
	3/4	−0.005802	0.08690
DADEDU	1/4	−0.02343	0.06411
	2/4	0.04780	0.06203
	3/4	0.01983	0.06464
MOMPROF	1/4	0.1386	0.4645
	2/4	0.1847	0.4350
	3/4	0.3235	0.4543
DADPROF	1/4	−0.2580	0.3910
	2/4	−0.03474	0.3715
	3/4	−0.3188	0.3899
NUMSIBLS	1/4	0.1416	0.1195
	2/4	0.05898	0.1159
	3/4	0.2082[c]	0.1198
SIBLOEDU	1/4	0.5500[c]	0.3349
	2/4	0.02062	0.3213
	3/4	0.1882	0.3351
FAMILY14	1/4	−0.3677	0.5126
	2/4	−0.8289[c]	0.4744
	3/4	−0.4849	0.5094
Regional characteristics			
SMSA	1/4	0.3767	0.3576
	2/4	0.7674[b]	0.3510
	3/4	−0.09287	0.3592
SOUTH	1/4	0.3733	0.3542
	2/4	−0.3334	0.3434
	3/4	−0.1732	0.3559
School factors			
EDULOAN	1/4	−0.8297[b]	0.3716
	2/4	−0.3937	0.3456
	3/4	−0.9582[a]	0.3749
PUBLIC12	1/4	−0.1865	0.4853
	2/4	0.07949	0.4697
	3/4	0.05801	0.4971
XINCS		0.0005262[a]	0.0000718
INTERCEPT	1/4	0.08358	1.1992
	2/4	−0.2568	1.1748
	3/4	0.1069	1.2315
Other statistics			
Sample size		562	
Log of the likelihood function		−677.5167	
Chi-square statistic of the model (degrees of freedom)		136.3081 (43)	

[a] Significantly different from zero at the 1% level.
[b] Significantly different from zero at the 5% level.
[c] Significantly different from zero at the 10% level.

Table 6
Estimates of mixed model stratified subsamples

Sample	XINCS	SUCCESS	XEARNG	Number of observations
Full	0.0005262[a]	2.3948[a]	0.0006220	562
	(0.00007183)[d]	(0.4953)	(0.0004062)	
Stratified				
By gender				
Male	0.0007448[a]	4.0238[a]	0.0005811	304
	(0.0001084)	(0.7730)	(0.001106)	
Female	0.0003740[a]	0.9005	0.001484[a]	258
	(0.0001048)	(0.6953)	(0.0005313)	
By race				
White	0.0005251[a]	2.4249[a]	0.0008842[b]	480
	(0.00007879)	(0.5472)	(0.0004474)	
Non-white	0.0008331[a]	3.1574[c]	0.001169	82
	(0.0002331)	(1.6206)	(0.001353)	
By socioeconomic background				
Low[e]	0.0007285[a]	3.4733[a]	0.0004598	144
	(0.0001605)	(1.0577)	(0.0009398)	
Middle[f]	0.0004806[a]	1.7922[a]	0.0009646	287
	(0.00009873)	(0.7048)	(0.0005913)	
High[g]	0.0007331[a]	3.6044[a]	0.001666	131
	(0.0001961)	(1.2557)	(0.001061)	

[a] Significantly different from zero at the 1% level.
[b] Significantly different from zero at the 5% level.
[c] Significantly different from zero at the 10% level.
[d] ( ): Standard error.
[e] Based on family income ≤$14,990.
[f] Based on family income between $14,990 and $35,280.
[g] Based on family income ≥$35,280.

cess enhances the predictive power of a regression model using simple average earnings by field.[18] Breaking down the direct weighted aggregate elasticities of the variable XINCS by major, we obtain respectively a value of 5.94 for the business students, 4.68 for the liberals arts students, 5.63 for the science students and 5.55 for the students enrolled in education.[19]

These elasticities are substantial. We can also establish that at the mean values the elasticity of choosing a particular major with respect to the success variable is smaller than the elasticity with respect to the earnings of graduates. Since we suggested earlier that talented students will mainly react to the earning of graduates variable, then clearly to attract talented students to education, one has to raise the earnings of education graduates.

In Table 6, we report the results of the multinomial logit model applied to the full sample and to some stratified subsamples. Only the estimates for the college student expected earnings variable, XINCS, are presented, with the complete results available from the authors. To compare with specifications used in earlier studies, we also present in Table 6 the results for the probability of success variable, SUCCESS, and the earnings of graduates variable, XEARNG, obtained from separate mixed multinomial models.

The estimations of the mixed multinomial logit model by gender indicate that the statistically significant impact of the expected earnings variable is twice as great for men than for women. This result reflects the willingness of women to go into nontraditional careers. An alternative explanation is that women drop out for reasons related to nonacademic problems. Therefore, the probability of success is less important to them in selecting a major (see Siegfried, 1992). In the narrow specifications, the probability of success variable, SUCCESS, has a positive and statistically significant impact on the choice of major for men, while the coefficient of the earnings of graduates variable, XEARNG is insignificant. In contrast, SUCCESS for women is insignificant but XEARNG has a positive and significant influence. These results appear to support our interpretation of the results from the general specification.

[18] Note that a regression model using average earnings by field corresponds to our model assuming a different constant by major without introducing the person-specific measures of expected earnings.

[19] Computations are based on the work of Hensher and Johnson (1981).

When we stratify by race, the positive and statistically significant impact of XINCS is larger for the nonwhite population than for the white group. If preferences are important in choosing a major, they seem to play a greater role for whites. Here the narrow specifications produce results that are difficult to interpret with no significant variables for the nonwhite sample.

Stratification of the sample by socioeconomic background yields a significant and positive influence of XINCS with, however, no important differences between the groups. When defined separately, SUCCESS is a significant decision factor in choosing a major for the three socioeconomic groups, but not XEARNG. These results are also observed when the narrow specifications are applied to the full sample.

The narrow specifications are not nested in the expected earning variable complete specification and cannot be easily compared. However, in Eq. (2), we showed that for SUCCESS or XEARNG to be a correct specification for the model of choice of college majors, we have to assume a constant earnings stream across majors or a constant probability of success across majors. These two assumptions were not empirically supported by the results of Tables 3 and 4.

Finally, one well-known restriction of the mixed multinomial logit model is the Independent Irrelevant Alternatives hypothesis. The IIA property holds that for a specific individual, the ratio of the choice probabilities of any two alternatives is entirely unaffected by the systematic utilities of any other alternatives. In Table 7, we report for the full sample, the parameter estimates for our key variable XINCS from two procedures that avoid this restriction (thus, explicitly allowing in terms of Bamberger, the possibility of changing majors). In column one, we used an heteroscedastic extreme value model (HEV) developed by Bhat (1995) which assumes that the error term variances vary across alternatives. In the multinomial probit models (MNP), correlated error terms among alternatives are not assumed to be zero. The results obtained from these estimations are quite comparable to those reported in Table 5 with the parameter estimates for XINCS positive and statistically significant at the 1% level. Comparing the loglikelihood values obtained from these models, the IIA hypothesis does not appear to be a problem (note that the MNP model assuming σ_{ij}=0 implies the IIA and that the coefficient values of MNP and HEV are not directly comparable). A word of caution, however, is needed, as the HEV and MNP models are generally difficult to estimate with many alternatives.

7. Conclusion

Elements of equal opportunity and representativity, shortages or surpluses in occupations are important and complex issues related to educational choice. There are many elements entering the choice of concentration of college students. Preferences, information and the family socioeconomic background can all play an important role. In some cases, there can be elements of inequality in educational choice based on gender, race or wealth status of the student. Choosing a concentration is a decision under uncertainty. One major element of that uncertainty concerns the expected earnings with the concentration chosen. Here, in contrast to previous studies, we distinguished three parts to expected earnings: the perceived probability of success or perceived ability and effort needed to complete with success the concentration chosen, the (expected) earnings after graduation and the earnings alternative if the student fails to complete a college program. This paper has analyzed the extent to which the choice of concentration depends on the complete expected earnings variable in that concentration relative to other areas of concentration that could have been chosen.

Using data from the National Longitudinal Survey of Youth, we estimated the model with mixed multinominal logit and probit models and with an heteroscedastic extreme value model.

The results are robust and show that the choice of college concentration depends decisively on the expected

Table 7
Results from an heteroscedastic extreme value model and multinomial probit models[a]

	HEV	MNP		
	$\sigma_j^2=\pi^2/6\theta_j$	$\sigma_{13}\neq 0$	$\sigma_{24}\neq 0$[b]	$\sigma_{13}\neq 0$, $\sigma_{24}\neq 0$[b]
XINCS	0.000526	0.0003695	0.0003804	0.0000397
	−1585	−5908	−6926	−73
Loglikelihood at convergence	−67762	−67826	−67662	−67684

[a] The results of the mixed multinomial logit model reported in Table 6 were obtained assuming θ_j=1 and σ_{ij}=0. The loglikelihood of this last model is −677.52 and XINCS=0.0005262 (0.00007183). For the mixed multinomial probit assuming σ_{ij}=0, the loglikelihood is −678.56 and XINCS=0.0003803 (0.00005400).

[b] Saddle points have been reached at convergence.

earnings in a particular concentration. There are, however, differences in the impact of the expected earnings variable by gender and race. Women are less influenced by this variable compared to men and nonwhites more than whites.

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Appendix A

Table 8 shows the determinants of the probability of success.

Table 8

Variable	Estimated coefficient (standard error)			
	Business	Liberal arts	Science	Education
GENDER	0.09626	−0.2171	0.1869	−1.4103[b]
	(0.2790)	(0.2295)	(0.2950)	(0.6453)
WHITE	−0.3320	0.04989	−0.06136	0.08811
	(0.4276)	(0.3440)	(0.3326)	(0.6951)
ASVABSC1	2.5000E-04	−1.0000E-05	3.1000E-04	7.0000E-05
	(2.0000E-04)	(2.0000E-04)	(2.0000E-04)	(4.0000E-04)
ASVABSC2	1.7000E-04	1.5000E-04	−4.0000E-05	4.5000E-04
	(2.0000E-04)	(2.0000E-04)	(3.0000E-04)	(4.0000E-04)
ASVABSC3	2.0000E-04	3.4000E-04	2.2000E-04	1.2600E-03[a]
	(3.0000E-04)	(2.0000E-04)	(2.0000E-04)	(4.0000E-04)
ASVABSC4	−2.0000E-04	2.0000E-04	−3.1000E-04	−5.8000E-04
	(2.0000E-04)	(2.0000E-04)	(3.0000E-04)	(5.0000E-04)
ASVABSC8	6.8000E-04[a]	3.2000E-04	4.5000E-04	−5.0000E-04
	(3.0000E-04)	(2.0000E-04)	(3.0000E-04)	(4.0000E-04)
ASVSC10	−2.2000E-04	−2.3000E-04	2.0000E-04	3.6000E-04
	(3.0000E-04)	(2.0000E-04)	(2.0000E-04)	(5.0000E-04)
SIBLOEDU	0.1026	0.06328	0.1021	−0.3729
	(0.2353)	(0.2006)	(0.2290)	(0.4151)
SMSA	−0.1346	−0.6239[a]	0.3759	0.4561
	(0.2733)	(0.2502)	(0.2659)	(0.5154)
SOUTH	−3.9500E-03	0.07413	0.1658	1.1291[a]
	(0.2574)	(0.2529)	(0.2593)	(0.4688)
EDULOAN	0.2127	−0.2201	0.2790	−0.1815
	(0.2733)	(0.2413)	(0.2658)	(0.4394)
PUBLIC12	−0.01302	−0.4926[c]	0.09217	−0.2193
	(0.3162)	(0.2673)	(0.3407)	(0.6968)
INTERCEPT	−0.7974	(0.1218)	−1.7276[a]	−0.1013
	(0.5844)	(0.5205)	(0.5786)	(0.8682)
Other statistics				
Sample size	150	189	157	66
Likelihood ratio χ^2	3283	3896	3236	245
Degrees of freedom	13	13	13	13
P-value	2	0	2	27

[a] Significantly different from zero at the 1% level.
[b] Significantly different from zero at the 5% level.
[c] Significantly different from zero at the 10% level.

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