Do Human Arts Really Offer a Lower Return to Education?*

Carl-Johan Dalgaard[†]   Esben Anton Schultz[‡]   Anders Sørensen[§]

July 2012

Abstract

Is the wage gap between majors in human arts and other fields caused by their education per se? If the educational choice is endogenous, the gap may instead be caused by selection. We document that individuals' educational choice is correlated with that of older students, and argue that it should not influence wages directly. Exploiting this "cohort dependence" as an instrument for educational choice, our 2SLS estimates show that the hourly wage gap is attributable to selection. However, only half of the gap in annual earnings is explained by selection, whereas the other half is due to lower work hours.

Keywords: Returns to education, human arts, instrumental variables
JEL Classification codes: I21, J24

1 Introduction

The notion that education is a key determinant of individual productivity has a long and distinguished history in economics, going back (at least) to the work of Mincer (1958), Houthakker (1959) and Miller (1960). At the conceptual level one may distinguish between three dimensions of a formal education which hold the potential to affect individual productivity: The quantity of education, the quality of education, and the subject matter studied.

While the quantity of education can be measured by years of schooling, the quality of education is harder to account for. Still, one may attempt to gauge the impact from quality by adding reasonable proxies to otherwise standard wage regressions, such as test score results. Alternatively, one may try to infer the impact from quality by including characteristics of the school attended in earnings regressions (e.g. pupil/teacher ratios and school size). As is well known, standard theories would predict a positive impact from both of these dimensions of education on individual productivity (Becker, 1967), as well as on macroeconomic outcomes (e.g. Lucas, 1988). This proposition has been tested (and debated) intensely over the years.[1]

The third dimension of human capital accumulation, which has received considerably less attention by academic researchers, is what we focus on in the present study. The issue is whether the particular field of study, or the contents of the curriculum, has a separate impact on individual productivity. Existing studies, surveyed below, suggests this is the case. A typical finding is that the labor market pay-off from pursuing an education within the humanities is substantially smaller than that associated with most other types of education. For example, ordinary least squares (OLS) estimates for Denmark, reported below, suggests that the hourly wage rate earned by individuals with a tertiary education within

---

[1]See Card (1999, 2001) for a review of the literature which attempts to estimate the causal impact from an additional year of schooling on individual wages; Card and Krueger (1996) review the literature on the impact from school quality on labor market outcomes at the level of the individual. Bills and Klenow (2000) provide an analysis of the education/growth nexus at the aggregate level; Hendricks (2002) examines the contribution from quality differences in human capital in accounting for cross-country wage differences.

the humanities is 23% lower than that associated with other tertiary degrees.[2]

These findings could suggest that some types of education provide the individual with more productive human capital than others. At the same time, large wage premia across different fields of study are somewhat puzzling. If wage differentials (of a considerable magnitude) appear one would *a priori* expect changes in the distribution of students across fields of study; a process that would continue (in theory) until wages are equalized.

An alternative explanation for the above mentioned findings is that existing OLS estimates are not identifying the impact of different types of education on wages. Instead, the results may be attributed to a lack of control for differences in relative cognitive abilities, or, "comparative advantages" in intellectual pursuits. It seems plausible that comparative intellectual advantages matter when the individual chooses which *type* of education to pursue. That is, a relatively mathematically skilled student may be more partial to pursue an education where mathematics is used intensively, compared to a gifted student with comparative advantages in verbal abilities. Moreover, some types of ability do seem to yield a higher labor market pay-off than others. For example, Dougherty (2003) finds that numeracy has a strong positive impact on individual wages, whereas literacy has a much smaller (and often insignificant) impact.[3] Accordingly, if relative cognitive abilities determine the type of education, the individual pursues *and* affects the final wage, existing return estimates to the *type* of education may be biased.

The Danish educational system is well suited for studying the returns to different types of education. The reason is that university degrees in Denmark are highly specialized. For example, if one chooses to study economics then this is the subject matter pursued

---

[2]We refer to the groups under consideration as having obtained a "tertiary" education. Note that all individuals in our sample below have attained a master's degree. Hence, the number of years of schooling for all individuals in our sample is rather homogenous.

[3]See also Bishop (1992) and Joensen and Nielsen (2009) who find that greater skills in mathematics goes along with higher individual level wages. Interestingly, similar results are obtained in the aggregate data. Hanushek and Woessmann (2009) document that the link between average test scores in mathematics and science is more strongly related to *aggregate* growth than test scores in reading; when all three types of test scores are included in the regression the latter turns insignificant.

throughout the entire time at the university; both during the undergraduate and the graduate level. Intellectual excursions into other fields only occur to a very modest extent, in contrast to what may be the case under e.g. a US-type system. Consequently, examining the labor market performance of Danes holding different types of tertiary education is likely to convey information about the extent of human capital production within different fields of study. In addition, Danish universities are publicly funded which reduces the scope for marked quality differences.

Accordingly, the present paper contributes to the literature by attempting to elicit information about the causal effect of *the field of study* on individual productivity, as it manifests itself in individual hourly wages. The data set underlying the empirical analysis covers the part of the Danish population which completed high school during the period 1981-1990.[4] Narrowing the focus to the group of individuals which subsequently proceeded to a tertiary education, and ended up in wage-employment, we examine whether wage rates differ systematically across previous field of study. Specifically, we examine the relative labor market performance of individuals who chose to study within the broad fields of human arts and other types of tertiary educations.[5] Conditional on standard determinants of wages an OLS regression reveals that individuals who pursued an education within the human arts fared much worse, as noted above, than individuals with other majors.

Still, OLS estimates are unlikely to capture the causal effect of the type of education on individual productivity, unless relative cognitive abilities are controlled for. Accordingly, we subsequently try to control for comparative intellectual advantages by invoking individual-level information about academic specialization in the Danish high school system. In addition, we are able to utilize information about the high school attended and high

---

[4]When we refer to the Danish high school in this paper, we mean the ordinary high school ("gymnasium"). The Danish high school takes three years to complete.

[5]We have also attempted to examine a finer division of studies. Unfortunately, we have not be able to disentangle the returns to education in this more disaggregated setting; our instrument turns out to be weak in this setting. A possible interpretation is that we need a description of relative abilities in more dimensions than the two dimensional "verbal" versus "mathematical" ability division that we apply here.

school GPA, as well as data on parental education. Upon including such controls in the wage equation, the wage gab between human arts majors and other majors narrows. Still, a significant difference persist; the wage difference between human arts majors and others is now 17% (reduced from 23%).

Ultimately it is hard to rule out that other – unobserved – factors could simultaneously impact on the choice of education type as well as productivity. As a result, we try to make additional headway by employing an instrumental variables (IV) approach to the issue at hand.

To identify the impact of the field of study on wages, we begin by studying the educational choice itself. That is, the choice of which type of tertiary education to pursue. Specifically, we model the choice of field of study as a function of (relative) academic abilities, and variables thought to capture the observed academic tastes of older students in the individuals' high school. While the former turns out to be linked to final wages, the latter determinants should not affect the productivity of the individual, once we carefully control for high school fixed effects (perhaps reflecting variation in teacher quality etc.), the curriculum studied by the individual in high school and the academic achievements of the individual when graduating from high school. As a consequence, characteristics of older students may serve as *instruments* for the individuals' choice of field of study.

As documented below, student choices are indeed interdependent. Specifically, we find that there is a high correlation between the ultimate education choices of seniors and the ultimate educational choice of the two years younger freshmen. There is a good reason why the interdependence should appear between seniors and first year students (rather than between seniors and second year students) during the period we study. The institutional set-up was such that students decided on which "course package" to select, for the remaining two years of high school, after the first year of high school. This choice was of considerable importance to which type of education the student could pursue directly after graduation, due to course requirements at the university level. Hence, if effects from older students

were to be of importance to students ultimate choice of university education, it would be precisely after the first year. Moreover, the (two year older) seniors would likely be the group who possessed the greatest information on various types of education, as they were about to make their own choices on which type of education to pursue post graduation. Consequently, it would be plausible that their choices could influence younger students, who were contemplating which academic track to follow.[6]

We interpret the link between educational choices of freshmen and seniors as reflecting the influence from student interaction about the attractiveness of various fields of study. That is, it reflects the consequences of informational updating. The type of information conveyed is unlikely to be about labor market earnings; raw labor market earnings are relatively easy to observe. However, it is considerably harder to assess the broader "quality-of-life" pay-off to a specific education. For instance, what is the associated status, work environment and so forth? We hypothesize that student interaction serves to convey this kind of information. In addition, we conjecture that students with (revealed or hypothesized) preferences for particular fields of study likely hold an informational advantage *within* their preferred area. Accordingly, if an individual is more exposed to a group of older students with preferences for the human arts, the more likely it will be that new information about the "quality-of-life" aspects of a working life with a human arts degree is brought forward. This new information may affect the educational choice.[7]

In sum, we argue that the high school specific fraction of seniors choosing an education within the human arts, is a viable instrument for the choice of which type of tertiary education individuals pursue. With this instrument in hand, we proceed to estimate the impact of choosing an education in the humanities using an IV model.

Our IV point estimates differ substantially from the conventional OLS counterparts.

---

[6] We elaborate on the identifications strategy, as well as on the institutional setup of the Danish High-School system before 1990, below.

[7] Note that since the hypothesis emphasizes information *updating*, it does not follow that more information about (say) the humanities necessarily will *increase* the probability that one would choose an education within this field of study. Section 6 contains a more detailed discussion of this issue.

After instrumenting the difference in hourly wages between human arts majors and other majors is reduced to about 0.5% and in fact slightly positive, but insignificant. Thus, we find *no significant difference* in the impact from the educational choice on hourly wages. Hence, we are led to the following conclusions: Relative cognitive abilities seem to have a substantial impact on wages, and comparative intellectual abilities do seem to matter for the choice of which education to pursue. In this sense, *relative ability sorting* play a major role in explaining the observed wage gap. However, it seems that the impact from the education *per se* on relative hourly wages only depends on the field of study to a very limited extent.

We also perform the analysis using annual earnings from wage work, instead of hourly wages, as dependent variable. As in the analysis based on hourly wages, we present results for the income gap based on OLS as well as variation in the returns to education across majors based on IV. Our IV estimates suggest that relative ability sorting can account for about half of the difference in annual earnings between human arts majors and other majors, whereas the other half is due to the education *per se*; human arts majors work fewer hours suggestive of a weaker labor market attachment.

Naturally, one may question our identification strategy. In particular, one could argue that the first stage correlation between the educational choices of different high school specific groups is simply picking up (unobserved) school quality in various dimensions. Since such quality differences may influence productivity and wages this reasoning would suggest that our instrument is invalid.

We believe that such concerns are unfounded in the present case for a number of reasons. First, Danish high schools are (generally) publicly funded, from a regional source. Hence, the type of local "neighborhood effects", known to be operative in e.g. the US, whereby high income municipalities can provide better funding for educational facilities, are not operative in Denmark. Second, all Danish high schools follow the same curriculum, and all students attend the same (centrally devised) written exams. Third, in our analysis we are able to control for the identity of the high school, the individual have attended. If a specific high

school happens to deliver high quality teaching, a high school fixed effect picks it up. Finally, we show that the correlation between the educational choice of a particular cohort and its contemporaries in their high school exhibit a "cohort effect". For instance, there is *no* (significant) correlation between the ultimate educational choice of a given cohort and the ultimate educational choice of a *one year* older cohort, a *three years* older cohort, or a *four years* older cohort. But there *is* an association between the ultimate educational choice of a cohort and the ultimate educational choice of a *two years* older cohort. This general pattern is hard to explain away by appealing to high school specific (quality) effects.

The paper proceeds as follows. Section 2 provides a brief review of the existing literature which estimates the return to different types of education. Section 3 presents the empirical strategy and section 4 describes the data and provides some institutional background on the Danish educational system. Section 5 presents the baseline OLS results. Section 6 presents the identification strategy and the IV results, while 7 concludes.

2   Related Literature

While the literature on the return to schooling is vast, only a relatively limited number of studies have attempted to come to grips with the return to *type* of education.

James et al (1989) is the earliest contribution which provides evidence of differences in human capital remuneration by field of study. Specifically, they add dummy variables to an annual earnings equation capturing college majors. Their sample includes earnings and various individual specific characteristics (including the college attended) of 1241 males, drawn from the *National longitudinal study of the high school class of 1972* (NLS72). They find very large differences in the "return" to college major. For instance, a student who chose his major in the humanities, instead of engineering, should expect 45% lower annual earnings in 1985, *ceteris paribus*; a truly remarkable return difference. Indeed, as James et al. concludes (p. 251): "*[...] while sending your child to Harvard appears to be a good*

8

investment, sending him to your local state university to major in Engineering, to take lots of math, and preferably to attain a high GPA, is an even better investment." On *a priori* grounds, however, their estimates may not reflect a causal impact on productivity for two reasons. First, their labor market data concerns annual earnings. As a result, some of the observed difference may be attributed to differences in number of hours worked in different occupations. Second, the choice of major is treated as exogenous.[8]

Blundell et al. (2000) draw on the UK *National Child Development Survey,* which contain data on family background of children born in 1958 (between March 3 and 9), their educational choice (including the subject studied) along with labor market data on hourly wages. The wage is observed for the year 1991, when the subjects were 33 years old. In contrast to previous studies, Blundell et al. (2000) also attempt to deal with the endogeniety problem by invoking matching methods to identify the impact from higher education on hourly wages. Specifically, individuals with a higher education were compared with individuals who could have taken a degree (based on previous educational performance) but chose not to, while sharing various observable characteristics (like ability, family background etc.).[9] In line with previous studies, Blundell et al. also detect differences in labor market rewards across fields of study. For example, chemistry and biology exhibits the lowest return, whereas economics, accountancy and law the highest. In many cases, however, the effects from educational type are not very precisely estimated, presumably because of a rather limited sample size.

Bratti and Mancini (2003) also examine data from the UK. Like Blundell et al. (2000) they invoke matching methods. In addition, they also consider the problem that selec-

---

[8]Daymont and Andrisani (1984) also contain information about fields of study; but their focus is on showing that the gender gap in wage regressions shrink, once the choice of major is accounted for. Other studies that investigates earnings differential across majors include Dolton and Makepeace (1990), Grogger and Eide (1995) and Loury and Garman (1995). A common feature of these studies is that they also (in contrast to the present study) treat the choice of type of education as exogenous.

[9]This approach is similar to the OLS wage regressions reported below; like the National Child Development Survey our data contain very rich socio-economic background information of the individuals pursuing a higher education, which we control for along side more standard variables like work experience etc. Naturally, this only resolves the endogeniety problem if all relevant individual specific characteristics are controlled for. If unobservable characteristics matter for wages and choice of education the estimates remain biased.

tion may take place over unobservable variables. In ensuring identification they rely on a multinomial-logit-OLS (MLO) set up, where the choice of education is estimated and then the impact of education type on wages. As in the present paper they invoke an IV methodology. In Bratti and Mancini the exclusion restriction is that choices made in previous education (specifically: A-level curriculum) and the age of the student does not matter for wages directly, controlling for type of degree and standard Mincer-type controls. While their OLS results suggest that graduates from economics and business subject did better than the rest, their MLO results lead to no clear-cut ranking of subjects; the pecking order appears to change over time. One may argue, however, that their data is not optimal. The reason is that the data source (University Statistical Research data) does not include information about salaries. Since the authors do have access to fairly detailed information about occupation, they can construct salaries for individuals. This is done by using data from the New Earnings Survey; individual's salaries are computed as (p. 9) *"the average gross weekly pay of individuals employed full time (in the same occupation) in the year following the questioner"*. Hence, by construction there is no within-occupation variation in earnings in their sample. As a result, their results are likely to speak to the impact from the type of education on occupations, rather than on wages *per se*; potentially valuable information pertaining to *differences* in wages across individuals with different educational backgrounds *in similar occupations* cannot be used for the purpose of identification.

Finally and most closely related to the present paper, Arcidiacono (2004) examine the return to college major, by modelling the educational decision explicitly. Arcidiacono, like James et al. (1989), rely in the NLS72 data set, implying the return estimates speak to earnings, rather than wages *per se*. The study documents that selection is indeed taking place. Moreover, controlling for selection, Arcidiacono still finds considerable return differences across majors; as in James et al. students majoring in e.g. the natural sciences fare better in the labor market.

3 Empirical Strategy

In estimating the relative return to field of study we specify a wage equation that includes the individuals choice of educational type. The wage earned by individual i is denoted by y_i. S_i measures the education type (major in human arts or other types) chosen by individual i and is the binary endogenous variable of interest. S_i equals one for having a master's degree within human arts and zero otherwise; the return estimate of human arts is therefore *relative* to other majors. This indicator is used because we restrict our self to include tertiary educations of about equal duration, and because the Danish educational system is such that one specializes in one topic only at the university.

Our wage regression is

$$\log(y_i) = \alpha + \rho \cdot S_i + \mathbf{x}_i \boldsymbol{\beta} + d_{i,c} + d_{i,t} + d_{i,s} + u_i. \tag{1}$$

The parameter ρ captures the relative return on a degree within the humanities; it is the key parameter of interest. The vector $\mathbf{x}_i$ consists of observed background variables to be described below; this set includes standard controls in wage regressions. The variables $d_{i,j}$ $- j = c, t, s$ – are various fixed effects which we introduce to try to control for ability; both the absolute level and the relative level. We expect these fixed effects to affect wages, and the choice of educational type, S_i.

The fixed effects are $d_{i,c}$ for high school **c**urriculum, which should capture the individual's own assessment of the costs of acquiring specific skill types. We describe this variable in greater detail below. The variable $d_{i,t}$ controls for time effects. More precisely, this is the year of graduation from high school. Finally, $d_{i,s}$ is included to control for the attended high **s**chool and thereby potential quality differences in skills formation.

Ultimately we will treat S_i – the indicators for educational type – as endogenous. In order to obtain consistent estimates for ρ we therefore employ a two-step IV procedure suggested by Wooldridge (2002). The first step involves estimating a probit model for the choice of

educational type

$$P_i(S_i = 1|\mathbf{x}_i, d_{i,c}, d_{i,t}, d_{i,s}, \mathbf{z}_i) = G_i(\mathbf{x}_i, d_{i,c}, d_{i,t}, d_{i,s}, \mathbf{z}_i; \gamma_i) \qquad (2)$$

where $P_i(.)$ denotes the probability for $S_i = 1$ and $G_i(.)$ is the cumulative distribution function of the standard normal distribution.

We estimate (2) using maximum likelihood, and the notation for the controls are the same as above. Hence, the *only* new entry is $\mathbf{z}_i$; determinants of educational choice which do not matter to wages themselves. That is, our instruments for S_i. From a theoretical point of view, we consider variables which have an impact on the individuals expectations about the value of each type of education. Empirically, our instruments have to satisfy the two requirements that (A) they are orthogonal to u_i and (B) they are highly correlated with the choice of education type, S_i.

Having estimated equation (2) we subsequently obtain the fitted values from the regression, $\hat{G}_i$. The second step of our two-step IV approach involves estimating equation (1) using 2SLS with $\mathbf{z}_i$ as the instrument. As we control for all the determinants of S_i, except for $\mathbf{z}_i$, this provides us with IV estimates for the relative return to a degree in humanities.

4   Data

The data we use in our empirical analysis is a data set covering the Danish population of individuals graduating from Danish high schools during the period 1981-1990. The data are administered and maintained by Statistics Denmark that has gathered the data from three administrative registers: the Integrated Database for Labor Market Research (IDA), the Danish Income Registry and the Danish Student Registry.

For each individual, we have complete data on educational and labor market histories along with detailed information on other socioeconomic characteristics. The educational data comprise detailed codes for the type of education attended (level, subject, and educational

institution) and the year for completing the education. The labor market data contain the *hourly* wages; measured as the annual labor income divided by total hours worked. Below we refer to annual labor income as annual earnings.

4.1 Sampling of Data

In our main estimation sample we focus on individuals that satisfy the following two criteria: (i) graduated from high school between 1981 and 1990 and proceeded to obtain a master's degree and (ii) was wage-employed in 2000; in the main regressions below we use the wage rate in 2000 as dependent variable. These restrictions leave us with a main estimation sample that consists of 29,700 individuals.

We confine attention to high school graduates from the period 1981-1990 since this period was characterized by a particularly useful institutional setting, from the point of view of identification, which allows us to proxy comparative intellectual abilities. After 1990 the Danish high school system changes. We describe the nature of the institutional setting in some detail below.

Using 2000 as the "base year" is a choice made for practical reasons. The last high school cohort in our sample graduated in 1990. In Denmark it is not uncommon for students to take a sabbatical before beginning their university studies. Moreover, few students manage to complete their studies within the prescribed period of usually five years. Hence, in order to include all cohorts in the sample 2000 is a reasonable starting point.

To even out potential yearly fluctuations in wages, we also use the average wage over the period 1999-2001 and 1999-2003 as dependent variable. After all, the null is that the choice of education matters to permanent income; averaging should increase the signal-to-noise in the dependent variable. Still, using time averages is not critical to the results, which is documented by using alternative definitions of the dependent variable and samples.

Finally, we also use annual earnings as dependent variable in addition to hourly wages when investigating the returns to different majors. We do this because this income measure

is used in the literature in addition to hourly wages. Consequently, we investigate differences in the returns to education based on different income measures.

4.2 Explanatory Variables

4.2.1 High School Information

Figure 1 show graphically how a student proceeded through the Danish educational system, from lower secondary school to tertiary education, during the period 1981-1990. Individuals usually enter the Danish high school immediately after completing lower secondary school, and graduates after three years.

When applying to a high school for admission, the student was required to specify an overall track to follow: "mathematical" or "language". After completing the first year, students then self-selected into various "branches", available for each track, as illustrated in Figure 1. Under the math track students could choose between math/physics, math/natural sciences, math/social sciences, or math/music, while under the languages track students could choose between languages/social sciences, languages/music, modern languages, or classical languages.[10] Hence, individuals were grouped into eight distinct branches. During this institutional arrangement the curriculum was determined after strictly defined course packages, implying that knowing the track and branch provide fairly precise information about the curriculum, the students completed.

<Figure 1 around here>

The information about which *branch* the individual pursued in high school appear in (1) and (2) as the curriculum fixed effect (i.e., $d_{i,c}$) to control for relative cognitive abilities directly. Hence, the basic idea is that the choice of "branch" provides information about

---

[10]In the last years of the sample a few experimental branches was allowed; e.g., Math/English and Math/Chemestry. Only very few students pursued these branches; they are excluded from our sample.

the individual students' *relative* abilities; a math/social science major was likely not quite as mathematically inclined as a math-physics student; at least the level of math taught was objectively speaking higher in the math/physics branch compared to the math/social science branch.

The "branch based system" was in place until 1990; from 1991 onwards students were given much greater autonomy with regards to course packages. Hence, the reason why we only sample high school graduates up until 1990 is precisely because it marks the end of the branch based system.

Eventually we do not have to rely on being able to fully control for relative ability, since we pursue an IV approach. However, as will be seen: branch choices hold considerable explanatory power vis-a-vis post-university wages, suggesting that relative abilities across subjects indeed matter.

In order to control for "absolute ability", we use the grade point average (GPA), which enters into $\mathbf{x}_i$. The GPA is a weighted average of the grades at the final exam at each course. The quality of the courses as well as the GPA is comparable across high schools since all students within the same cohort face identical written exams; all exams and major written assignments are evaluated by the student's own teacher as well as external examiners; high school teachers from other high schools. The external examiners are assigned by the Danish Ministry of Education.

Completed high school is a general admission requirement for tertiary educations, as suggested by Figure 1. We have information on which high schools individuals attended (149 in total). This information enters as the high school fixed effect, (i.e., $d_{i,s}$) and serve as controls for high school quality. Moreover, we have information on year of graduation from high school, which enters as the graduation year fixed effect, i.e., $d_{i,t}$. This dummy captures information on experience in equation (1).

4.2.2 Tertiary Education

As mentioned above, we focus exclusively on individuals who ultimately obtain a master's degree. The reason is that we want to avoid any selection bias in our results due to the choice of education length. Moreover, we partition the type of tertiary education into two bins: human arts vs "others".[11] This information enters in the regressions as individual choice of education type, i.e., in S_i.

4.2.3 Other Explanatory Variables

We also apply individual information not related to high school attendance as explanatory variables, i.e., variables that enter into $\mathbf{x}_i$. These are gender and parental education. Gender is included to control for the gender wage gap in (1), whereas it enters (2) to control for gender differences in relative abilities or preferences.[12] Parental education is controlled for by including a set of indicators for each parent regarding both the length and type of their education.

Table 1 displays selective descriptive statistics for the samples. The sampling unit is the individual, and the table presents the distribution on type of tertiary education, the distribution of students on high school branches, their high school grade point average, and their gender.

---

[11] In Denmark, a tertiary education in humanities includes the following main disciplines: ancient and modern languages, literature, history, philosophy, religion and visual and performing arts. Academic disciplines such as psychology, anthropology, cultural studies and communication are considered as social sciences.

[12] There is evidence to suggest a gender bias in the context of educational choice. In an influential study, Benbow and Stanley (1980) examined nearly 10,000 mathematically gifted boys and girls at the ages of 12 to 14. Their main empirical finding was a significant gender difference in mathematical reasoning in favor of boys as measured by the SAT-M. This observed difference could not be ascribed to differential course-taking accounts. Moreover, 20 years later Benbow et al. (2000) revisited the sample and studied the educational and career outcomes of the students; they document a significant difference *in education choices*, with boys (now around 33) more likely to have chosen an education within the natural sciences; girls were more likely to pursue an education within the humanities. Admittedly, it seems hard to assess whether (and to what extend) these findings have a "genetic" or cultural origin. But either way it would appear that women are more partial to the humanities, compared to men. We detect a similar pattern below.

<Table 1 around here>

Some aspects of the data are worth remarking on. Almost 5/6 chose the math track in high school, while only 1/6 chose the language track; the largest high school branch is math/physics. Recall, these statistics are all conditional on completing a tertiary education and being wage employed in 2000. As regards subsequent choice of education type, other educational types attract the most students compared to human arts that attract 10.5% of the students. Moreover, almost 60% consist of men. The high school GPA is 8.8, which is above average as expected.[13]

5 Baseline OLS Results

In Table 2, we report the results from the standard wage regression. That is, the endogeneity problem is ignored.

<Table 2 around here>

To recapitulate: These regressions are performed for individuals with a tertiary education, who are wage-employed in 2000. In column 1 of Table 2, only indicators of the choice of education type are included in order to study the raw wage differences between human art majors and other majors. The "raw" wage gaps reveal that human arts graduates have 23% (exp[-0.2580]-1) lower wages than other graduates.

In columns 2-5 of Table 2, more information is gradually introduced into the log wage regression to study how the estimated wage difference changes. In column 2, we introduce a gender dummy in the regression that enters negatively and significantly with a parameter

---

[13]A numerical grading system is used in Denmark. The possible grades were at the time: 0, 3, 5, 6, 7, 8, 9, 10, 11 and 13; 6 were the lowest passing grade, and 8 were given for the average performance.

corresponding to women earning an average wage that is about 15% lower than the average wage for men. In column 3, we introduce high school GPA and find that the average wage increases by around 2% per grade point. Column 4 includes curriculum fixed effect or the choice of high school branch that proxies for relative talent. It is evident that those who studied at the math/physics branch in high school earned the highest wages compared to any other branch. A high school curriculum in classical languages or language/music led to the lowest wages that on average were about 11% lower than that of math/physics. In general, those who chose the language track tend to earn lower wages than those that chose the math track. This suggests that mathematical abilities are valued more in the labor market than linguistic abilities. Finally, column 5 includes all above mentioned explanatory variables. In addition, we also include dummies for graduation year from high school, information for education length and type of parents and high school fixed effects. High school fixed effects come in addition to, for example, the effect of parental education and may comprise, e.g., teacher quality etc.

Over-all, when control variables are progressively added we observe that the relative difference in returns across fields of study shrinks from -23% to -17%, but remains statistically (as well as economically) significant.

6   Identification and IV Estimates

As already mentioned, an obvious criticism of the results presented above is that there may be unobserved factors that are correlated with both the choice of education type and wages, which will bias the OLS estimates. To deal with this concern, we employ an IV strategy based on the idea that individuals' educational choice is influenced by that of older students in their high school. This section proceeds in four steps. First, we provide a simple theoretical argument which motivates our identification strategy. Second, we explain how our instrument is constructed and discuss its validity. Third, we discuss our baseline

IV results. Fourth, we investigate the consequences of using annual earnings as dependent variable instead of hourly wages. A comparison of results based on the two income measures is interesting because some studies are based on annual earnings and others on hourly wages.

6.1 The Logic of the IV Strategy: Theory

Consider an individual who is to decide which type of education to pursue. The individual derive utility from wage income, y, and "quality of life" more broadly, q. The latter variable is thought to capture, in a parsimonious way, factors such as status, work environment and job satisfaction associated with being employed using education of type $i = H$(uman arts), O(ther). Without loss we assume that wage income is observable, whereas q is something individuals hold expectations about. Utility is separable in the two arguments (y, q), and the expected level of utility for an individual (the index of whom is suppressed in the interest of brevity) is therefore

$$E\left[U\left(y, q\right)\right] = u\left(y\right) + \int v\left(q\right) f\left(q\right) dq,$$

where $f\left(\cdot\right)$ is the density function for q.[14]

We assume $f\left(\cdot\right)$ supports a given variance σ^2 and mean μ; both may be specific to either type of education: $\left(\mu_i, \sigma_i^2\right)$, $i = H, O$. Importantly, both σ_i^2 and μ_i are thought to reflect the individuals' *perception* of the moments of the distribution of q. We treat both as known with subjective certainty in the derivations below, but both may vary from one individual to the next. In this sense we capture, in a simple way, differences in the information set of individuals at the time of optimization. Accordingly, these are the parameters which may be influenced by student-to-student interaction.

---

[14]See e.g. Fershtman et al. (1996) for an analysis of the allocation of talent in a society where individuals derive utility from consumption and social status. In the present case, however, we define "q" more broadly to include other aspects of final employment that individuals may value like work environment and job satisfaction.

The felicity functions $u(\cdot)$ and $v(\cdot)$ exhibit positive and diminishing marginal utility: $u_y > 0$, $u_{yy} < 0$, $v_q > 0$, $v_{qq} < 0$. If we Taylor approximate v around the mean, μ, we obtain

$$v(q) \simeq v(\mu) + v_q(\mu)(q - \mu) + \frac{v_{qq}(\mu)}{2}(q - \mu)^2.$$

Evaluating expected utility we obtain, after some rearrangements, a simple representation of the preferences, which depends on income, expected quality of life and the variance of the latter[15]

$$E[U(y, q)] \approx u(y) + v(\mu) + \frac{v_{qq}(\mu)}{2}\sigma^2.$$

Now, suppose an individual with these preferences are to choose between two alternative types of education: H and O. Realistically, the individual undoubtedly will have different aptitude to the two forms of education. That is, different relative ability levels, which manifests itself in different wages. To capture this we may define the levels of income in final occupation as $y_H \equiv y(\alpha_H)$, and $y_O \equiv y(\alpha_O)$.[16] The parameter α_i captures ability, and we expect the *relative* level of ability (α_H/α_O) to differ across individuals, reflecting variation in comparative cognitive ability. Hence, some students may have a comparative cognitive advantage in the humanities, implying $\alpha_H > \alpha_O \Rightarrow y_H > y_O$. For others, of course, it may be the other way round. The pertinent characteristic of α_i is that it is predetermined at the time of optimization; it may have been determined earlier in life, or simply at birth.

Next, one may suppose the perceived mean and variance of q in the two potential endeavours of life differ. For simplicity, suppose only the latter differs. If so the individual will

---

[15]See the Appendix for derivations.

[16]Of course, we could easily admit wages to be affected explicitly by years of schooling etc. Say, by assuming $y_i = \alpha_i e^{\rho_i u_i}$, where ρ_i is the (potentially) field-specific return to a year of (field specific) education, u_i. Similarly, at the cost of some more notation, we could allow both dimensions of ability (α_H, α_O) to affect wages in either form of occupation; say $y_i = e^{\rho_i u_i} \Pi \alpha_i^{\beta_i}$. In general, then, we would allow the return to these abilities to differ; $\beta_H \neq \beta_O$. Finally, we abstract from "absolute" ability. This too could be introduced, perhaps defined as an average of the two components (α_H, α_O).

prefer H to O iff

$$u\left(\left[y\left(\alpha_H\right)\right]\right) + \frac{v_{qq}\left(\mu\right)}{2}\sigma_H^2 > u\left[y\left(\alpha_O\right)\right] + \frac{v_{qq}\left(\mu\right)}{2}\sigma_O^2.$$

Hence, individuals with high ability in H will be more likely to choose this type of education. However, greater uncertainty with respect to q (i.e., σ_H^2) may persuade the individual to do otherwise.

Accordingly, uncertainty about the non-pecuniary consequences of the educational choice may impact on what the individual decides, as a consequence of risk aversion. We hypothesize that *some* of the uncertainty may be resolved by interacting with fellow students. In particular, if the individual is exposed to students with information about q, this will lower σ^2.

Naturally, the interaction could affect perceived μ as well. As a consequence of these multiple channels of influence, *the net impact* on the inequality from "more information" is ambiguous. For instance, if the result of the interaction is simply to lower σ_H^2 (say) then interaction should make it more likely that the individual chooses H. Alternatively, suppose the student-to-student interaction reveal information about μ. Naturally, if the information update implies $\mu'_H > \mu_H$ (with μ'_H being the revised mean), it should also make it more likely that the individuals chooses H. But if $\mu'_H < \mu_H$, the converse is true.

The key point, however, is that neither μ nor σ^2 matters to wages, y; they only affect the educational choice. Accordingly, factors that lead to changes in (μ_i, σ_i^2) may be useful in identifying the impact of the educational choice itself. We hypothesize that student-to-student interaction, and thus the characteristics of the fellow students of the individual, may serve this purpose.

6.2 Constructing the Instrument and its Validity

Hence, our identification strategy is based on the idea that co-students influence the information set on which the individual base his or her final choice of a tertiary education. We do not doubt that individuals own abilities and interest are central. However, it would seem plausible that fellow students influence the individuals' choice of education. This influence can take many subtle forms, including providing students with a sense of what a certain type of education implies in terms of job satisfaction given the individuals ability and interest. Such information could affect the individual's expectations about the consequences of obtaining an education.

More concretely, we apply a measure of *older* student's educational choice at the high-school as an instrument for the educational choice of younger students. The instrument is constructed as follows: First, shares of individuals with tertiary education in humanities out of the total number of individuals with a tertiary education are constructed; the shares are determined for the group of individuals within the same high school and high school track. This implies that, two shares are calculated for each high-school per graduation year; one for the math track and one for the language track.[17]

Second, the shares are lagged *two* years, to capture the influence from seniors on freshmen. It is important to stress that seniors and freshmen (in Denmark they are two years apart) are *not* paired up arbitrarily. During the period we study students were to choose their academic specialization in high school *after* the first year.[18] It seems plausible that high school specialization could give rise to a tendency to academic path dependence; early specialization affecting the ultimate form of specialization. Hence, if fellow students were to have a particularly strong impact on individuals choice of ultimate tertiary education, a major influence would be possible after one year of high school studies. This is the hypothesis

---

[17]We calculate the instrument for each high school track separately because students had to choose track upon entry to high school.

[18]See Section 4.2.1.

we examine in the next section.

Table 3 presents summary statistics for the shares of students choosing human arts lagged two years. It is seen that the mean share of individuals with a tertiary education in humanities equals 0.22. The variable varies considerable from 0 for the 5 and 10 percentiles to about 2/3 for the 95 percentile. As described above, the variable is measured by high school, high school track, and graduation year, resulting in 2,252 clusters for the main sample of 29,700 individuals.[19]

<Table 3 around here>

Before we turn to our IV estimates it is worth reflecting on whether this instrument is likely to fullfil the exclusion restriction. Although we control for high school fixed effects, one may reasonably question whether our instrument is really capturing effects from two year older students. An alternative interpretation could be that it captures some unobserved quality aspects of individual high schools.

For instance, it might well be the case that some schools have a stronger faculty in human arts courses than others, for which reason a larger fraction of a cohort eventually chooses human arts as their tertiary education. This is a dimension of high school quality that is not captured by high school fixed effects. If this constitutes a persistent effect (and it likely would be, of course), we would expect that the unobserved quality effects shows up as a (spurious) cross-cohort correlation in the ultimate educational choice. Worse, the underlying quality effects might influence wages directly, thereby rendering the instrument invalid.

Observe, however, that this interpretation suggest a time-invariant cross-cohort correlation. If what we are picking up is a quality fixed effect, we would expect to see that the partial correlation is relatively unaffected if we instead employed (say) the fraction of the students in a one year older or three years older cohort, that eventually chooses human arts.

---

[19]The main reason that there are only 2,252 clusters in the main sample (and not 2,980) is that not all of the 149 high schools exist over the entire period 1981-1990.

But that is not what we find.

Figure 2 depicts the changes in the partial correlation between cohorts educational choice, when we use an extended lag structure; the "lag 2" entry represent the instrumental variable applied in the tables below.[20] The interesting finding is that the partial correlation displays a distinct pattern. The correlation with one year older cohort ("lag 1") is essentially nil. There is a positive correlation when we examine the educational choices of the two to four years older cohorts. The maximal effect is found when considering a two year older cohort (i.e., the educational choice of seniors) that is also significantly different from zero. Lagging further leads to a gradually diminishing correlation; where a three year older or four years older cohorts have positive, but insignificant, effects.

<Figure 2 around here>

This pattern is no mystery if we consider the institutional setting, as described in Section 4.2.1. After the first year, recall, freshmen were to choose their area of specialization. Hence, this is the time where a potential influence from older students should be at its peak, which is consistent with the pattern depicted in Figure 2.

Hence, while this pattern is consistent with the proposed hypothesis - involving cross-cohort informational spillovers - it is hard to explain by "quality effects". We view this check as a strong indication that our instrument is *not* picking up some unobserved high school specific quality effect.[21]

---

[20] The full set of explanatory variables as used in column 5 of Table 2 are included in the regression behin Figure 2. Other explanatory variables that the instruments are gender dummy, high school GPA, curriculum fixed effects, dummies for graduation year from high school, information for education length and type of parents, and high school fixed effects.

[21] Another (somewhat related) concern is that the student body of high schools with graduates that proceed to study human arts might be systematically different from high schools where this is not the case. That is, perhaps our instrument is simply capturing student self-selection and thus systematic (unobserved) student ability variation across high schools. To try to evaluate this concern, we restrict our sample to students with no or very limited opportunities to self-select into high schools. Doing so, we obtain findings (not reported here) that are very similar to those obtained with the full sample, although less precisely estimated due to the reduced sample size. This suggest that self-selection into high schools are unlikely to be responsible for

6.3 Baseline IV Estimates: Hourly Wages

Table 4 reports our main IV results, where the dependent variable is the hourly wage in 2000. The upper panel shows the second stage of the 2SLS regression, whereas the lower panel displays the results from the probit model: the probability model of the choice of education type. The results are estimated using clustering that allows for dependence in residuals within clusters.

<Table 4 around here>

Starting with the latter, the variable of particular interest is that from which we obtain identification: The share of students two cohorts ago choosing human arts. As is clear from column 1, there is a statistically positive influence from the ultimate educational choice of the two years older cohort. This effect emerges despite the fact that we simultaneously control for gender, high school GPA, parental education, fixed effects for the branch chosen in high school, graduation year dummies and high school fixed effects.

In column 2 we also include the square of the share of students two cohorts ago choosing human arts in addition to the share itself in the linear prediction. In this case, the squared share enters positive and is highly significant, whereas the share itself has a negative parameter that is significant at the 10%-level only. This result suggests that higher order terms of the share should be included. From columns 1 and 2 it is evident that the instrument is significant, with a χ^2-test about 8 for the linear specification and around 17 for the specification based on the first and second order terms in the share of students choosing human arts, suggesting that our instrument is not weak (Staiger and Stock, 1997). We have also estimated the first stage regression using share-dummies where a share-dummy is defined for each 0.1-interval between 0 and 1. The results are seen in column 3. In this case, a similar result as in column 1 and 2 is documented. In this case the χ^2-test is about 20.

Turning attention to the 2SLS estimate for the ultimate educational results, we observe

_____

our findings.

a dramatic change: The point estimates are numerically very close to zero and in fact slightly positive in columns 1-3, but are insignificant. This can be compared to the OLS results reported in column 5 of Table 2, where we found that a human arts education was associated with about 17% lower wages that other types of education.

As a result, we are led to the conclusion that the relative wage pattern observed in the (raw) data is primarily caused by selection into education types based on observed and especially unobserved relative ability; we refer to this type of selection as *relative ability sorting*. The fact that human arts majors earn much lower hourly wages than the average academic employee is caused by the composition of their ability endowments and the returns to these endowments in the labor market rather than their field of study. Simply put, human arts majors are particularly negatively selected in terms of the market values of their ability endowments.

The standard error of the point estimate increases from 0.0060 to about 0.044; that is the standard error of the 2SLS is about 7 times larger than the OLS standard errors. In other words, the point estimate of the 2SLS regression is less precisely estimated than the point estimate of the OLS regression in Table 2. However, as is well-known, larger confidence intervals is a price we must pay to get a consistent estimate on the relative returns to education. It should be emphasized that the magnitude of the increase in standard errors is in line with those usually found in the literature on returns to schooling, see e.g. Angrist and Krueger (1991), Card (2001), and Fersterer, Pischke and Winter-Ebmer (2008). Finally, the endogeneity test of the indicator for educational type is about 20, which implies that the null hypothesis – that the indicator for educational type can be treated as exogenous – can be rejected at the 1% significance level.

In column 4-5, two additional regressions are presented. The results in column 4 are based on a 3-years average wage rate for the sample of 23,434 individuals that were employed in wage work for all three years during the period 1999-2001, whereas the results in column 5 are based on a 5-year average wage rate for the sample of 20,674 individuals that were

employed in wage work in all five years during the period 1999-2003. In the first stage both the share of students choosing human arts and the squared share are used as instruments. It is seen that the stage two results are similar to those obtained in the regression using the same instruments in column 2: The return to human arts majors and other majors are fairly similar. Moreover, the first-stage probit regressions in column 4 and 5 are very similar.

6.4   IV estimates: Annual Earnings

A final issue to be addressed is the use of hourly wages versus annual earnings from employment in wage work. In the section on related literature above, it is clear that some studies are based on the former measure, whereas others are based on latter. Studies that use annual earnings finds that human arts majors have significantly lower earnings than other types of majors. Studies based on hourly wages are less conclusive, which is likely due to data issues. Blundell et al. (2000) have a fairly small sample, whereas Bratti and Mancini (2003) do not have proper data on hourly wages.

The variation in returns across majors may differ when these are estimated using annual earnings instead of hourly wages. Differences may exist if human arts majors and other majors systematically have different numbers of work hours. To address this issue, we present results for the gap in annual earnings and variation in the returns to human arts majors and other majors when based on annual earnings. Results similar to those presented in Tables 2 and 4 above are presented next with the only difference that the dependent variable is measured as the logarithm to annual earnings from wage work.

Table 5 presents the OLS results when annual earnings are used. The results are directly comparable to those of Table 2.

Table 5

It is clear that the difference in annual earnings between human arts majors and other

27

majors is larger than for hourly wages. More precisely, the raw difference in annual earnings is almost 30% compared to around 23% for hourly wages, whereas the difference after controlling for the full set of control variables is 22% for annual earnings, compared to 17% for hourly wages. In other words, the difference in labor income across majors is larger for annual earnings than for hourly wages.

Table 6 presents the IV estimates based on annual earnings. These results are directly comparable to the results presented in Table 4, which uses the hourly wages as dependent variable. The overall picture is that the return to human arts is up to 15% lower than the return to other majors. Moreover, it is evident that the return to human arts explaining around half of the gap in annual earnings. In other words, *relative ability sorting* explain half of the gap in annual earnings between human arts majors and other majors, whereas the other half is due to the education per se.

Table 6

By comparison of the estimated return to human arts based on hourly wages and annual earnings as dependent variable, we establish an important result: The return to human arts is significantly lower that the return to other majors when annual earnings are used as dependent variable. There is no difference in returns to different majors when hourly wages are used as dependent variable.

The explanation is obviously that hours worked differ across majors; quantitatively the difference in hours worked can be determined as the difference between the estimated coefficients in Tables 4 and 6. If we use the results in Column 1 of the Tables 4 and 6 we find a difference of -0.138 (=-0.1321-0.0059), or 13%. Similar results are found for columns 2 and 3, implying that hours worked for human arts majors are 13-16% lower than that of other majors.

The difference in the returns across majors is less pronounced when average annual

earnings over a number of years are applied. This is evident from columns 4-5. In this case, the difference in returns to human arts drops to 5-7% and loses statistical significance. An interpretation of this result is that human arts majors that are well-established in the labor marked, i.e., are employed for an unbroken period of 3 or 5 years, have annual earnings of similar magnitude as graduates of other majors. This point to a weak attachment to the labor market for a relative large share of majors in human arts compared to graduates from other majors. This interpretation is supported by the fact that the share of individuals with a degree within human arts drops with the extension of the period under investigation; from 10.5% when we focus on annual earnings for 2000, to 9.1% when focus is on the 1999-2001 average, and further to 8.3% for the 1999-2003 average.

In sum, the insight from Tables 4 and 6 is that while there is no difference in the relative returns to education between human arts majors and other majors in terms of hourly earnings, there is a difference in annual wage: human arts majors appear to work shorter hours than graduates from other areas.

7   Conclusions

In this paper, we have examined the efficiency of human capital production across different types of education by exploiting Danish register data. If some fields of study are more efficient in producing human capital, this should manifest itself in a superior labor market performance of its graduates. Baseline OLS regressions reveal that students of human arts fare the worst in the Danish labor market with an hourly wage rate about 20% below that of graduates within other majors.

One may suspect, however, that the partial correlation between the type of education and wages does not convey accurate information about human capital production. If the selection into educational types is non-random, the OLS estimates will be biased. Our analysis confirms that selection seems to be at work. Socioeconomic circumstances, absolute

ability, as well as relative cognitive abilities, measured by high school course work, influence the choice of education type.

Consequently, we invoke instruments for education type to address the selection problem. Our instrument is based on the influence from other students on individuals' choice of education type. Strikingly, once education type is instrumented, we find no statistically significant difference in the hourly wage gab between human arts majors and other majors. This result suggests that a tertiary degree in humanities do not provide individuals with significantly less productive human capital than other types of tertiary education. Accordingly, the relatively poor wage performance of human arts majors in the Danish labor market is mainly due to selection according to relative cognitive ability, rather than to low human capital production at universities. Hence, the main explanation for the wage gap is *relative ability sorting*. The flip side of the result that humanities do not provide individuals with less productive human capital is that humanities provide individuals with a relatively weak labor market attachment. This result is established when annual earnings are used instead of hourly wages as measure of labor market income.

The present analysis raises new questions worth exploring in future research. First, wage differences seem to be related to relative cognitive abilities; mathematics appears to be important, for example. But why is that? Is it because such abilities are relatively scarce in the population or because they are particularly productive? If the latter is the case, then it would be useful to try and discern why such abilities are in high demand. Further motivation for pursuing this question is found at the macro level where test scores in math and natural sciences seem to be a stronger linear predictor of aggregate growth than test scores for reading (Hanushek and Woessmann, 2009).

Second, how are relative abilities in, e.g., math and human science formed? As they determine both educational choices and wages, it would be useful to know whether these cognitive traits have a genetic origin, or are acquired during primary and secondary schooling. If the former is the case, education policies cannot be invoked to influence them; and

conversely if relative talents are acquired.

References

[1] Angrist, J. and A. Kruger, 1991. Does Compulsory School Attendance Affect Schooling and Earnings? *Quarterly Journal of Economics,* 106, 979-1014.

[2] Arcidiacono, P., 2004. Ability sorting and the returns to college major. *Journal of Econometrics,* 121, Issues 1-2, 343-375.

[3] Becker, G., 1967 : Human Capital and the Personal Distribution of Income. Ann Arbor Michigan: University of Michigan Press.

[4] Benbow, C.P., D. Lubinski, D.L. Shea, and H. Eftekhari-Sanjani, 2000. Sex Differences in Mathematical Reasoning Ability at Age 13: Their Status 20 years later. *Psychological Science*, 11, 474-480

[5] Benbow, C.P. and J.C. Stanley, 1980. Sex Differences in Mathematical Ability: Fact or Artifact?, *Science*, 210, 1262-1264

[6] Bishop, J. H., 1992. The impact of academic competencies on wages, unemployment, and job performance. *Carnegie-Rochester Conference Series on Public Policy*, 37, 127–194.

[7] Blundell., R., LL. Dearden, A. Goodman. and H. Reed, 2000. The Returns to Higher Education in Britain: Evidence from a British Cohort. *Economic Journal*, 110, 82-89.

[8] Bills M. and P. Klenow, 2000. Does Schooling Cause Growth? *American Economic Review*, 90. 1160-82

[9] Bratti M. and L. Mancini, 2003. Differences in Early Occupational Earnings of UK Male Graduates by Degree Subject: Evidence from the 1980-1993 USR. IZA Discussion Paper No. 890

[10] Card, D., 1999. The Causal Effect of Education on Earnings. In *Handbook of Labor Economics*, Ashenfelder, O. and D. Card (eds), Vol. 3, Ch. 30. Elsevier.

[11] Card, D., 2001. Estimating the return to schooling: progress on some persistent econometric problems. *Econometrica,* 69, 1127-60.

[12] Card, D. and A. Krueger, 1996. Labor Market Effects of School Quality: Theory and Evidence. NBER working paper 5450.

[13] Daymont, T. and P. Andrisani, 1984. Job preferences, college major, and the gender gap in earnings. *Journal of Human Resources*, 19, 408–428.

[14] Dolton, P. J. and G.H. Makepeace, 1990. The Earnings of Economic Graduates. *Economic Journal,* 100, 237-250.

[15] Dougherty, C., 2003. Numeracy, literacy and earnings: evidence from the National Longitudinal Survey of Youth. *Economics of Education Review*, 22, 511-521

[16] Fershtman, C., K. Murphy and Y. Weiss, 1996. Social Status, Education, and Growth. *Journal of Political Economy*, 104, 108-132

[17] Fersterer, J., J.-S. Pischke and R. Winter-Ebmer, 2008. The Returns to Apprenticeship Training in Austria: Evidence from Failed Firms. *Scandinavian Journal of Economics*, 104, 733-753

[18] Grogger, J., and E. Eide, 1995. Changes in college skills and the rise in the college wage premium. *Journal of Human Resources*, 30, 280–310.

[19] Hanushek, E. and L. Woessmann, 2009. Do better schools lead to more growth? Cognitive skills, economic outcomes and causation. *Journal of Economic Growth*, Forthcoming.

[20] Hendricks, L., 2002. How Important Is Human Capital for Development? Evidence from Immigrant Earnings. *American Economic Review*, 92, 198-219.

[21] Houthakker, H.S., 1959. Education and Income. *Review of Economics and Statistics*, 41, 24-28.

[22] James, E., A. Nabeel, J. Conaty and D. To, 1989. College quality and future earnings: where should you send your child to college?. *American Economic Review,* 79, 247–252.

[23] Joensen J. and H.S. Nielsen, 2009. Is there a Causal Effect of High School Math on Labor Market Outcomes? *Journal of Human Resources*, 44, 171-198.

[24] Loury, L. and D. Garman, 1995. College selectivity and earnings. *Journal of Labor Economics*, 13, 289–308.

[25] Lucas, R. Jr., 1988. On the Mechanics of Economic Development. *Journal of Monetary Economics*, 22, 3-42.

[26] Mincer, J., 1958. Investment in Human Capital and Personal Income Distribution. *Journal of Political Economy*, 66, 281-302

[27] Miller, H.P., 1960. Annual and Life Time Income in Relation to Education. *American Economic Review*, 50, 962-86.

[28] Staiger, D. and J.H. Stock, 1997. Instrumental Variables Regression with Weak Instruments *Econometrica* 65, 557-586.

[29] Wooldridge, J. M., 2002: Econometric Analysis of Cross Section and Panel Data. Cambridge, Massachusetts, The MIT Press.

A   Deriving Expected Utility

The second order Taylor approximation

$$v\left(q\right) \approx v\left(\mu\right) + v_q\left(\mu\right)\left(q - \mu\right) + \frac{v_{qq}\left(\mu\right)}{2}\left(q - \mu\right)^2$$

Observe that $\left(q - \mu\right)^2 = q^2 + \mu^2 - 2q\mu$. Hence

$$v\left(q\right) \simeq v\left(\mu\right) + v_q\left(\mu\right)\left(q - \mu\right) + \frac{v_{qq}\left(\mu\right)}{2}q^2 + \frac{v_{qq}\left(\mu\right)}{2}\mu^2 - \mu q v_{qq}\left(\mu\right)$$

Inserted into the utility function we obtain

$$
\begin{aligned}
E\left[U\left(y,q\right)\right] \approx{} & u\left(y\right) + v\left(\mu\right) + v_q\left(\mu\right)\int qf\left(q\right)dq - \mu v_q\left(\mu\right) \\
& + \frac{v_{qq}\left(\mu\right)}{2}\int q^2 f\left(q\right)dq + \frac{v_{qq}\left(\mu\right)}{2}\mu^2 - \mu v_{qq}\left(\mu\right)\int qf\left(q\right)dq.
\end{aligned}
$$

A useful result regarding means and variances is that $\int q^2 f\left(q\right)dq = \mu^2 + \sigma^2$. Using it in the expression above we get

$$E\left[U\left(y,q\right)\right] \approx u\left(y\right) + v\left(\mu\right) + \frac{v_{qq}\left(\mu\right)}{2}\sigma^2$$

Figure 1. A Sketch of the Danish High School System, 1981-1990

Figure 2. Significance of Instrument using Lags of Instrument

Notes: The figure presents point estimates (horizontal lines) and 95% confidence intervals (vertical lines) for 4 instruments in the probit regression based on the average hourly wage rate in 2000 as the dependent variable. The instruments is defined as the shares of graduates within human arts. The applied instruments are: the squared shares of one year older cohort (lag 1), two years older cohort (lag 2), three years older cohort (lag 3), and four years older cohort (lag 4). Other explanatory variables are gender dummy, high school GPA, curriculum fixed effects, dummies for graduation year from high school, information for education length and type of parents, and high school fixed effects. The sample size equals 26.227 individuals.

Table 1. Summary Statistics for the Main Estimation Sample

	Mean	Std. Dev.
Log(wage rate)	5.436	0.322
Subsequent Education Type		
Human Arts Share	10.5%	
Other Educational Types	89.5%	
High School Branch		
Math-Music	5.9%	
Math-Physics	40.8%	
Math-Natural Sciences	20.8%	
Math-Social Sciences	15.9%	
Modern Languages	7.1%	
Classical Languages	0.4%	
Language-Social Sciences	7.6%	
Language-Music	1.4%	
High School GPA	8.824	0.8529
Men	59.9%	
Number of individuals	29,700	

Table 2. OLS Log Wage Regression Estimates

	(1)	(2)	(3)	(4)	(5)
Human Arts	-0.2580***	-0.2242***	-0.2241***	-0.2054***	-0.1890***
	(0.0059)	(0.0058)	(0.0058)	(0.0062)	(0.0060)
Women		-0.1567***	-0.1594***	-0.1365***	-0.1355***
		(0.0037)	(0.0036)	(0.0037)	(0.0036)
High School Grade			0.0208***		0.0333***
			(0.0021)		(0.0020)
High School Branch (ref: Math-Physics)					
Math-Music				-0.1254***	-0.0425***
				(0.0077)	(0.0081)
Math-Natural Sciences				-0.0886***	-0.0856***
				(0.0048)	(0.0047)
Math-Social Sciences				-0.0610***	-0.0332***
				(0.0052)	(0.0051)
Modern Languages				-0.0531***	-0.0803***
				(0.0076)	(0.0074)
Classical Languages				-0.1111***	-0.1364***
				(0.0270)	(0.0264)
Language-Social Sciences				-0.0952***	-0.0868***
				(0.0071)	(0.0069)
Language-Music				-0.1103***	-0.0919***
				(0.0153)	(0.0151)
Parental Education	NO	NO	NO	NO	YES
Graduation Year Fixed Effects	NO	NO	NO	NO	YES
High School Fixed Effects	NO	NO	NO	NO	YES
R-squared	0.0607	0.1172	0.1202	0.1342	0.2117
Number of Individuals	29,700	29,700	29,700	29,700	29,700

Notes: Standard errors clustered by high school, high school track and graduation year are reported in paratheses. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level. All specifications are estimated using OLS. The dependent variable in all specifications is the hourly wage rate in 2000. The independent variable of interest is "Human Arts" and the reported coefficients of this variable can be interpreted as the return to human arts majors relative to that of other majors.

Table 3. Summary Statistics for the Instrument

Fraction of Students Two Cohorts Ago Choosing Human Arts:

	Mean	Std. Dev.
Over-all	0.216	0.217
5th percentile	0.000	
10th percentile	0.000	
25th percentile	0.050	
50th percentile	0.121	
75th percentile	0.355	
90th percentile	0.556	
95th percentile	0.667	
Clusters	2,252	

Table 4. IV Estimates for log Wage Regression Estimates

2nd Stage of 2SLS	(1)	(2)	(3)	(4)	(5)
	Linear instrument	Linear and squared instrument	Share Dummies	Linear and squared instrument	Linear and squared instrument
Dependent variable:	wage rate, year 2000	wage rate, year 2000	wage rate, year 2000	3-year avg. wages	5-year avg. wages
Human Arts	0.0059	0.0028	0.0037	-0.0143	-0.0356
	(0.0436)	(0.0444)	(0.0435)	(0.0470)	(0.0516)
Women	-0.1420***	-0.1418***	-0.1419***	-0.1382***	-0.1403***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0040)
High School GPA	0.0354***	0.0354***	0.0354***	0.0336***	0.0354***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0024)
Probit model					
Fraction of Students Two Cohorts Ago Choosing Human Arts	0.2998***	-0.4201*		-0.4593	-0.5841*
	(0.1068)	(0.2456)	Not	(0.2841)	(0.3026)
Fraction of Students Two Cohorts Ago Choosing Human Arts Squared		0.8992***	reported	0.9269***	1.0380***
		(0.2846)		(0.3242)	(0.3384)
Women	0.2195***	0.2204***	0.2209***	0.1981***	0.1968***
	(0.0231)	(0.0232)	(0.0232)	(0.0272)	(0.0300)
High School GPA	-0.0692***	-0.0689***	-0.0691***	-0.0494***	-0.0590***
	(0.0139)	(0.0139)	(0.0140)	(0.0165)	(0.0178)
Other Controls					
Parental Education	YES	YES	YES	YES	YES
High School Branch Fixed Effects	YES	YES	YES	YES	YES
Graduation Year Fixed Effects	YES	YES	YES	YES	YES
High School Fixed Effects	YES	YES	YES	YES	YES
Cluster-Robust Chi-squared-Test	7.88	16.80	20.43	13.19	8.197
Clusters	2,252	2,252	2,252	2,186	2,158
Share of Individuals with a Human Arts degree	10.5%	10.5%	10.5%	9.1%	8.3%
Number of Individuals	29,700	29,700	29,700	23,434	20,674
Endogeneity test	20.561	18.954	19.987	13.551	19.518
	0.0000	0.0000	0.0000	0.0002	0.0000

Notes: Standard errors clustered by high school, high school track and graduation year are reported in paratheses. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level. All specifications are estimated using 2SLS with probit in the first stage regression. The independent variable of interest is "Human Arts" and the reported coefficients of this variable can be interpreted as the return to human arts majors relative to that of other majors. Share-dummies are used as instrument in column 3. A share-dummy is defined for each 0.1-interval between 0 and 1.

Table 5. OLS Log Annual Earnings Regression Estimates

	(1)	(2)	(3)	(4)	(5)
Human Arts	-0.3406***	-0.2939***	-0.2938***	-0.2721***	-0.2542***
	(0.0076)	(0.0075)	(0.0062)	(0.0080)	(0.0078)
Women		-0.2060***	-0.2198***	-0.1900***	-0.1889***
		(0.0047)	(0.0047)	(0.0048)	(0.0047)
High School Grade			0.0291***		0.0453***
			(0.0027)		(0.0026)
High School Branch (ref: Math-Physics)					
Math-Music				-0.1573***	-0.0491***
				(0.0100)	(0.0105)
Math-Natural Sciences				-0.1174***	-0.1127***
				(0.0062)	(0.0061)
Math-Social Sciences				-0.0675***	-0.0320***
				(0.0067)	(0.0056)
Modern Languages				-0.0641***	-0.0971***
				(0.0098)	(0.0096)
Classical Languages				-0.1026***	-0.1338***
				(0.0350)	(0.0344)
Language-Social Sciences				-0.1154***	-0.1030***
				(0.0092)	(0.0090)
Language-Music				-0.1480***	-0.1330***
				(0.0199)	(0.0196)
Parental Education	NO	NO	NO	NO	YES
Graduation Year Fixed Effects	NO	NO	NO	NO	YES
High School Fixed Effects	NO	NO	NO	NO	YES
R-squared	0.0607	0.1172	0.1294	0.1421	0.2110
Number of Individuals	29,691	29,691	29,691	29,691	29,691

Notes: Standard errors clustered by high school, high school track and graduation year are reported in paratheses. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level. All specifications are estimated using OLS. The dependent variable in all specifications is the hourly wage rate in 2000. The independent variable of interest is "Human Arts" and the reported coefficients of this variable can be interpreted as the return to human arts majors relative to that of other majors.

Table 6. IV Estimates for log Annual Earnings Regression Estimates

2nd Stage of 2SLS	(1)	(2)	(3)	(4)	(5)
	Linear instrument	Linear and squared instrument	Share Dummies	Linear and squared instrument	Linear and squared instrument
Dependent variable:	annual earnings, year 2000	annual earnings, year 2000	annual earnings, year 2000	3-year avg. annual earnings	5-year avg. annual earnings
Human Arts	-0,1321**	-0,1575***	-0,1669***	-0,0492	-0,0746
	(0.0592)	(0.0604)	(0.0602)	(0.0539)	(0.0559)
Women	-0.1930***	-0.1921***	-0.1918***	-0.1840***	-0.1875***
	(0.0051)	(0.0052)	(0.0051)	(0.0044)	(0.0044)
High School GPA	0.0466***	0.0463***	0.0462***	0.0403***	0.0416***
	(0.0029)	(0.0029)	(0.0029)	(0.0026)	(0.0026)
Probit model					
Fraction of Students Two Cohorts Ago Choosing Human Arts	0.2989***	-0.4227*		-0.4590	-0.5841
	(0.1068)	(0.2457)	Not	(0.2841)	(0.3026)
Fraction of Students Two Cohorts Ago Choosing Human Arts Squared		0.9011***	reported	0.9265***	1.038***
		(0.2847)		(0.3242)	(0.3384)
Women	0.2195***	0.2205***	0.2210***	0.1981***	0.1968***
	(0.0232)	(0.0232)	(0.0232)	(0.0272)	(0.0300)
High School GPA	-0.0691***	-0.0689***	-0.0691***	-0.0494***	-0.0590***
	(0.0140)	(0.0139)	(0.0139)	(0.0165)	(0.0178)
Other Controls					
Parental Education	YES	YES	YES	YES	YES
High School Branch Fixed Effects	YES	YES	YES	YES	YES
Graduation Year Fixed Effects	YES	YES	YES	YES	YES
High School Fixed Effects	YES	YES	YES	YES	YES
Cluster-Robust Chi-squared-Test	7.83	16.79	20.38	13.18	13.35
Clusters	2,252	2,252	2,252	2,186	2,158
Share of Individuals with a Human Arts degree	10.5%	10.5%	10.5%	9.1%	8.3%
Number of Individuals	29,691	29,691	29,691	23,432	20,674
Endogeneity test	4.236	2.541	2.093	2.541	4.562
	0.0396	0.1109	0.1479	0.1109	0.0327

Notes: Standard errors clustered by high school, high school track and graduation year are reported in paratheses. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level. All specifications are estimated using 2SLS with probit in the first stage regression. The independent variable of interest is "Human Arts" and the reported coefficients of this variable can be interpreted as the return to human arts majors relative to that of other majors. Share-dummies are used as instrument in column 3. A share-dummy is defined for each 0.1-interval between 0 and 1.