IS THERE A HIDDEN TECHNICAL POTENTIAL?*

Hessel Oosterbeek**

Dinand Webbink***

Abstract

This paper analyzes the determinants of choosing a technical study at university level and of persistence in it. We find that - in the Netherlands - there is a low correlation between the probability of a student choosing a technical study and the probability of persistence in it. This implies that a substantial number of technically talented people choose non-technical studies. Especially female students and students from high income families are unlikely to attend a technical study but these students are relatively successful in such studies. A large fraction of these technically talented students are attracted to medical studies and law schools, where they are no more likely to persist in these schools than other medical and law students. This finding is predicted by the tournament model in which rewards are based on relative performance instead of absolute performance.

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** Department of Economics; University of Amsterdam; Roetersstraat 11; 1018 WB Amsterdam; The Netherlands; Max Goote Centre for Vocational Education and Training, and Tinbergen Institute; E-mail: hessel@fee.uva.nl.

*** Foundation for Economic Research; University of Amsterdam, Roetersstraat 11; 1018 WB Amsterdam; The Netherlands.

1 Introduction

In many countries, concern is being expressed about the shortage of technically skilled workers. Enrolment rates in higher education are increasing in most western countries, but the market share of technical studies is declining.[1] Table 1 gives a picture of current enrollment patterns by subject in selected countries.

[Table 1]

Figures like these have led one commentator to conclude that "the universities continue to churn out humanities-trained generalists at a time of soaring demand for scientists and engineers".[2]

Of course, it can be questioned whether technical studies really are more desirable than non-technical studies. According to a recent analysis by Murphy *et al* (1991), "countries with a higher proportion of engineering college majors grow faster; whereas countries with a higher proportion of law concentrators grow more slowly" (p.503). This finding supports the same authors' theoretical model in which talented people are allocated over rent-seeking activities on the one hand, and entrepreneurship and innovation on the other. Lawyers are typically engaged in rent-seeking activities (which is bad for growth) while engineers are typically engaged in entrepreneurship and innovation (which is good for growth). A similar point is made in a recent book by Frank and Cook (1996) who discuss the emergence of what they call "Winner-Take-All" markets. In such markets relative rather than absolute performance determines earnings, and a small difference in performance may lead to substantial differences in rewards. Such markets attract inefficiently large numbers of persons since individuals typically tend to overestimate their

[1] In the Netherlands for instance, the market share of science and engineering in university education decreased from 34.8% in 1960 to 22.1% in 1989. This overall decline is the result of declines from 39.4% to 31% for males and 13.9% to 9.4% for females, and an increase in the proportion of females (NCBS, 1992, 120/1).

[2] Wooldridge, Adrian, Coming top, a survey of education, The Economist, November 21, 1992, 3-18.

chances of winning. According to Frank and Cook, of all winner-take-all markets they discuss in their book, "the evidence of overcrowding is clearest in the legal profession" (p.219).

Governments in different countries have introduced various measures to attract more students to technical studies. Policy instruments include information and advertising, reduction of tuition fees, and extending the duration of study programs. But at best these measures have slowed down the decline; they have not produced an increase in the market share of these studies.

In any case, attracting more students to technical studies would not guarantee the production of more graduates in these areas. Due to current patterns of self-selection, it is quite likely that the students who opt for a technical study are also the ones likely to succeed in completing the course, while those who do not attend technical courses may have chosen not to do so because of a high (perceived) probability of failure.

In this paper, therefore, we address the issue of whether current enrolment patterns hide a substantial group of persons who could have been expected to graduate from a technical study. To that end we deal with two interrelated questions: (i) What are the determinants of choosing a technical study, and (ii) conditional upon attendance, what are the determinants of persistence in technical studies? Subsequently, we use the findings to identify students who have technical talent, but nevertheless have chosen non-technical studies.

The remainder of this paper is organized as follows. Section 2 sketches the theoretical framework underlying our empirical analysis. Section 3 describes the statistical model to be employed in this paper. Section 4 introduces the data set and discusses the choice of variables. Section 5 presents and discusses the empirical findings. Section 6 deals with the implications of our findings, and Section 7 summarizes our conclusions.

2 Theoretical background

This paper deals with educational choices. The standard economic framework to analyze such choices is the human capital theory (e.g. Becker (1967) and Mincer (1974)).

According to this theory, educational choices are based on investment decisions, quite analogous to firms' decisions to invest in physical capital. Individuals are assumed to compare the benefits and costs of different alternatives and to choose the alternative with the highest internal rate of return.[3]

There is a wide variety of empirical models analyzing educational choices from a human capital perspective. The seminal paper in this field is Willis and Rosen (1979). In that paper the choice whether or not to attend college is analyzed with a probit model. For those who went to college and for those who did not, separate earnings equations and earnings growth equations are estimated to impute the expected earnings gain from college as an explanatory variable in the college choice equation. It is found that a larger expected earnings gain leads to a higher probability to attend college. Instead of analyzing the dichotomous choice of whether or not to attend college, Garen (1984) estimates a model where education is a continuous variable measured by the number of years of schooling. The schooling equation therefore has an OLS structure. More involving is the sequential choice (logit) model developed by Hartog, Pfann and Ridder (1989). At each level of schooling, students can choose between the options of stopping, graduating from the next level or dropping out from the next level.[4] A common feature of these models is that information about expected earnings is based on realized earnings; implicitly these models therefore operate on the strong assumption that students' expectations about future earnings are unbiased *ex post*. A different approach is followed by Kodde (1985) who asked respondents about there earnings expectations with and without further schooling. Although the source of earnings information is very different, Kodde also finds that a higher expected earnings gain from further schooling is associated with higher probabilities to stay on in school. Similar results are reported in Oosterbeek and Webbink (1995).

This short description of the empirical literature on educational choices indicates that a number of very different models have been used. But although the education variable

[3] With regular patterns of costs and benefits, alternative measures to evaluate investments, such as the cost-benefit ratio or the net present value, will lead to the same decision.

[4] Other versions are the tobit model applied by Kenny et al (1979) and the ordered probit model applied by Harmon and Walker (1995).

has been measured in different ways, all these measures more or less describe the same dimension of education, namely its level. Other relevant dimensions of education that may in principle be subject to individual choices are: the quality of schooling, the choice for a particular college or university, and the field of study.[5] This paper is concerned with this latter dimension. Most economic studies that deal with the choice of field of study use aggregated data instead of individual data. These studies relate the number of entrants into specific fields such as law or teaching to earnings prospects of these fields (examples include: Freeman 1975, Zabalza 1979, Zarkin 1985, Rosen 1992). Freeman (1975) concludes that students enrolling in law schools tend to behave myopically thereby causing "legal cobwebs". The more recent studies in this line of research find support for more sophisticated expectations models.

An exception to the studies that are based on aggregated data is Berger (1988). In this paper, Berger analyzes the choice between different main subjects of study at US colleges. Using a multinomial logit model, he distinguishes five subjects: business, liberal arts, engineering, science and education. In addition to the choice equation, Berger also estimates subject specific earnings equations.[6] For this he uses information about the realized earnings of the persons who chose a particular subject. From the estimated coefficients Berger calculates for each person in the sample expected earnings streams for all five subjects and imputes these in the college choice equation. He finds that the probability that a student will choose a particular main subject increases with the relative present value of the predicted future earnings of that subject. Notable is also the finding that the choice of a particular subject is not significantly influenced by predicted relative starting earnings from that subject. This indicates that using starting earnings as a proxy for lifetime earnings may underestimate the importance of financial aspects in educational choices.

The analysis in this paper is related to Berger's model, but differs from it in some important aspects. These differences are due to the different focus that we have, and to data

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[5] The choice of quality of education has been analyzed by Venti and Wise (1982); the choice for particular economics departments in the Netherlands has been analyzed by Oosterbeek, Groot and Hartog (1994).

[6] Using a procedure proposed by Trost and Lee (1984) these earnings equations are corrected for selectivity bias.

limitations. First, instead of distinguishing five different fields of study, we only distinguish between the clusters of technical studies and non-technical studies. Performing the analysis in this paper with more narrowly defined fields of study would certainly be an improvement, but the numbers of observations per field in our data set are too small to allow this. Given that we are primarily interested in technically versus non-technically talented students, we do not consider this a real disadvantage.

Second, the most important determinants in Berger's choice equations are the earnings prospects from the different fields of study. As we mentioned, these earnings prospects for, say, engineering are calculated from the earnings realized by those students who majored in engineering. In our model, earnings prospects are not included in the analysis. This is not because we dispute the importance of earnings prospects for educational choices. It is "simply" a matter of not having the information in our data set. The data we use in this paper (see Section 4 for more details) are from students who started their studies in 1991. Only a very few of them already finished their education and reported their realized earnings. This number is too small to apply Berger's procedure. The data set does, however, include information about the earnings which the respondents expect to earn after graduation. In principle we could perform Berger's analysis and use these expected earnings instead of realized earnings. For that purpose, we ran some preliminary "expected earnings" equations; the results were, however, extremely poor (very low R-squares and t-ratios). Therefore we decided not to use these results to calculate earnings prospects for the technical and non-technical studies.[7] Not including earnings prospects into the educational choice equation does not mean that our model is at odds with the human capital framework. We do include a number of explanatory variables in the education choice equation that can be considered as determinants of earnings prospects in the technical and non-technical occupations. In that sense, our specifications do justice to the human capital model in a reduced form mode (see below).

[7] But even when these expected earnings equations would have given better results, the usefulness can be questioned. As we mentioned, Berger finds significant effects on educational choices from predicted present values of earnings streams and not from predicted starting earnings. And the data about expected earnings in our data set, relate to expected starting earnings.

The third, and - in our view - most important difference between Berger's model and our model is that we deal with the issue whether a student is successful in the preferred field of study. Berger does not consider this issue. A related study is Venti and Wise (1983), which deals with the relation between choosing to attend college and completion of college. That study finds that "persons who are unlikely to attend are very likely to drop out without a degree should they attend and persons who are likely to attend are unlikely to drop out" (p.28). The economic importance of this finding is that it indicates that the selection process into US colleges is highly efficient; not many resources are wasted by admitting students who have a high probability to drop out, and also there is no waste of talent by not admitting students who would have been successful. Our analysis is an extension of the analysis by Venti and Wise, in the sense that we analyze the determinants of attending different fields of study (instead of attendance in general), and of success in technical studies (instead of success in college). With the results we can address related efficiency issues: (i) whether the resources spend on the (expensive) technical studies go to students who have a high probability to graduate, and (ii) whether there is no waste of technically talented students in the non-technical studies.

3 Statistical model

The two dependent variables in the analysis are both binary: whether or not to attend a technical study, and whether or not to persist in it. The usual method of modelling such variables is to apply a probit (or logit) procedure. As it cannot be assumed *a priori* that the error terms of the two equations that determine the dependent variables are uncorrela-ted, we specify a bivariate probit model rather than two separate probit equations. A further complication is that one of the dependent variables is censored. We cannot observe whether students who did not choose a technical study would have persisted had they done so. For that reason we apply the bivariate probit model with censoring. This model was first propo-sed by Van de Ven and Van Praag (1981), and is described in Greene (1990, p.664).

Let y_1^* be a latent variable that measures the net gains from attending a technical study, and let y_2^* be a latent variable that measures the net gains from persisting in it. y_i^* is affected by a vector of observed explanatory variables x_i and a disturbance term ε_i. The latent variables y_1^* and y_2^* are not observed. Instead we observe the dichotomous realizations y_1 and y_2. We propose the following model structure:

$$y_1^* = \beta_1' x_1 + \varepsilon_1, \quad y_1 = 1 \textit{ if } y_1^* > 0,\ 0 \textit{ otherwise}.$$

$$y_2^* = \beta_2' x_2 + \varepsilon_2, \quad y_2 = 1 \textit{ if } y_2^* > 0,\ 0 \textit{ otherwise}.$$

The disturbance terms ε_1 and ε_2 are assumed to follow a joint normal distribution with $E[\varepsilon_1] = E[\varepsilon_2] = 0$, $Var[\varepsilon_1] = Var[\varepsilon_2] = 1$ and $Cov[\varepsilon_1,\varepsilon_2] = \rho$.

With these assumptions, the log-likelihood function reads

$$LogL = \Sigma_{y_1=0} \log[1-\Phi(\beta_1' x_1)] + \Sigma_{y_1=1,y_2=0} \log\Phi_2(\beta_1' x_1, -\beta_2' x_2, -\rho) + \Sigma_{y_1=1,y_2=1} \log\Phi_2(\beta_1' x_1, \beta_2' x_2, \rho),$$

where Φ is the distribution function of the univariate normal and Φ_2 is the distribution function of the bivariate normal. The first term on the right-hand side relates to the censored observations for students who do not choose a technical study. The second and third term relate respectively to the dropouts and to students who persist in their technical studies.

4 Data and choice of variables

The data set employed in this paper is a sub-sample of a nationwide longitudinal sample of all Dutch students. In that sample, about 6,000 students were interviewed first in 1991. Annual follow-ups were held in 1992-1995. The sub-sample that we have selected consists of all students who were already enrolled in university education in 1991 but had not yet fulfilled the requirements for the first year. The remainder of the sample consists of students who had at this time already passed the first year examinations, those who were then still in secondary education, and students in higher vocational education. The sample is stratified, with the strata being defined in terms of the stage of study (first-year and more advanced students) and the type of study (eight different fields were distinguished).[8]

[8] The estimation procedure needs to take account of this choice-based sampling design. To remedy this defect, Manski and Lerman (1977) propose to add weighing factors to the individual probabilities in the log-likelihoodfunction. The weighing factors are the ratio of

Analyses regarding the representativeness of the sample indicate that for some sectors of study it includes over-representation of females and younger students. For the other sectors there is no indication of any systematic bias. A detailed description of the collection of the data along with all kinds of cross-tabulations can be found in De Jong *et al*. (1992).[9]

The first dependent variable in our analysis is the chosen subject of study, clustered in the two categories technical and non-technical. Technical studies consist of engineering and science. Agriculture and medicine, together with economics/business studies, social sciences, law and languages, are assigned to the non-technical cluster. The second dependent variable is a measure for the student's success in a technical study. The measure that we employ is whether or not the student fulfilled the requirements for the first year. Students who fulfilled those requirements are those who persisted in their technical studies. A better measure for a student's success would be whether or not a degree is obtained. Unfortunately, only very few respondents have reached this stage; most cases are censored. Moreover, the later follow-ups of the data set suffer from a significant amount of panel attrition. However, the measure of passing the first year examinations is believed to be very close to the `ideal' measure of graduation, since it is known from other sources that very few students who successfully complete the first year drop out later. The apparent sorting role of the first year is an explicit policy aim in Dutch universities; the stated purposes of the first year are orientation and selection. Success in first year examinations indicates the ability to graduate. In our final sample of 853 cases, 212 (25%) chose a technical study and, 158 (75%) of these persisted after the first year.

We use two types of explanatory variables in our analysis: background characteris-

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the population proportion to the sample proportion of the alternative. It turns out that the combined fractions of students in science and engineering in the sample is 25%, which is very close to the population fraction of 22%.

[9] Another Dutch data set with information from students is the RUBS-survey, which registers the destination of a large sample of Dutch school-leavers in secondary education six months after their final exams. Since this survey has no follow-ups, it includes no information about the success of the students who have chosen a university study. Consequently this data set is not suitable for our analysis.

tics and measures of the student's ability. The background variables that we use are gender, education of the parents (measured as the maximum of the father's and mother's level of education), parental income, the number of children in the student's family (number of siblings plus one) and the respondent's age at the time of starting the university study. Indicators of the student's ability are: the average marks achieved in secondary school-leaving examinations for different clusters of subjects (languages, science and humanities), the number of times that the student repeated a class and the type of secondary education, advised at the end of primary school. In addition we include two variables which measure the student's motivation. The first measure is a weighted average of the scores on questions about the importance of labor market perspectives in choosing a study and is believed to proxy extrinsic motivation. The second measure is based on the answers to questions relating to interest in the contents of the study and is an indication of intrinsic motivation. All explanatory variables are allowed to affect both dependent variables; the bivariate probit model with censoring requires no exclusion restrictions.

As discussed in Section 2 already, earnings prospects are not included as a determinant of the choice of field of study. We believe, however, that the variables that are included in this equation may be regarded as capturing the human capital notion in a reduced form manner. From a human capital perspective it is the net present value of lifetime earnings which matters. This variable is based on two ingredients: the earnings stream and the individual's discount rate. The future earnings stream is determined by a number of different factors. Some of these factors are related to future labor market conditions which are unknown at the moment that the student decides which type of study to attend. An important factor affecting future earnings, and about which some information is available already is the student's level of ability. The ability variables included in the choice equation can thus be seen as proxies of earnings prospects. The second ingredient of the net present value of lifetime earnings, the individual discount rate, is never actually observed. It is common practice, however, to assume that this discount rate varies in line with a person's social economic status (cf. Willis and Rosen 1979). Some of the background variables that we included as explanatory variables (parents' income and parents' education), reflect social economic status.

The Dutch system of upper level secondary education is such that students do their final examinations for seven subjects only. These seven subjects are chosen by the student from a larger number of possible subjects. There are some restrictions regarding the choice of subjects. As a result of students' selection of subjects, some take examinations for a larger number of science-related subjects than others do. One might argue that the type of subjects chosen in secondary education (for instance measured by the number of science-related subjects) should be included as explanatory variable in our model. A good reason for doing so is that a number of technical studies at the university level require the student to have taken at least three subjects from the cluster mathematics, natural science, chemistry and biology in secondary education. For students who took less than three subjects from this cluster, this requirement restricts the potential choice of subjects which can be studied at university. An argument against including the number of science-related subjects as an explanatory variable is that the choice of secondary school subjects and the choice of university study can be seen as different manifestations of the same decision making process. In that case the number of science-related subjects can not be treated as an exogenous variable. Treating the number of science-related subjects as an endogenous variable is, however, not feasible; the statistical model would become too complex and other true exogenous variables would be required to identify the different endogenous variables. To do justice to this problem, we estimate two versions of the model. In the first version we use the entire sample, and do not include the number of science-related subjects in the list of regressors. In the second version we use the sub-sample of students who took examinations in at least three science-related subjects in secondary education.

The Appendix to this paper gives a description of each of the variables and also reports the mean values and standard deviations for each variable, separately for each of the three groups of students: students in non-technical studies ($y_1 = 0$); students in technical studies who did not persist ($y_1 = 1$ and $y_2 = 0$); and students in technical studies who persisted ($y_1 = 1$ and $y_2 = 1$).

5 Empirical findings

We estimated the bivariate probit model with censoring for the full sample and for the sub-sample of students who took examinations in at least three science-related subjects in secondary education. For both versions, we find a value for the correlation coefficient of the error terms in the bivariate probit model (rho) which does not differ significantly from zero. We formally tested whether we could impose the restriction of rho being equal to zero, and in both cases we could not reject this restriction. As the estimates for the remaining parameters in the restricted model are more efficient than those in the unrestricted model, the remainder of this discussion is based on the outcomes of the restricted models.[10]

Table 2 presents the estimation results for the full sample. The results in the first column relate to the probability of choosing a technical study. The results show that females are less likely to choose a technical study than males. Evaluated at mean values of the other explanatory variables, a male student has a probability of 32.5% of choosing a technical study, while for a female student this probability is only 10.8%. This lower probability of females choosing a technical study is consistent with the lower participation rate of female students in these studies in the Netherlands. The result in Table 2 indicates that this is a pure gender effect which still arises if we control for other characteristics. Students who choose a technical study also tend to be younger than the non-technical students. Raising the student's age at the start of the study by two standard deviations above the mean (and holding the other characteristics constant at mean values) decreases the probability of choosing a technical study by 8.5%. One reason for this finding might be that a person's ability to learn abstractions is believed to decrease with age. Another explanation might be that, on average, students in technical studies stay at university longer. This longer average study duration increases the (opportunity) costs of the education while at the same time - by shortening the revenue period - lowering potential benefits. Both the reduction of benefits

[10] The results of the unrestricted versions of the model are available from the authors on request.

and the increase in costs have less impact on younger students. The negative relation between age and the probability of choosing a technical study might, however, also be due to the fact that technical studies attract better students and that better students tend to be younger when they go to university.

A remarkable finding is that children from high income families have a significantly lower probability of choosing a technical study. Increasing family income by two standard deviations above the mean reduces the probability of a technical study by 6.2% (evaluated at mean values for other variables). This result is consistent with the theory of the French sociologist Bourdieu (1984) that scientific disciplines can be ordered on a scale with scientific prestige and social prestige at its furthest points. The ordering of disciplines on this scale depends on a complex set of relations which express economic, social and cultural differences. From the social extreme to the scientific extreme, the current ordering is: law and medicine, arts and social sciences, natural science and mathematics. Children from higher income families are more likely to have a preference for social rather than scientific prestige. The influence of family earnings on the probability to choose a technical study is compatible with the human capital model if age-earnings profiles of graduates from technical studies are less steep than those of graduates from non-technical studies. With steep profiles a large part of the returns is realized later in career. Persons from lower income families are assumed to have higher discount rates and will therefore attach less weight to these late-career returns.

Furthermore, a higher average mark for science-related subjects in the secondary school-leaving examinations increases the probability of a technical study being chosen. This effect is quite large; adding two standard deviations to this average mark increases the probability of a technical study by 35.6% (again evaluated at mean values for other variables). Within the human capital framework this finding is explained as those with higher average marks for science-related subjects having better relative earnings prospects in occupations requiring a technical study than the students with lower average marks for these subjects. Finally, the results in the first column show that students with a higher level of intrinsic motivation are more likely to choose a technical study. Note that this is again consistent with Bourdieu's typology: sciences have a high level of scientific prestige and those who choose these studies have a genuine academic interest in them.

The results in the second column relate to the conditional probability of persistence, given that a technical study has been chosen. With one exception, the outcomes in this column deviate considerably from those in the first column. The exception is that students who received higher average marks for science-related subjects in secondary education not only have a higher probability of choosing a technical study, but are also more likely to persist in it. On the other hand, female students in the technical studies are more likely to persist than male students, although female students are less likely to choose a technical study in the first place. Likewise, students from high income families have a lower probability of choosing a technical study but, given that a technical study has been chosen, these students are more likely to persist than students from low income families. Thus, gender and family income have exactly opposite effects on the probability of choosing a technical study and the probability of persisting in it. Furthermore, we find that neither age nor the level of intrinsic motivation has a significant effect on the probability of persistence. Although younger students and students with more intrinsic motivation are more likely to embark on a technical study, they are no more likely to persist in such a study than students who lack these characteristics.

As already mentioned, the results in Table 2 are based on the restriction that the correlation coefficient of the error terms in the bivariate probit model is equal to zero. We could not reject this restriction. This implies that omitted variables which affect the two probabilities are uncorrelated. Hence, taken together, the unobserved characteristics that increase the probability that a student will choose a technical study are not correlated with the unobserved characteristics that affect the probability of persistence in it. Our results do not say that the effects of these variables in the two equations are unrelated, but rather that these effects are balanced by the effects of other omitted variables.

To shed some more light on the results in Table 2, we calculated for each respondent in the sample the predicted probabilities both of choosing a technical study and of persistence in it. As the results in Table 2 already suggest, the relation between the two (predicted) probabilities is not very strong; the simple correlation coefficient is 0.204 and differs significantly from zero. Those with a high probability of choosing a technical study are more likely to persist than those with a low probability of choosing one. As the reported correlation is rather low, this does not imply, however, that there is no latent technical talent among students on other courses. Especially among females and students from high-income families, there may be a hidden technical potential.

In Table 3 we report the estimation results for the same model but now using only the sub-sample of students who took final examinations in at least three science-related subjects in secondary education.

[Table 3]

The results are basically similar to those in Table 3. The only notable difference is that the influence of family background on the choice of field of study is now captured by parents' level of education instead of family income. The correlation between the predicted probabilities of choosing a technical study and persisting in also quite low (0.248), and is again significantly different from zero. These findings show that the results in Table 2 are robust with respect to conditioning on the number of science-related subjects in secondary education. Therefore all further analyses are based on the results in Table 2.

6 Implications

The results reported in the previous section can be used to identify the students who did not choose a technical study, but had an above-average probability of persisting in it had they done so. We identify this technical potential using the estimation results from Table 2. Table 4 indicates the areas of study in which these technically talented students are currently located.

[Table 4]

The procedure applied here searches for talented students by identifying females from high income families who had high average marks for science-related subjects in secondary school. Students with latent technical talent outside the technical studies, are almost uniformly distributed over all studies, with a modest over-representation in economics, medical sciences and agriculture. Whether or not it is desirable to attempt to channel these people into technical studies depends on their performance in their current studies. In other words, on whether those students who are identified as having latent technical talent also have high persistence probabilities in their current studies. To address this question, we estimated simple probit equations where the dependent variable is the dichotomous variable which indicates persistence in the current study and the single explanatory variable is a dummy variable which equals unity if the person is considered as having technical talent (i.e. an above average probability of persisting in a technical study). Estimations were performed for each non-technical study separately. Table 5 contains the results.

[Table 5]

The results indicate that harmless extraction could take place from the medical schools and law schools. This suggests that there is a waste of students with technical talent in medical and law studies. These studies attract substantial numbers of technically talented students, while these students have no higher persistence probabilities than those of other students in this field. This finding is, however, much stronger for medical sciences than for law. Firstly, the effect of being a technically talented student on success in law studies is almost significant implying that extraction of these students from law studies may lower the average level of law students. Secondly, when applying the condition of at least three science-related subjects in secondary school exams, the number of technically talented law students reduces from 44 to 12, whereas the number of these students in medical studies remains virtually unchanged (from 61 to 60).

An important question is why these technically talented students choose medical and law studies, in which they have no comparative advantage? According to Murphy *at al* (1991) lawyers are typically engaged in rent-seeking activities. We will argue that the Dutch educational system and Dutch labor market institutions make it likely that this also applies to medical professions. The Dutch system of university education has virtually no rationing; students who have passed their secondary school-leaving examinations and applied for a particular study are generally admitted. There are few exceptions to this rule, the most important being medical schools. Currently, the number of applicants to medical schools is about three times as large as the number of places available. Admission to medical schools is determined by a weighted lottery scheme, where the weights depend on the average mark in the secondary school-leaving examinations. Applicants must also have taken at least two science-related subjects at secondary school level. Higher tuition fees are not used as a means to limit the number of applicants for medical schools. Tuition fees for medical studies are as low as those for any other university study and bear no relation to the cost of education, which are much higher for medical studies than for most other studies. Furthermore, the medical professions in the Netherlands are among the most protected occupations in the country. There is no competition whatsoever, and as a result the incomes of doctors and medical specialists are fairly high. An indication of the high earnings expectations of students in law schools and medical schools can be found in a recently collected data set among 2,500 first years university students. The respondents have been asked what they think their maximum earnings will be after finishing their studies, and also what their maximum earnings would have been had they chosen a technical study.[11] Medical students expect on average as maximum earnings from their own field 6792 Dutch guilders per month, and from a technical study 5545. The respective amounts for law students are 6634 and 5566. The only other field where students expect higher earnings from their own study than from a technical study is economics/business.

Frank and Cook (1996) analyze what they call "Winner-take-all-societies". Basically they apply the tournament model originally developed by Lazear and Rosen (1981) to a large number of markets. In the tournament model earnings are not determined by absolute performance but by relative performance. Performing slightly better than one's competitor may lead to enormous differences in rewards. This is well-known from professional sports and entertainment, but according to Frank and Cook applies to other labor markets as well. The legal and medical professions are prime examples in their book (e.g. pp.219-221). The tournament structure leads to overcrowding of markets; young students overestimate their chances of winning the prizes and many choose for the risky prospects of the legal and

[11] Note that these data are not suitable to estimate the effect of earnings prospects on the choice of field of study as it has not been asked to students in technical fields what they expect what they would have earned with another study.

medical professions instead of the more secure earnings prospects of engineering and teaching. Frank and Cook argue that the best way to remedy the wastes caused by this type of markets, is to "bring individual and social incentives more closely into line" (p.20). Applied to the Dutch case of medical students this would include to increase the tuition fees for medical studies.

Overcrowding in the Dutch medical profession is curtailed by the lottery system at the entrance of medical studies. This can be considered as an advantage of the lottery system. But the fact that the system uses a weighted lottery procedure, where weights are based on secondary school performance, leads the most talented students towards medical studies and away from technical studies. This can be considered as a disadvantage of the current allocation system.

7 Conclusions

In this paper we analyzed the determinants of choosing a technical study at university level and of persistence in such a study. The analysis applies to the Netherlands. We find a low correlation between the probability of a student choosing a technical study and the probability of persistence in it. This implies that a substantial number of technically talented people choose non-technical studies. Especially female students and students from high income families are unlikely to attend a technical study but these students are relatively successful in such studies. A large fraction of these technically talented students are attracted to medical studies and law schools, where they are no more likely to persist in these studies than other medical and law students. This finding is predicted by a tournament model in which rewards are based on relative performance instead of absolute performance. Given the finding that being female and coming from a high income family are the characteristics that make people qualify as hidden technically talented persons, it is not unexpected that these students can be found in the medical studies and law studies. In Dutch law school about 50% of the students is female, while in medical schools this is about 60%. Furthermore students in these schools on average come from families with above average incomes.

During the Summer of 1996, headlines in Dutch newspapers paid much attention to one particular case which perfectly fits the results of this paper. A very bright girl (presumably from an upper-class family), who achieved the highest possible marks for her final examinations in secondary school, applied for a place at the medical school of the university of Rotterdam. Against the favorable odds that the weighted lottery scheme gave her, she was not admitted. The board of the university to which she applied announced to admit her anyway, thereby disrespecting the Dutch law. A professor in physics who is a regular columnist in one of the Dutch quality newspapers (Lagendijk in De Volkskrant), commented on this case by asking why such a smart girl wants to study medicine instead of the more demanding courses thought to science students. The results in this paper support this view, and (partially) answer this question.

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Table 1: University degrees as a percentage of total degrees, by field (1992)

country	medical science	natural and physical science	engineering and architecture	law and business	humanities
Canada	6.7	12.0	7.0	22.6	51.7
US	7.1	10.3	8.1	27.3	47.3
Japan	5.3	7.3	21.6	39.4	26.3
Germany	11.7	17.6	22.2	24.7	23.7
Netherlands	15.6	9.7	16.0	20.5	38.1
UK	6.8	17.1	15.2	21.8	39.1
OECD country mean	11.7	12.7	14.7	22.3	37.7

Source: OECD (1995), p.222/3

Table 2: Estimation results full sample; probit equations

variable	technical study	persistence
gender (female = 1)	-0.784 (7.1)**	0.541 (2.1)**
age	-0.063 (2.2)**	0.016 (0.3)
parents' education	-0.004 (0.1)	-0.103 (1.0)
parental income	-0.055 (2.1)**	0.130 (2.0)**
children in the family	-0.040 (0.7)	-0.026 (0.3)
average mark languages	-0.137 (1.7)*	-0.061 (0.4)
average mark science subjects	0.533 (7.5)**	0.360 (2.4)**
average mark humanities subjects	-0.066 (0.9)	0.255 (1.4)
advice primary school teacher	0.022 (0.6)	-0.022 (0.3)
repeated classes	0.035 (0.3)	-0.317 (1.3)
extrinsic motivation	0.012 (0.4)	0.042 (0.8)
intrinsic motivation	0.095 (2.7)**	0.042 (0.6)
number of observations	853	
loglikelihood	-498.720	

absolute values of asymptotic t-values in parentheses; ** indicates significance at the 5%-level; * indicates significance at the 10%-level.

Table 3: Estimation results for sub-sample with at least three science-related subjects in secondary education; probit equations

variable	technical study	persistence
gender (female = 1)	-0.729 (5.3)**	0.499 (1.8)*
age	-0.067 (1.8)*	-0.023 (0.3)
parents' education	-0.097 (1.7)*	-0.070 (0.6)
parental income	-0.046 (1.5)	0.112 (1.7)*
children in the family	-0.093 (1.5)	-0.040 (0.4)
average mark languages	-0.037 (0.4)	-0.066 (0.4)
average mark science subjects	0.555 (6.3)**	0.351 (2.3)**
average mark humanities subjects	-0.134 (1.4)	0.322 (1.7)*
advice primary school teacher	0.004 (0.1)	-0.036 (0.4)
repeated classes	0.177 (1.2)	-0.188 (0.7)
extrinsic motivation	0.053 (1.6)	0.057 (1.1)
intrinsic motivation	0.060 (1.4)	-0.025 (0.3)
number of observations	490	
loglikelihood	-377.573	

absolute values of asymptotic t-values in parentheses; ** indicates significance at the 5%-level; * indicates significance at the 10%-level.

Table 4: Identifying technical potential; absolute numbers and in brackets as the share of all respondents in the current study	
current study	
economics	73 (0.59)
social sciences	58 (0.48)
medical sciences	61 (0.60)
agriculture	64 (0.63)
law	44 (0.49)
languages	46 (0.45)

Table 5: Effect (dP/dX) of latent technical talent on persistence probability in current study: probit results; t-values in brackets

current study	effect
economics	0.202 (2.8)**
social sciences	0.123 (1.8)*
medical sciences	0.039 (0.6)
agriculture	0.094 (1.9)*
law	0.123 (1.4)
languages	0.179 (2.0)**

absolute values of asymptotic t-values in parentheses; ** indicates significance at the 5%-level; * indicates significance at the 10%-level.

Appendix: Description of variables; means and (in brackets) standard deviations			
variable	non-technical study	technical study & persistence	technical study & non-persistence
gender; dummy: female = 1	0.57 (0.49)	0.26 (0.44)	0.14 (0.36)
age at start of university study	19.75 (2.81)	19.13 (1.96)	19.25 (1.34)
parents' education; the maximum of the father's and mother's level of education measured on a scale from 1-5	3.48 (1.18)	3.37 (1.23)	3.40 (1.05)
parental income; parents' gross monthly income measured on a scale from 0-14	4.84 (2.31)	4.62 (2.07)	4.29 (1.69)
children in the family; number of siblings plus one	2.65 (0.95)	2.59 (1.00)	2.69 (1.04)
average mark languages	6.93 (0.71)	7.01 (0.77)	6.78 (0.77)
average mark science subjects	6.57 (0.87)	7.39 (0.86)	6.92 (0.75)
average mark humanities subjects	6.84 (0.75)	7.12 (0.75)	6.82 (0.67)
advice primary school teacher; measured on a scale 1-7	5.80 (1.37)	5.87 (1.43)	5.86 (1.26)
repeated classes in primary or secondary education; dummy: repeated = 1	0.31 (0.46)	0.20 (0.40)	0.37 (0.49)
extrinsic motivation; measured on a scale 0-10	5.54 (1.97)	5.59 (1.82)	5.51 (2.17)
intrinsic motivation; measured on a scale 0-10	8.66 (1.50)	9.00 (1.35)	8.80 (1.79)
number of cases	641	158	54