Estimating the Impact of School Quality, Selection, and Supply on Student's Achievements: Evidence from The Czech Nation-wide Testing of Youth.

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Abstract

I analyze causal relationships in skills formation of 18 years old pupils in the final year of their upper-secondary studies in the Czech Republic in late 1990s. I am using rich microdata and two-stage regression methodology accounting for selection and unobserved heterogeneity of pupils. I contrast estimates with spurious correlations and OLS estimates. Students graduating from highly demanded grammar schools - program with general curriculum - show notably better achievements. One third of the performance differential is due to differentials in observed initial characteristics as initial skills and social background. Selection based on unobservables plays minor role. Almost half of the differential is due to pure school quality effect. School quality differential explains persistent excess demand for grammar school programs. Estimates of local average treatment effects support policies advising to expand the share of slots at grammar schools. Students who would benefit from expansion would gain more than average student in the vocational program.

1 Introduction

Growing number of policy debates is challenging the issues of productive skills acquisition. Educational system is considered as the most important determinant, at least in developed economies. In this respect, educational system has two important characteristics; ability to enhance human capital accumulation and the impact on the formation of societal inequality. These characteristics are largerly determined by the design of specific educational system. Design itself is by virtue an outcome of public policies. Moreover, direct expenditures on schooling constitute large proportion of public budgets and the opportunity costs of time incurred by the educated population are huge. Nevertheless, parental background and social environment also play important role in the process of skills formation as many important life-skills are acquired in the continuous process of one's lifetime. Skills acquired early in person's life become important determinant of further skills acquisition at school. Consequently, pupils with more wealthy social background are likely to acquire skills in school more easily.

Social and parental background can be also a determinant of schooling quality due to differences in school accessibility. In mature developed economies, where we observe closer relation between parent's skills and wealth (or earnings), richer parents are likely to seek and find better schooling options for their children. Parents can do so choosing a residence in good quality schooling district. This is common phenomena in countries with high residential mobility like in the US or the UK.[1] Richer parents have higher propensisty to pay tuition if private schools provide an alternative to tuition-free public schools. From the policy and normative perspective, one would like to have a schooling system which does not discriminate on other factors than students abilities. Desirable schooling system would provide skills to students irrespective of their social background. The lower

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[1] According to *The 2003 National Association of Realtors Profile of Home Buyers and Sellers*, schools were listed as a deciding factor for 17% of home buyers (http://www.realtor.org). Refrences to other studies can be found at Bogart and Cromwell (1997, 2000).

schooling level the more one would like the system to supply life-skills to pupils who cannot acquire them at home.

The situation in transitional countries is specific in this respect. In communist countries, there had been weaker correlation between parents' skills and education on one hand and earnings and wealth on the other. This was so because communist system was ideologically build on egalitarianism. Social and political changes following the demise of the communist regime downgraded social status and accumulated advantages of families participating in the communist nomenclatura. Large scale privatization following the dismissal of central planning was guided by new unsettled legal system and the process of wealth redistribution was frequently on or beyond the frontier of fraud. Education and skills happened to be only second order determinant of newly emerging wealth distribution. As a result, the correlation between newly distributed wealth and education was lower than in mature market economies. Shortly after the wave of pro-market reforms, competitive forces started to push the convergence of earnings and wealth distribution. Returns to human capital started to grow and individuals possessing more human capital started to reach higher earnings. Richer and more educated adults becoming parents started to transmit more skills to their children. The transmition of skills happens partly thanks to skill creative social environment and partly because parents have preferences and tools to acquire better quality education for their children. This generational transmission is likely to last for decades and the schooling system will be an important determinant.

As of now, relatively little is known about the impact of educational systems on inequality and about the relative contribution of formal schooling and of parental background to human capital accumulation. Mixed empirical evidence is provided by a line of studies.[2] Based on the evidence from the UK, Galindo-Rueda and Vignoles (2004a) find declining role of pupil's cognitive ability on

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[2]Fogelman (1984), Kerckhoff (1986), Harmon and Walker (2000), Jesson (2000) and Dearden, Ferri and Meghir (2003).

future educational achievement and attribute it to declining selectivity of the schooling system in UK during 1970s and 1980s and increasing role of family background. Galindo-Rueda and Vignoles (2004b) investigate the inter-relationship between school selection, ability and educational achievement. Using regression and matching methods and data from more and less selective schooling systems they find that *"...the most able bodied pupils in the selective school system did do better than those of similar ability in the mixed ability school system"*.

Little is known about these phenomena in post-communist countries. Sociologically oriented studies[3] explore the influence of social origin on the chances of making a successful transition between secondary and tertiary education. Matějů et al. (2003) use data from various surveys carried out between 1998 –2000 and in the years between 1948 and 1999 in the Czech Republic and find evidence of *"...growing effect of [social] class origin in the period after 1989..."* and find increasing socioeconomic inequalities. They interpret this trend by insufficient expansion of the tertiary sector of education in the country. On related issue, Matějů and Straková (2004) explore social selectivity of the Czech basic and upper-secondary schooling level and its impact on the reproduction of educational inequality. They identify sorting of students through the educational system as the major source of variation in students' achievements while variation is almost entirely accounted for by socioeconomic background of students.

This study is an attempt to identify origins of sizeable differentials in mean tests scores of students across different upper-secondary programs as they exist in the Czech Republic operating typical Central European schooling system. I consider following determinants: (i) school quality, (ii) observed, and (iii) unobserved heterogeneity of students. To perform my empirical analysis, I collected rich individual data containing standardized study aptitude test (SAT) scores and many other descriptors allowing me to control for initial conditions, social and school characteristics. The data cover whole cohort of students in their last year of studies before graduation from upper-

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[3]Mateju et al. (1990, 1993, 1999).

secondary schools. I estimate and quantify the impact of various factors on skills accumulation and provide evidence on the selectivity of the schooling system.

In section (2) I describe the essentials of the educational system, in section (3) I describe the data. I lay out my estimation strategy in section (4) and present estimated results in section (5). Section (6) concludes.

2 Educational system

The upper-secondary system of schooling in the Czech Republic is typical continental schooling system with roots going back to the period of Austrian-Hungarian empire. The schooling system also possesses features originating from decades of central planning. In particular, schools are still overly focused on memorization rather than creative thinking (Tomášek et al., 1997). In its principal characteristics and outcomes, the system is similar to systems operated in European countries like Germany, Austria, and Hungary.[4] These schooling systems rely heavily on vocational programs of various specializations vis-a-vis relatively small share of schools providing general education. This makes these systems different from systems typically operated in Scandinavian countries and countries like Ireland. In those countries, the predominant type of school at the upper-secondary level provides very similar and general curriculum. At the upper-secondary level, Czech students choose from three programs which differ in terms of duration, curriculum and final graduation certificate: apprenticeship programs last 2-4 years, vocational and grammar schools[5] programs last 4 years. Apprenticeship programs rely a lot on manual training at a workplace and the proportion of time devoted to in-class instructions is small. Vocational and grammar schools rely on in-class instructions. Both programs teach general subjects like grammar, foreign language, and

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[4] According to OECD (1997), in 1995 the Czech Republic, Germany, Austria and Hungary had the lowest proportion of pupils enrolled in general upper-secondary programs; 16, 23, 23, and 27 respectively, among all OECD countries.

[5] Grammar schools are called *gymnásia* and vocational schools are called *střední odborné* školy.

math. Grammar schools provide more general and wider education in social and natural sciences. Important component of curriculum at grammar schools is provision of skills fostering success at college[6] entry test. Vocational schools provide curicullum more focused on specific labor market professions like nursing, electrotechnics, engineering, etc. Shares of the three upper-secondary programs and the change during 1990s is depicted in Table 1. While the proportion of grammar schools stayed the same, the proportion of vocational schools and students grew at the expense of apprentices programs. Fewer than one in five upper secondary students in the Czech Republic are enrolled in grammar schools, the lowest proportion among all OECD countries (OECD, 2001).

Table 1: Share of Upper-secondary Schooling Programs [in %]

Share of schools		
Grammar Schools	18	19
Vocational	30	48
Apprentices	52	33
Share of students		
Grammar Schools	18	18
Vocational	28	48
Apprentices	54	35

Upper-secondary level of schooling in the Czech Republic is preceded by nine years long studies at primary and lower-secondary programs provided usually by single school units. Pupils enrol to primary schools at age of six or seven years and compulsory education lasts 11 years. This requirement forces all primary schools graduates to opt for at least 2 additional years at full-time state-certified educational program at the upper-secondary level. Students enrol into upper-secondary schools depending on their preferences, abilities, willingness to pay, and number of slots in accessible residential area. Apprentices programs typically draw from the lower end of the quality distribution of pupils. The left panel of Figure 1 shows notable differences in mean SAT score across three upper-secondary programs.

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[6]Great share of tertiary programs in 1998 were 4-6 years long programs. In 1998, all institutions providing accredited tertiary education were public.
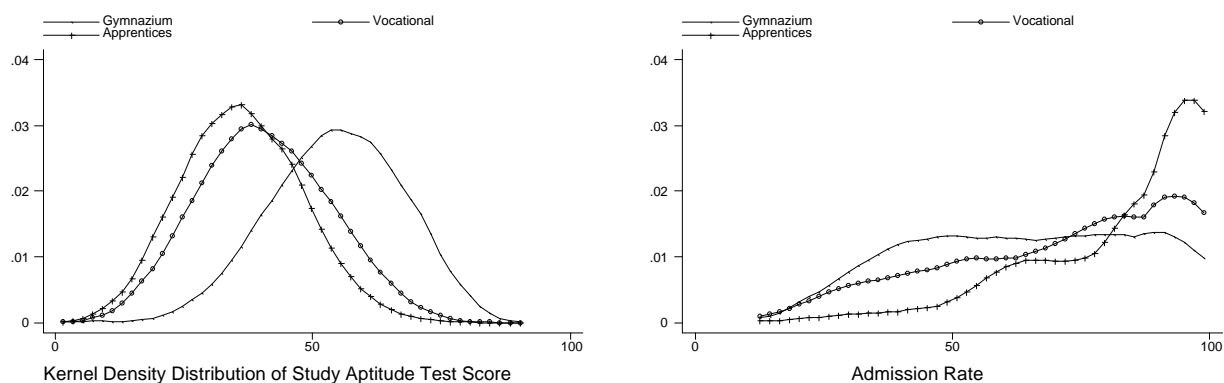
Figure 1: Kernel Density Distributions

Excess demand persists for vocational and especially for grammar schools. Admission to over-subscribed programs is being rationed mainly on the basis of an entry exam. Evidence on excess demand based on the data used for my analysis is presented in the right panel of Figure 1. The figure shows kernel density distribution admission rates into the three school-types at the upper-secondary level. Probability of admission to most apprentices schools is very high and frequently close to 100 percent. This contrasts with two other programs with notably smaller enrolment probability. Note that the admission to grammar schools is very uniformly distributed implying high variance in admission chances across locations and schools.

Apprenticeship graduates do not qualify for college studies. Eligible for college studies are only graduates from four years long upper-secondary programs concluded by certified exam.[7] For this reason, vocational and grammar school programs are sometimes called *complete* upper-secondary programs. During 1990s, the demand for college education had been driven by fast and sustained

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[7]Existing certified exam is not country wide standartised exam. Exam results are not comparable across schools and information is not gathered centraly. However, exam certificate is recognized by public colleges and public employers. Private firms are not legaly obliged to recognize these certificates but most of them do so.

growth of returns to education. Münich et al. (2004a, 2004b) provide empirical evidence based on a retrospective survey of labor market histories tracking Czech workers from 1996 backward. They find that men's and women's return to college education more than doubled from 19 and 32 percent in 1989 to 37 and 41 percent in 1996. More recent evidence is provided by Jurajda (2003). Using employee microdata he finds that returns to college reached 50 and 45 percent in 2002. Despite this, the unconditional probability of being admitted to college has been steadily low at about 50 percent since early 1990s. Table 2 presents statistics on application and enrolment rates to colleges. Almost all, 91 percent, of grammar school students seek admission to college while only each second student from vocational school does so.

Table 2: Application and Enrollment Rate to College [%]

School-type	Applied	Enrolled	Excess Demand
Grammar School	91	58	23
Vocational	50	18	30
Apprentices	27	10	37

The discrepancy in admission probability and follow-up enrolment is even more pronounced. Almost 60 percent of grammar schools students enroll to college compared to 18 percent of students from vocational schools. Moreover, grammar schools students manage to enroll to more demanded colleges as indicated by the excess demand index. The index is computed in following way: for each student who enrolled to a college I compute college specific ratio of enrolled to applying students. Number presented in the table is average ratio computed across all students from given school-type who enrolled a college.

Communist regime imposed state monopoly and control over school management and curriculum. Although schools were also used as a vehicle for political indoctrination, the curriculum was similar to the one taught in non-communist countries. International literacy surveys[8] run in mid 1990s show that educational achievements comparable to levels found in countries like Austria or

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[8]International Literacy Survey (IALS) run in 1992 and Second International Adult Literacy Survey (SIALS) run in 1995 provide internationaly comparable literacy scores for the adult population. According to OECD (2000) average

(West) Germany. Reforms introduced in early 1990s gave more decision-making power to parents and individual schools. Reforms opened space for greater flexibility and differentiation between schools. Non-state schools received legal grounds in 1990. Private and church schools[9] were established primarily at the upper-secondary level. Compared to state schools, private and church schools are partly and fully publicly funded through capitation grants based on enrolled students. Private schools are free to charge and set tuition while church schools are not if they opt for full funding formula. More details on the funding system can be found in Filer and Münich (2003). In 1998, non-state schools constituted about 24 percent of all schools. Due to their smaller size, non-state schools enrolled only 12.5 percent of students in corresponding age cohort. These shares seem to be small but given the short period they exist and compared to many other countries, the proportion of non-public schools in the Czech Republic is large. Non-state schools are frequently regarded with fears. It is partly due indoctrination under communism, partly by their short history since all of them were established after 1990. The fears are also strengthened by higher risk school closure in case of financial or other distress.

2.1 Pros and cons of the schooling system

The type of upper-secondary schooling system operated in the Czech Republic has its typical pros and cons. Dominant vocational schools provide skills well suited for specific occupations and specific industrial sectors. The implied advantage is that school leavers are already well prepared for their job and quickly become highly productive not needing additional on-the-job training. The role of vocational programs had been particularly important during industrialization era and four decades of central planning. During communist times, residential and occupational mobility was extremely

Czech adult ranked 12th, 7th, and 3rd in prose, document, and quantitative literacy, among 22 OECD countries. According to TIMMS (2000a,b) survey run in 1999 focussing on 15 years old population Czech 8-graders ranked 8th and 15th in science, math from about 40 countries.

[9]Congregational or diocesan

low and job security high. These days, economic developments of individual industries and demand for specific skills is much more volatile and very difficult to predict. Physical capital, firms and know-how are mobile while residential mobility of the population stays low. Moreover, the service sector demanding general skills is steadily growing while the share of the manufacturing requiring specific skills is shrinking. Finally, permanent technology innovations put pressure on continuous accumulation of skills. In such a dynamic environment, former advantages of vocational schools are turning into disadvantages.

Another important trend challenging the existence of vocational programs in the country are growing educational ambitions of the young population. More pupils entering upper-secondary school have ambitions to get prepared for and continue studies at a college. Studies at a grammar school offer better option. General curriculum offered by grammar schools is better suited for college studies. Moreover, since slots at colleges are in short supply and are rationed based on college entry tests, grammar schools are much better in preparing students for such exams. In this respect, selectivity of the schooling systems seems to be important determinant of skills distribution in the population. The selection starts already at lower levels of the schooling system. Admission to highly demanded grammar schools is rationed. Enrolment to a grammar school at the age of 15 years is perceived as extremely important precondition for individual life-long carrier. The later reason is important because college education bring high expected monetary return and non-negligible improvement in social status and recognition. My analysis provides quantified counterparts of perceived pros and cons of the incumbent schooling system.

3 Data

In this section I provide general description of two major data sources used. I am using data from national wide testing[10] of upper-secondary school graduates in the Czech Republic *(SM98)*. *SM98* data-set contains standardized test scores based on written test in native (Czech) and a foreign language, math, and study aptitude skills. Whole population of students in their last year at high-school was subject to standardized testing in the Spring 1998. This represents about 60 percent of the whole age cohort. Students in standard apprenticeship programs were not subject to testing and were not surveyed at all. Limited number of special apprenticeship schools called *integrated schools* participated in the survey. These schools have been established in the middle of 1990s on the grounds of better performing apprenticeship programs to provide thier students the option of final certified exam. I present basic statistics for these schools but it should be understood that statistics are not representative of the whole apprenticeship segment. Given that participating schools represent best performing schools in the segment, statistics provide usefull information on lower or upper bounds in my comparative overview.

SM98 examination was run simultaneously and results were processed centrally. Data also contain basic demographic information on each student, parents and detailed information is provided about school and class. Among many descriptors, reported are student's achievements in math and native language graded at the end of the 5th year at the primary school.

The second data-source I use is a database of individual college applications for the academic year 1998/1999. Applicants' IDs in both databases allowed me to merge the data to *SM98* data file. About one third of applicants did not participate in the *SM98* testing because they had graduated one or more years ago. On the other hand, some students in the *SM98* database did not submit

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[10]The testing was called *Sonda Maturant 1998 (Maturity Probe)*. The research database was saved for research purposes thanks to Petr Matějů. Extremely usefull was the data management assistance provided by Jindrich Krejčí, from the Sociological Institute of the Czech Academy of Sciences. I highly appreciate their extraordinary help.

application to any college. Variables capturing district specific factors are obtained from statistical survey of districts[11] published annually by the Czech Statistical Office.

4 Estimation strategy

My primary goal is to quantify the impact of various determinants of students' achievements. Various measures of skills are being used in the literature; pecuniary returns to education, admission rate to college, unemployment and employment rates, and standardized test scores. None of these measures captures comprehensively the whole diversity of human achievements and each of these measure suffers from some imperfections. In my analysis, I use study aptitude test (SAT) score as achievement measure. The usual criticism of test scores among economists is that they are not necessarily good predictors of future pecuniary returns and employment. Having both test scores and labor market performance indicators would be obviously better ground for my analysis. However, large share of graduates from upper-secondary schools I study entered labor market only very recently. Moreover, no information is available to track them since they have passed the SAT in 1998. While such tracking is common in some western countries like the US, the UK and Scandinavian countries, longitudinal panels in former communist countries have been established only recently. Standardized test scores I use are rarely available in post-communist countries. Its availability for in the Czech Republic allows for unique analysis. Moreover, the data contain rich information about the past allowing me to control for initial conditions.

Conclusions based on simple comparison of average schooling outcomes can be misleading due to spurious relationships. To model formation of skills and explain observed differentials I account for observed and unobserved determinants and for sorting of students through the schooling system. In order to estimate separately effects of school quality and school choice on student's SAT score

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[11]Annual publication of the Czech Statistical Office *Okresy České republiky.*

Y, I employ stylized switching regression model

$$Y_i^0 = X_i\beta^0 + u_i^0 \tag{1}$$

$$Y_i^1 = X_i\beta^1 + u_i^1 \tag{2}$$

$$D_i^* = Z_i\theta + u_i^D. \tag{3}$$

First two equations describe the determination of potential achievements Y^0 and Y^1 of student i graduating from two different school types; superscript 0 stands for vocational school and 1 for grammar school. Important feature of the model is that either Y_i^0 or Y_i^1 is observed for each student, but the pair, (Y_i^0, Y_i^1), is never observed because a choice of one school-type automatically precludes the choice of the alternative. Selection into school of given type is guided by continuous latent variable D_i^*. Specification in (3) should be viewed as reduced form. It captures both application to school of given type and the admission decission.[12] Therefore, vector Z_i contains students characteristics affecting both determinants and local schooling supply-demand conditions Since D_i^* is latent variable, the actual outcome is indicated by indicator variable

$$D_i(Z_i) = 1[D_i^*(Z_i) \geq 0] = 1[Z_i\theta + u_i^D \geq 0]. \tag{4}$$

The key problem of the estimation strategy is the link between enrolment to grammar school $(D = 1)$ and potential outcomes Y^0 and Y^1 implying inequalities $E(Y^0|D = 0) \neq E(Y^0)$ and $E(Y^1|D = 1) \neq E(Y^1)$. This link translates into correlation of unobserved terms u^0 and u^1 with u^D, as shown in detail in the Appendix. Identification of model parameters requires exclusion restrictions such that there is non-empty subset Z_i^k, of Z_i which is not contained in X_i. This generates heterogeneity in the probability of treatment not affecting potential outcomes Y. I estimate model (1)-(3) using two-step procedure proposed by Heckman et al. (2000) and reviewed in the Appendix. Further on,

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[12] The admission is ussualy based on the outcome of an entry exam and other observable characteristics like previous study performance.

I estimate following treatment measures.[13]

The *Average Treatment Effect* $ATE \equiv E(Y^1 - Y^0)$ represents the average gain from attending school-type 1, for randomly enrolled student. ATE can be expressed as a function of covariates X so that $ATE(X) = E(Y^1 - Y^0|X)$. It is common to evaluate ATE at average values of X. An alternative is to compute unconditional value of ATE for various subsets of the population. The natural choice is to compute average ATE over the population of X as it appears in the data.

Another treatment of interest is the *Average Treatment Effect on the Treated*, $ATE^1 = E(Y^1 - Y^0|D = 1)$. It is the mean gain of those who actually enrol in school-type 1. Only under specific conditions, it holds that

$$ATE = ATE^1 \tag{5}$$

In particular, equality (5) holds if the treatment is randomized and statistical unrelated to outcomes. It can be easily shown that sufficient condition is that $E(Y^0|D = 0) = E(Y^0)$. However, even this weaker condition is relatively strong since enrolment D likely depends not only on Y^1 but also on Y^0. In other words, students with relative disadvantage for studies in vocational school are likely to prefer grammar school. Similarly, one can define *Average Treatment Effect on the Untreated*, $ATE^0 = E(Y^1 - Y^0|D = 0)$. It is the hypothetical mean gain from chooisng school-type 1 of those who actually enrol into school-type 0.

The information provided by ATE measures is not necessarily relevant to evaluate the impact of a policy. This is because ATE is average gain computed across the whole population. If the population considered includes students who are not eligible for treatment, ATE will provide little information about potential impact of policy change of marginal size. In the case of this study, great majority of students who end up in apprenticeship programs would not have sufficient study

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[13] An explicit assumption is that treatment of student i has an impact on outcome Y of this student but does not have impact on the outcome of another student j. In the literature, this assumption is known as *stable unit treatment value assumption, SUTVA*.

aptitude for intellectually oriented studies at grammar schools. Exclusion of these students from the whole analysis, although due to data limits, should not have impact on my results. However, some vocational students, included into the analysis, do not consider studies at grammar schools. These students eneter the computation of ATE although the gain to treatment does not have policy meaning in their case. An alternative to ATE is therefore *Local Average Treatment Effect* ($LATE$) defined by Imbens and Angrist (1994). $LATE$ measure is useful from the policy perspective. It captures average gain experienced by students who would select into school-type 1 just as a result of a change in one or more variables in vector Z which are not contained in X. An estimate of $LATE$ therefore depends on availability of such instruments. Moreover, point estimate of $LATE$ also depends on the type of instruments used. While parameters ATE do not depend on the choice of instruments, there are different $LATE$ parameters for different instruments.

The *Marginal Treatment Effect* (MTE) measures the gain to selection into school-type 1 for students with different values of unobservable characteristics u^D, so that $MTE(u^D)$. It can be shown that the MTE is the limit value of the $LATE$ parameter for infinitely small change in $Z_i\theta$. Formal definition of individual treatment effects and expressions for different treatment parameters are provided in Appendix and in more elaborate form in Heckman et al. (2000).

4.1   Decomposition

To identify contribution of individual factors to the raw SAT score gap differential, I use methodology more commonly used to analyze gender wage gap. In this framework,[14] the raw mean gap is

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[14]Winsborough and Dickenson (1971), Jones and Kelley (1984), Daymont and Andrisani (1984).

decomposed as

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\begin{aligned}
\overline{Y}^1 - \overline{Y}^0 &\equiv E(Y^1|D=1) - E(Y^0|D=0) \\
&\equiv \overline{X}^0(\beta^1 - \beta^0) + (\overline{X}^1 - \overline{X}^0)\beta^0 + (\overline{X}^1 - \overline{X}^0)(\beta^1 - \beta^0) + \qquad (6) \\
[E(U^1|D &= 1) - E(U^0|D=0)] \\
&\equiv C + E + CE + S
\end{aligned}
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where bars denote sample means. The decomposition in (6) is based on the assumption that the base group corresponds to grammar schools $(D_i = 1)$.[15] The first component (including the intercepts), C, is due to different *coefficients* and corresponds to ATE^0. Second term, E, is due to different *endowments*, and term CE is due to *interaction* between coefficients and endowments. The last term S is due to selection on unobservables.

In the discrimination literature, one is interested in the whole unexplained part of the wage gap because it captures the scope of discrimination. The interaction term is algebraically allocated between explained and unexplained part depending on auxiliary choice of the base group being considered as non-discriminatory. I focus only on endowment, coefficient and selection components and do not speculate about allocation of the interaction term.

5   Empirical findings

In this section I review basic statistics, present estimates of model in (1)-(4) and compare them to simple OLS estimates and IV estimates. I present detailed decomposition of the raw SAT score differential into contributions from individual observable factors and estimates of different treatment effects as outlined in section 4.

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[15] Oaxaca (1973) proposed to slect one of the two groups as the base. Reimers (1983) proposed to use the mean coefficients between both groups as the base. Cotton (1988) identified the base weighting coefficients by group size. Neumark (1988) proposed to identify base estimating the pooled model.

5.1 Basic statistics

Simple descriptive statistics and commonly used OLS methods provide basic instructive insight important for more sophisticated analysis. The distribution of SAT score ranges between 0 and 100 and Figure 1 depicts SAT score distribution for each of the three school-types.[16] Differences in raw SAT score distributions are obvious. While school-type specific variances in SAT scores look similar for all three school-types, grammar schools students have notably higher average SAT score.

Summary statistics describing all variables used in further analysis are provided in Table 3. Statistics are provided separately by school-types and for pooled data. Average SAT score of grammar schools students exceeds the score of students in vocational and apprentices programs by more than one standard deviation and the difference constitutes 35 and 51 percent, respectively.[17] Patterns revealed in Table 3 are in line with widespread perception of the three school-types in the Czech Republic. Average grammar school students also performed better in math and native language if measured by corresponding grade at the end of the 5th year at primary school.[18] Grammar students have in average more educated parents as indicated by high average values of dummies for higher education of parents; apprenticeship, upper-secondary, and college education, while the base group represents primary education and less. Proportion of parents with upper-secondary education is similar for students in both grammar and vocational programs but extraordinary high proportion of students at vocational and apprenticeship programs have parents with apprenticeship education only. The share of students with single parent[19] is small (3 percent) in grammar

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[16]The distribution of SAT scores is bounded from bottom and from above. Use of linear least squares regression is therefore not perfectly correct since it relies on unbounded distribution of error term. Given that empirical distributions of SAT scores, as depicted on Figure 1, are located far from both boundaries, the imperfections of least squares should be minor.

[17]Computed from Table 3 as $Y^G/Y^{VOC} = 54.7/40.7 = 1.35$ and $Y^G/Y^{APP} = 54.7/36.2 = 1.51$.

[18]The grading system used in the Czech Republic assigns grade 1 to best and grade 5 to worst performance.

[19]Data do not allow me to differentiate between statutory and biological parent.

schools and ranges from 6 to 9 percent in other two school types. Other factors possibly affecting pupils' achievements such as district specific proportion of population with at least upper-secondary education and municipality size do not differ across school-types.

Proportion of women in both school-types is about 60 percent. This is because disproportionately more men are enrolled into apprenticeship programs. This is not only supported by aggregate administrative statistics but also by notably lower enrolment of women in my small subsample of students from *integrated schools*.

5.2 Basic regression results

Simple OLS regression provides better insight than unconditional statistics because it controls for partial correlations in regressors. Table 4 presents three OLS regressions of the SAT score on a set of observable determinants. Models (I) and (III) assume equality of all slope coefficients except the intercept represented by grammar school dummy variable. Models (II a,b) and (IV) allow for different slopes. Netting out the impact of observed heterogeneity in models (I) and (II), SAT score differential drops from 14.03 to 9.79 in model (I) and drops to 7.23 in model (II).[20] In model (III),[21] grammar school dummy variable is instrumented by a set of instruments constituting exclusion restrictions. Estimated gain to treatment is 7.34 of SAT score points and it is almost identical with the point estimate in model (II). While OLS estimates are prone to biases due to endogeneity of the treatment, linear *IV* model in (III) is subject to misspecification of functional form and linear *IV* estimates will generally depend on the instrument used.[22] The hypotheses of joint equality of coefficients $\beta^1 = \beta^0$ in models (I) and (IV) is rejected at the level of 5 percent.

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[20] The differential is given by the difference between intercept coefficients.

[21] It is treatment effect model using Heckman's two-step consistent estimator. The model considers the effect of endogenous binary treatment of enrolment to a grammar school on the test score, conditional on two sets of independent variables.

[22] See Manning (2003).

Comparing models (II) and (IV), difference in estimated intercepts is relatively small, (0.4), but there is notable difference between some slope coefficients. It is the case of coefficients on math and language 5th year grades and coefficients on upper-secondary education dummy variables for both parents.

5.3 First stage estimates: school-type choice

The first stage selection model (4) is estimated by binomial probit model. Dependent variable, D_i, takes value of one if student is enrolled to a grammar school and zero if enrolled to vocational school. Regressors included into Z are plausible, observable and available determinants of grammar school enrolment. I include dummy variables identifying the highest level of educational attainment of both parents. In this way, I control for parental human capital and life-skills as important determinant of pupil's initial skills and school choice. As additional controls of initial skills I include pupil's primary school math and native language grades in the 5th year of the primary school.[23] I control for demographic changes affecting enrolment probability using absolute annual change in district specific cohort size of 13 and 14 years old individuals.[24] This variable captures possible positive impact of year-to-year demographic decline on enrolment probability. During the period studied, there was substantial decline in the size of age-cohorts of young Czechs. Majority of 77 districts was subject to this demographic decline. Average district experienced year-to-year drop in age cohort size of 149 individuals. Given that about 20 percent of an age cohort is enrolled by grammar schools and given that average class size is about 20 pupils, the demographic effect represents substantial drop comparable with the size of one class. Being older should have positive (or no) impact on

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[23]I am using the grade in the 5th year grade at the primary school.. It is more appropriate than using 8th year grade being also available because small but still not negligible portion of students enrolled gymnazia.already after completition of their 5th or 7th year at the primary school.

[24]Taking into account cohort character of the effect, I compute the indicator for the end of year 1992 when the cohorts being analyzed enrolled upper-secondary schools.

grammar school admission probability as older pupils are likely to be more skilled. This is because other factors than previous schooling also affect skills acquisition. The variance in school entry age emanates from a legal rule guiding primary school enrolment. The rule requires that pupils enrolled into a primary school have reached 6 years of age by the day of enrolment (September 1). Pupils born during September-December period constitute about one third of an annual cohort and are enrolled with 9-12 month delay at the age of 7 years. I identify individuals born during September-December period by a dummy variable. Admission probability, ceteris paribus, should be positively related to available study slots at grammar schools in a district. I capture this effect by the proportion of grammar school and vocational school slots on the overall age-cohort size. Taking into account historically predetermined regional variance in the proportion of slots at grammar schools I enter log of population living in municipality as additional control variable.[25] I naturally control for gender.

First stage estimates provide Mill's ratio for second stage regressions but are also interesting itself because they quantify the impact of determinants on enrolment probability. Marginal probability effects from probit estimates are presented in Table 5. All coefficients are significantly different from zero and have expected and plausible signs. Following explanatory variables have positive impact on the probability of enrolment into grammar school: primary school entry age, math and native language grade at the 5th year of a primary school, parental education, local share of slots at grammar schools, and local demographic decline of the young population. Negative impact is estimated for the share of available study slots at vocational schools, and for municipality size.

Parental education is the most influential determinant. In particular, pupils with mothers with full secondary or tertiary education have grammar school admission probability higher by 12 and

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[25]For reasons I was not able to identify yet, the communist regime maintained disproportionately lower proportion of gymnazia slots available at larger municipalities. I measure municipality size in log of its population clasifying municipality into 7 groups.

31 percent respectively, compared to those having a mother with primary education only. Father's education other than college has negligible impact. The impact of college education, 15 percent, is only half of the mother's effect. As an example, a pupil having both parents tertiary educated has probability of grammar school enrolment higher by 34 percent, compared to observably identical pupil whose parents have upper-secondary education, and 46 percent compared to pupils with parents with apprentices education only. To underscore the scope of selectivity, note that 12 percent of students in the data have college educated parents and grammar schools enrol about 20 percent of an age cohort.[26] Missing parent in the family does not have statistically significant impact on enrolment probability.

Local schooling supply conditions have sizeable impact in the enrolment probability. One standard deviation in the proportion of slots at grammar schools increases the probability of enrolment by 45 percent.[27] Similarly, a standard deviation in the proportion of slots at vocational schools decreases the probability of enrolment to a grammar school by 20 percent. One standard deviation in 5th year math and language grade increases enrolment probability only by 6 and 7 percent. This indicates that local schooling supply conditions are much more important determinant of grammar schools admission than observed skills. This implies that two equaly skilled pupils living in two different regions frequently face notably different educational options.

Other determinants of grammar school admission have economically small effects. Women are slightly less likely than men to enrol in grammar schools (-1.8 percent). Entering primary school later increases the probability of grammar schools enrolment by 4 percent. District specific demographic decline by 200 children, corresponding approximately to one standard deviation of

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[26] This supports the finding of Filer and Münich (2003) based on an opinion survey run in the Czech Republic in the middle of 1990s. Fathers seem to be much less involved in schooling issues and schooling choice of their children. This holds at least for the primary and secondary level schooling.

[27] The change in probability as an outcome of a change in the enrolment ratio r, is computed as $\Delta P = \frac{\partial P}{\partial r} \Delta r = 1.39 \frac{.048}{.149} = .45$.

GYM==0   GYM==1
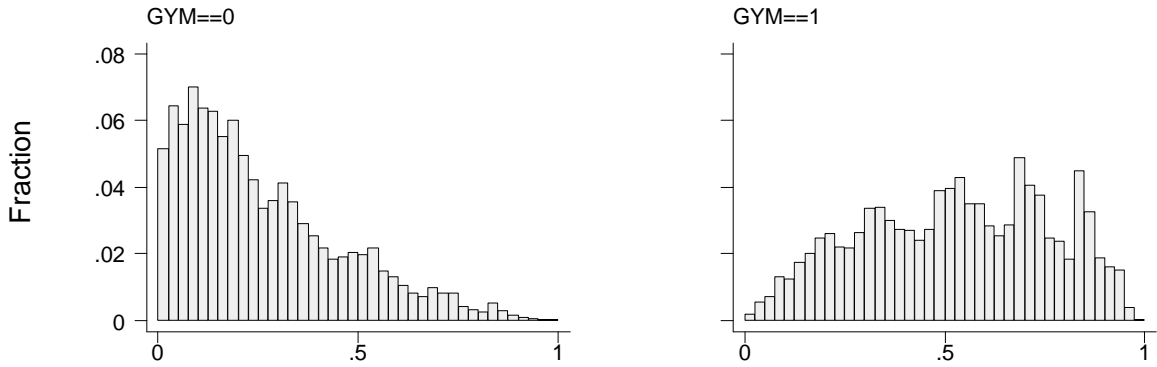
Figure 2: Histogram of Predicted Probability of Grammar School Enrolment

cross-district variation, implies an increase in enrolment probability by 4 percent.[28] It should be noted that all variables serving as identifying restrictions are statistically significant, corresponding coefficients have expected signs and their impact on enrolment probability is reasonably high.

Histograms in Figure 2 show distribution of predicted probability of grammar school enrolment among grammar and vocational schools pupils. The support of predicted probabilities, P, covers the whole interval $(0, 1)$. Relatively small number of observation appearing at the upper tail of the distribution is in line with relatively small number of slots at grammar schools.

5.4 Second stage estimates and decomposition

Variables in X explaining SAT scores differentials in the second stage model (1) and (2) are a subset of first-stage regressors plus variable measuring proportion of district specific population with at least complete secondary education. Variables affecting enrolment probability but not affecting student's potential achievements directly, are not included into vector X and fulfill the necessary

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[28]The impact is computed as $200.\partial P/\partial Dvek = 200.0,0002 = .04$.

exclusion restrictions.[29] Second stage estimates are presented in panels of Table 6. Left panel A presents estimated coefficients, variables means, and predicted values separately for each of the two schooling segments ($D = 0, 1$) plus coefficients from pooled regression. Panel B on the right presents decomposition of predicted differential into individual components in absolute and relative terms. Bottom panel C aggregates information from panels A and B. More systematic summary is provided in Table 7.

About one third of the mean raw difference in SAT scores (14.04) is due to heterogeneity in observable endowments (4.65). The differential due to coefficients (including intercepts) is 4.82. The difference due to intercepts, 6.41, is positive and the contribution from slopes, -1.58, is relatively small and negative. It should be noted that the total contribution from slopes is small because contributions from individual slopes have alternating signs and their aggregate sum is notably smaller than the sum of integer values.[30] The selection term constitutes 2.52 and the interaction term 2.04 SAT scores.

The causal meaning of endowment and coefficient effects in the model is following. Endowment effect captures student's *initial* skills and represents the projection of endowment measure on the SAT score scale. Alternatively, endowment effect can be viewed as the impact of student's endowment on the acquisition of *further* skills independent of school-type attended. In this respect, parental education and social environment of pupils affects acquisition of skills independent of school-type It is not possible to identify these two effects separately. As an example, pupils

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[29] Angrist and Evans (1988) use exogenous variation in family size as a source of exogenous variance. A line of studies by Ludwig (1997), Grogger and Neal (2000), Altonji, Elder, and Taber (1999) using U.S. data, rely on regional variation in Catholic religiosity as an instrument. Recent studies present evidence that casts doubts on validity of such instrument. Altonji et al. (2002) propose alternative approach using the degree of selection on observables as an indication of likely selection on the unobservables.

[30] The sum of integer contributions from individual slopes, not presented in Table 6, is 6.9, compared to simple sum being -1.6.

with more educated parents will have higher initial skills and will also acquire additional skills at upper-secondary school more effectively. The coefficient effect, on the other hand, captures different effectiveness of skills acquisition in different school-types. Different effectiveness could be due to different curriculum and teaching methods employed by different school programs.

5.4.1 Role of initial skills

Decomposition of the raw SAT score differential into contributions from individual factors is presented in panel B of Table 6. In the case of both the coefficient and the endowment effect, dominant role is played by primary school 5th year grade (math and language). Note, that these grades have some but minor impact on enrolment probability as reported in section (5.3). While coefficient signs are the same and negative,[31] the coefficient and endowment effects work in opposite directions. In the case of math grade, the endowment effect (2.4) is positive and dominates the coefficient effect (-1.34) summing up to a positive differential (1.42). This implies that initial math skills translate into skills being tested and are also more important for studies at grammar schools. One can put it in another way. Would average vocational school student enrol to a grammar school he would experience SAT score increase smaller than a decrease experienced by average grammar school student who would be placed into vocational school. Figure 3 depicts the case for better exposition.

The impact of initial language skills is slightly different. Negative coefficient effect (-2.65) dominates positive endowment effect (1.15) summing up to small negative differential (-0.84). As in the case of math skills, initial language skills contribute positively to the SAT score. Language skills seem to be more important for further skills acquisition in grammar schools. This is plausible finding implying that the curriculum at grammar schools relies more on language skills of students. Put in another way, would we move average vocational student to a grammar school, she would acquire skills there less effectively.

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[31]Note that lower grade corresponds to better performance.
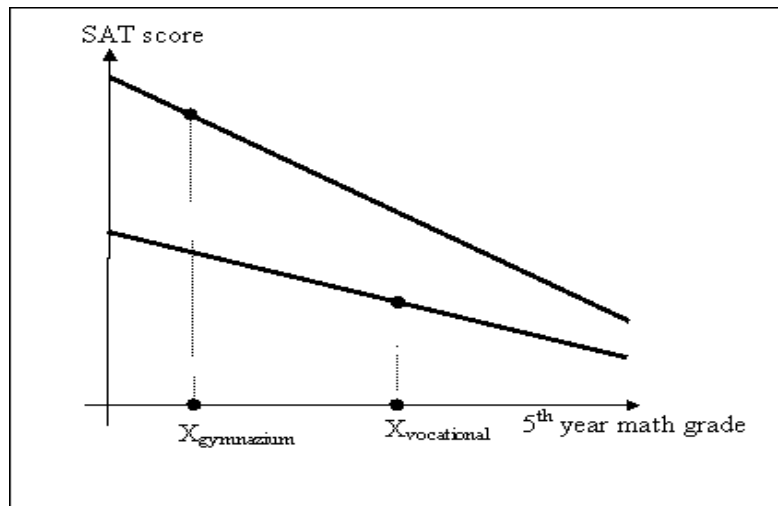
Figure 3: Endowment and slope effect.

Summing up, the *aggregate* contribution of initial math and language skills to observed differentials in SAT scores is small and comparable to other determinants. However, *individual* endowment and slope effects of initial skills are relatively high. To have a benchmark, I compute the share of individual contributions on the sum of integer contributions.[32] Measured in this way, the endowment effect of initial math and language skills constitutes 52 and 25 percent, slope effects are negative and constitute 10 and 20 percent, respectively.

5.4.2 Role of parental education

SAT score differential due to parental education is of particular interest. Tertiary education of both parents and mother's full secondary education are the second most important determinant of SAT score differential. A student having college educated parents, compared to a student with secondary educated parents, has SAT score higher by 2.51 points (19.2 percent of aggregated integer

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[32] Note that sum of integer values serves better as the base for comparisson. Simple sum could be in principle zero due to mutual elimination of negative and posssitive elements.

differentials in the SAT score[33]). Note that direct impact of parental education on the SAT score is smaller than its impact through the selection.[34] Both the endowment and slope effect are positive but the endowment effect is stronger. Differential due to endowment constitutes 14.5 percent and differential due to slopes constitutes 5.2 percent, relative to respective aggregate integer differentials. This finding is in line with the plausible believe that skills are also acquired out of school in the family. Positive coefficient effect of parental education implies that grammar schools students acquire skills more effectively if their parents are more educated. This indicates productive interactions between school and home skills acquisition. Reiterating that mother's education, compared to father's, is more important determinant of sorting through school-types, mother's education is also more important determinant of skills acquisition. Notable in this respect is the role of mothers with full secondary education (coefficient effect 0.70).

Differentials due to gender and out-of-school social interactions proxied by the proportion of population with at least full upper-secondary education, and due to missing parent are statistically significant but negligibly small and the coefficient effects dominate the endowment one. Net of intercept, typical woman in a grammar school performs slightly better than observably identical woman at a vocational school, ceteris paribus. However, compared to men women achieve notably lower SAT scores in both school-types (coefficients on gender dummy: -6.3 and -7.3). There are several plausible interpretations of underperformance of women. The simplest explanation is that school-age males outperform equaly old females. This finding is supported by the TIMMS survey (TIMMS 2000a,b) showing that average 15 years old Czech male performed statisticaly better in tests. Alternatively, the differential can be due to sorting-out of larger proportion of men from

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[33]Noting that coefficients on secondary education dummies are not statisticaly significant from zero, the share is computed from Table 6 as $\frac{1.347+1.274}{13.656} = 19.2\%$.

[34]Back of the envelop calculation shows corresponding impact of parental education on SAT score due to selection is $0.45 * 6.41 = 2.88$.

the bottom tail of initial skills distribution to apprenticeship programs. Following the same line of thinking, if women have specific skills which make them more likely to pass entry exams to secondary school, but do not translate to the SAT score, women in vocational and grammar school programs would have in average lower SAT score.[35] Gender asymmetry in the selection to upper-secondary school would cause an upward shift in mean unobserved initial skills of men in the sample and explain negative coefficient on female dummy. An alternative plausible interpretation is that initial skills of both genders are the same but the teaching methods at grammar and vocational schools are better suited for the process of skills acquisition by men.[36]

In sum, my results indicate that the large raw differential in standardized SAT scores is composed of various components. The key role is played by school-type as the difference due to intercept constitutes 46 percent of the whole differential. This component is unrelated to student characteristics and can be also viewed as value-added difference between grammar schools and vocational programs. Second most important is the difference due to different initial endowments representing 33 percent of the raw differential. Grammar schools enrol better endowed students in average and this effect should not be counted as better quality of grammar schools compared to vocational schools. The endowment differential can be attributed to direct projection of initial skills to the SAT scores and/or to the impact of initial skills on different efficiency of further skills acquisition. The differential due to different slopes excluding intercepts is the only negative component of the raw differential, 11 percent. It indicates that students choose school-type also according to observable covariates according to their comparative advantage.[37] Comparative advantages are dominated

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[35]Memorizing skills can be usefull at exams. Czech educational system has been for decased biased toward memorizing at the expense of providing other types of creative skills.

[36]I also considered separate estimation for male and female students. The results show greater impact of mother's education on both male and female student while the impact is slightly bigger in case of daugters (mother on a daugter). The impact estimated in the 2nd stage regression is very small.

[37]Students who enroll to grammar schools may be the worst students in the distribution of Y^0 such that $E(U_0|D = 0)$

by absolute advantage of getting educated at a grammar school. Self-selection on unobservables constitutes positive but relatively small component of the raw differential, 18 percent. It captures the sorting gain due to unobservable characteristics in u^0 and u^1. Its relatively small size suggests that observed covariates included in the 2nd stage regression are the major determinants of student performance measured by test scores. In addition to covarites included in X, I considered a number of other factors that could be theoretically considered as determinants of Y.[38] However, none of these variables had statistically significant effect and their inclusion affected results very little.

5.5   Estimated treatment effects

Table 7 presents empirical unconditional treatment effects computed from original estimates presented in Table 6 using formulas presented in the Appendix. Unconditional point estimates of ATE and ATE^1 are computed for the distribution of X as it appears in the data. Estimated $ATE = 5.55$ is the gain from grammar school enrolment for a student randomly chosen from the whole population of grammar and vocational schools students. ATE^1 conditional on X and Z, is given as $ATE^1(X, Z) \equiv E(Y^1 - Y^0|X, Z, D = 1) = X(\beta^1 - \beta^0)P(Z) + E(U^1 - U^0|Z)$. Empirical estimates of the relationship are shown on Figure 4. The component on the right is the sorting gain, $E(U^1 - U^0|Z)$, and it is declining in $\widehat{P}$ and approaches zero as the probability of treatment is approaching zero. This is because the sorting due to unobservables disappears as $\theta Z \gg u^D \Rightarrow \Phi(\theta Z) \to 1, \phi(\theta Z) \to 0 \Rightarrow \phi(\theta Z)/\Phi(\theta Z) \to 0$. The sorting gain dominates the ATE^1 at lower values of $\widehat{P}$ and both reach similar size at $\widehat{P} \simeq 0.4$. This forms the u-shaped relationship $ATE^1(\widehat{P})$ depicted on Figure 4.

Unconditional ATE^1 is higher than ATE ($ATE^1 = 9.6 = ATE(D = 1) + E(U^1 - U^0|D = 1)$).

$- E(U_0|D = 1) < 0$.

[38] Alternative covariates included local unemployment and vacancy rates, employment share in agriculture, distance to nearest college, density of population, and dummy variables for large urban aglomerations like capital city Prague, Brno, and Ostrava.
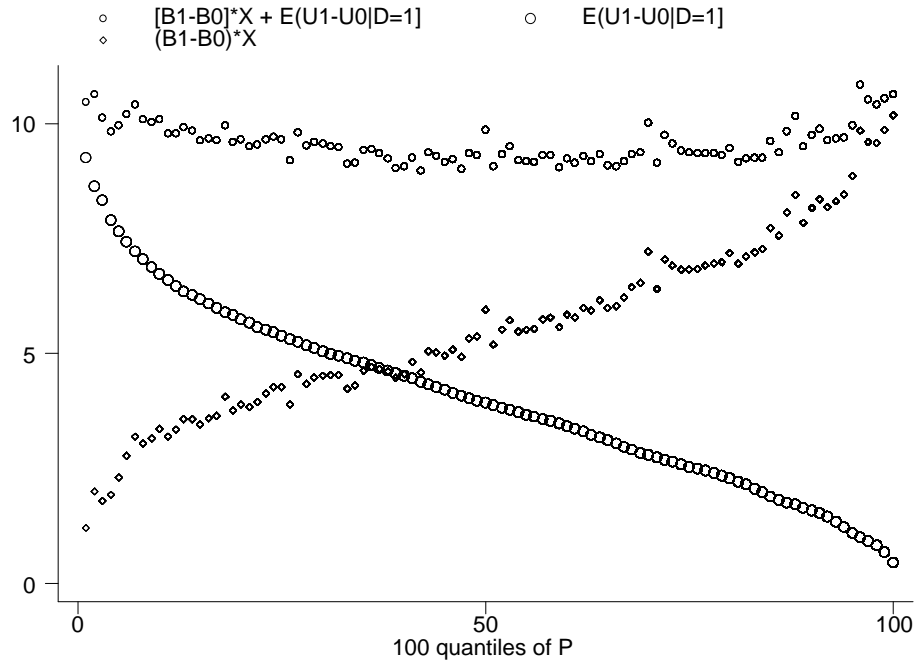
Figure 4: Estimated ATE^1 and its Components

It is partly because mean $X\beta$ differs for treated and untreated students ($ATE(D = 1) = 6.9$ and $ATE(D = 0) = 4.8$) and partly because the sorting gain for treated is positive ($E(U^1 - U^0 | D = 1) = 2.7$). Average sorting gain for nontreated students is negative ($E(U^1 - U^0 | D = 0) = -1.5$). Opposite signs of mean sorting gains imply that individuals do sort themselves into school-types according to their unobserved comparative advantage. Nevertheless, absolute size of the sorting gain is relatively small. Overall, following holds for estimated treatment parameters $ATE^1 > ATE > ATE^0$.[39] The impact of grammar school enrolment on the SAT score estimated by OLS in Table 4, (9.1),[40] is similar to estimated $ATE^1 = 9.6$.

ATE measures are not very instructive from the standpoint of schooling policies considering expansion of grammar schools and $LATE$ measure is more suitable. I estimate two $LATE$ estima-

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[39] The same ranking is found by Carneiro et.al (2003) who estimate pecuniary returns to college degree.

[40] $OLS = ATE^1 - [E(U^0 | D = 0) - E(U^0 | D = 1)] = 9.59 - (.0709 - (-.129)) = 9.4$

tors considering two different types of treatment to provide an answer to policy debates whether grammar schools program should be expanded. First, I consider hypothetical increase in the supply of available study slots at grammar schools. Leaving aside the option of structural schooling reform and limiting attention to a marginal supply shift, I estimate the mean SAT score gain experienced by marginal students who would enroll grammar school thanks to the marginal supply shift. I consider 1 percent increase in the number of available slots at grammar schools from mean z_k to z'_k so that $z'_k - z_k = 0.01$. Vector Z' differs from Z only in its k - th elements. Corresponding $LATE_a$ unconditional on X computed for the population distribution of X and Z in the data is 7.13 so that $ATE^1 > LATE_a > ATE$. It implies that *compliers*, students who would be enrolled due to marginal positive supply shock, would gain observably less than *always-takers*, students who enroll anyway. $LATE_a$ is still notably higher than ATE^0. In similar way I estimate the impact of a demographic decline by 10 percent. Point estimate $LATE_b = 7.18$ is not statistically different from the $LATE_a$. This is a plausible outcome because higher supply of slots at grammar schools is likely to affect similar group of applicants who would enroll thanks to uniform demographic decline.

Estimated coefficients on the inverse mill's ratio which controls for non-zero mean of the error terms in (1) and (2) have its economic meaning. As shown in the Appendix, these coefficients represent $\widehat{\sigma^1 \rho^1} = 3.24$ and $\widehat{\sigma^0 \rho^0} = 0.16$ where $(\sigma^i) = \sqrt{Var(u^j)}$ and $\rho^j \equiv Corr(u^j, u^D)$ for $j = 0, 1$. Variances represent implied variances in SAT scores and non-zero correlations reflect present selection on unobservables. Point estimates imply that: (i) mean test score of actual grammar school student, given X, is greater than mean test score of a student enrolling grammar school randomly, (ii) mean test score of actual vocational school student, given X, is greater than mean test score of a pupil enrolling vocational school randomly. This represents *positive sorting*, a terminology used by Borjas (1987).

6 Conclusions

In the empirical analysis I identify key determinants of the causal relationship of skills formation in the case of 18 years old pupils in the final year of upper-secondary school in the Czech Republic in late 1990s. I am using rich microdata and two-stage regression model to quantify individual and aggregate causal effects. I contrast commonly cited spurious correlations and OLS estimates with results taking into account schooling choices and selectivity.

I show that students graduating from highly demanded grammar schools - schools providing general type of education - have notably better achievements. I find that about one third of the performance differential is due differentials in observed initial characteristics including initial skills and social background. Self selection based on unobservables plays some but minor role. Almost half of the differential is due to the pure effect of better performing grammar schools. Although the pure effect is smaller than one would infer from the raw differential, the impact of grammar schools on student's achievements is still high and explains persistent and high excess demand for this program. My finding are supportive of policy recommendations to expand the number of slots at grammar schools. Estimating local average treatment effects I show that marginal students who would enrol grammar school thanks to such expansion would benefit less than students who are already enrolled. However, marginal students would gain more than average (randomly chosen) student in the vocational program.

My results are based on the subpopulation of students enrolled by two out of three school programs offered at the upper-secondary level. Data on apprentices students do not exist and I have only limited evidence that the population of apprentices students has lower average performance, weaker initial conditions and poorer social background than the population in two other programs. I cannot explore whether apprentices students would also benefit from the expansion of the grammar program. It could be that students currently enrolled by apprentices schools would benefit more

from expansion of vocational programs. This would be in line with notable expansion of vocational programs during 1990s, especially due to the expansion of non-state schools.

I prove that the upper-secondary segment in the Czech Republic, enrolling about two thirds of the whole age cohort, is highly selective. Local availability of grammar schools slots and parental educational background are very important determinants of grammar schools admission while pupil's initial skills are much less important.

I am aware of several important simplifications and imperfections of my approach. The literature on schooling production functions suggests a line of school quality determinants like school ownership, quality of staff and facilities, class size and peers effect. Taking into account that most of these phenomena represent another type of endogeneity, reflecting them in the model properly would extraordinary complicate the empirical analysis.[41] Another possible setback of my analysis emanates from the measure of skills I rely on - study aptitude test score. Although authors of the testing have been convinced that the score properly measures life-skills, there is no simple way to test how closely is the score related to future labor market outcomes or life-long carrier success of individual students. Natural extension of this research is to link my model to college admission outcomes and to expected labor market outcomes. Although it is not technically possible to follow-up students from my sample, approximate gains to college could possibly be imputed from other data surveys containing information on gender and individual schooling path.

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[41] Kane and Staiger (2002) have noted that mean test scores may provide a noisy measure of school performance due to large error variances, particularly among smaller schools. They conclude that mean test scores from a single year can provide a misleading ranking of schools.

7 Appendix

7.1 Model

The details of the model in (1)-(3) and treatment effects presented in section 4 and estimated in section 5 are following. Let Y_i^j denote potential SAT score of student $i = 1, ..., N$ at the moment of graduation from school of type $j = 0, 1$, where 1 stands for grammar school and 0 stands for vocational school. For each student i, only one outcome is observed depending on school being enrolled. The corresponding model is following

$$Y_i^0 = X_i \beta^0 + u_i^0 \tag{7}$$

$$Y_i^1 = X_i \beta^1 + u_i^1 \tag{8}$$

$$D_i^* = Z_i \theta + u_i^D \tag{9}$$

Variables in vector X_i represent observable determinants of test scores and parameters in β capture the impact of observables. The model allows for $\beta^0 \neq \beta^1$. D^* is a latent variable generating observable binomial outcomes $D \in (0, 1)$ according to indicator function

$$D(Z_i) = 1[D^*(Z_i) \geq 0]$$

Variables in Z are observed determinants of school-type enrolment such that some or all elements in X are contained in Z. Unobserved determinants of enrolment are captured by u^D. Observed SAT score can be therefore written as

$$Y \equiv Y^0(D - 1) + Y^1 D$$

Assumed relationship between error terms in (7-9) is such that

$$\begin{bmatrix} u^0 \\ u^1 \\ u^D \end{bmatrix} = N \left(\begin{bmatrix} \sigma_0^2 & \sigma_{10} & \sigma_{0D} \\ \sigma_{10} & \sigma_1^2 & \sigma_{1D} \\ \sigma_{0D} & \sigma_{1D} & \sigma_D^2 = 1 \end{bmatrix} \right)$$

Normalization $\sigma_{1D} = 1$ does not affect generality of the model. The major problem of OLS regressions are nonzero parameters $\sigma_{0D} \neq 0$, $\sigma_{1D} \neq 0$.

7.2 Model estimation

Following Heckman et al. (2000), two-step estimation of the model in (7-9) proceeds as follows. Parameter estimates $\widehat{\theta}$ are obtained estimating binary choice probit model assuming normality of u^D

$$\Pr(D = 1|Z) = \Pr(Z\theta + u^D > 0) = \Pr(Z\theta > -u^D) = \Phi(Z\theta)$$

where Φ is standard normal cdf. Resulting estimates are used to compute appropriate selection correction terms evaluated for $\widehat{\theta}$ as

$$\frac{\phi(Z_i\widehat{\theta})}{\Phi(Z_i\widehat{\theta})} \text{ for } D_i = 1 \text{ and } \frac{\phi(Z_i\widehat{\theta})}{1 - \Phi(Z_i\widehat{\theta})} \text{ for } D_i = 0. \tag{10}$$

Selection correction variables (10) are included in (1) and (2) as additional regressors multiplied by slope parameters γ^0, γ^1. The model is estimated by OLS procedure and provides estimated parameters $\widehat{\beta^0}, \widehat{\beta^1}, \widehat{\gamma^0}, \widehat{\gamma^1}$ and $\widehat{\theta}$. Standard errors of estimated parameters have to be adjusted because added regressors are stochastic parameters estimated in the 1st step.

7.3 Treatment effects

Estimated parameters can be used to obtain treatment parameters. In the following, I present general formula, expression used to compute treatment parameters conditional on X, and expression for unconditional treatment parameter. The last one is obtained by integration over the distribution of X in the data.

The Average Treatment Effect, ATE :

$$
\begin{aligned}
ATE(X, D(Z) &= 1) = X(\beta^1 - \beta^0), \\
\widehat{ATE}(X, D(Z) &= 1) = X(\widehat{\beta}^1 - \widehat{\beta}^0), \\
\widehat{ATE} &= \frac{1}{N}\sum_{i=1}^{N}\widehat{ATE}_i.
\end{aligned}
$$

33

The Average Treatment Effect on Treated, ATE^1:

$$
\begin{aligned}
ATE^1(X, D(Z) &= 1) = X(\beta^1 - \beta^0) + E(U^1 - U^0 | Z, D = 1), \\
\widehat{ATE^1}(X, D(Z) &= 1) = X(\widehat{\beta}^1 - \widehat{\beta}^0) + (\widehat{\gamma^1} - \widehat{\gamma^0}) \frac{\phi(Z\widehat{\theta})}{\Phi(Z\widehat{\theta})}, \\
\widehat{ATE^1} &= \frac{1}{N} \sum_{i=1}^{N} \widehat{ATE_i^1} D_i.
\end{aligned}
$$

The Local Average Treatment Effect, $LATE$:

$$
\begin{aligned}
LATE(X, D(Z) &= 0, D(Z') = 1) = X(\beta^1 - \beta^0) + E(U^1 - U^0 | Z\widehat{\theta} < u^D < Z'\widehat{\theta}), \\
\widehat{LATE}(X, D(Z) &= 0, D(Z') = 1) = X(\widehat{\beta}^1 - \widehat{\beta}^0) + (\widehat{\gamma^1} - \widehat{\gamma^0}) \frac{\phi(Z'\widehat{\theta}) - \phi(Z\widehat{\theta})}{\Phi(Z'\widehat{\theta}) - \Phi(Z\widehat{\theta})}, \\
\widehat{LATE} &= \frac{1}{N} \sum_{i=1}^{N} \widehat{LATE_i},
\end{aligned}
$$

where Z and Z' are identical except one of their elements so that $z_k' > z_k$.

It can be shown that following identities hold for regression parameters

$$
\begin{aligned}
\gamma^0 &= \sigma^0 \rho^0, \\
\gamma^1 &= \sigma^1 \rho^1.
\end{aligned}
$$

Denoting $\rho^j \equiv Corr(u^j, u^D) = \frac{Cov(u^j, u^D)}{\sigma_D \sigma_j}$ and taking into account auxiliary standardization $\sigma_D = 1$, estimated $\widehat{\gamma^0}$ and $\widehat{\gamma^1}$ represent covariance between u^D and u^j. In a special case of $\sigma^0 \rho^0 = \sigma^1 \rho^1$, pupils do not sort into school-types based on their unobservable SAT score gain and all the treatment parameters reduce to ATE so that $ATE = ATE^1 = LATE$.

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Table 3: Descriptive Statistics

Variable	Grammar Mean (I)	Std. Dev.	Vocational Mean (II)	Std. Dev.	Apprentices Mean (III)	Std. Dev.	Pooled (I) and (II) Mean (IV)	Std. Dev.	Difference (I) - (II) (V)	(I) - (III) (VI)
SAT	54.7	12.8	40.7	12.9	36.2	11.7	45.6	14.5	14.04	18.52
Dvek	153.315	196.131	145.646	190.881	117.830	157.150	148.361	192.788	7.67	35.48
BORN_F	0.309	0.462	0.268	0.443	0.308	0.461	0.282	0.450	0.041	0.002
r2SOS	0.311	0.114	0.334	0.111	0.303	0.112	0.325	0.113	-0.023	0.007
r2GYM	0.152	0.047	0.148	0.048	0.142	0.047	0.149	0.048	0.005	0.010
Lvel	11.162	1.484	11.246	1.405	10.960	1.361	11.216	1.434	-0.084	0.202
female	0.591	0.492	0.611	0.488	0.522	0.500	0.604	0.489	-0.020	0.069
CJ5	1.510	0.566	2.005	0.644	2.234	0.650	1.830	0.661	-0.495	-0.725
MA5	1.437	0.542	1.893	0.650	2.114	0.647	1.732	0.652	-0.456	-0.676
VMAT2	0.162	0.368	0.348	0.476	0.449	0.497	0.282	0.450	-0.186	-0.288
VMAT3	0.495	0.500	0.480	0.500	0.402	0.490	0.485	0.500	0.016	0.094
VMAT4	0.309	0.462	0.094	0.292	0.054	0.226	0.170	0.376	0.214	0.255
VMAT5	0.003	0.052	0.008	0.090	0.007	0.086	0.006	0.078	-0.005	-0.005
VOTE2	0.259	0.438	0.477	0.499	0.584	0.493	0.400	0.490	-0.218	-0.325
VOTE3	0.308	0.462	0.324	0.468	0.280	0.449	0.318	0.466	-0.016	0.028
VOTE4	0.419	0.493	0.172	0.377	0.103	0.304	0.259	0.438	0.247	0.315
VOTE5	0.003	0.058	0.009	0.095	0.009	0.093	0.007	0.084	-0.006	-0.005
edu23	0.314	0.083	0.311	0.081	0.300	0.069	0.312	0.082	0.003	0.014
Nobs	15336		27982		12991		43318			

Variables described on the next page

Dependent variable

SAT   Study Aptitute Test score

Variables in Z only

Dvek   Year-to-year change in the size of district specific cohort of 13 years old (in 1992)

BORN_F   dummy = 1 if pupil born during September-December period, = 0 othervise

r2SOS   Share of 1st year slots in vocational schools on the population of 15 years old

r2GYM   Share of 1st year slots in grammar schools on the population of 15 years old

Lvel   Log of municipality population

Variables in X and Z

female   dummy = 1 if women, = 0 othervise

CJ5   Native (Czech) language grade in the 5th year at the primary school. It ranges in 1 to 5, from best to poor

MA5   Math grade in the 5th year at the primary school. It ranges in 1 to 5, from best to poor

           Mother's highest educational attainment dummies

VMAT1   -primary or less (excluded base)

VMAT2   -secondary w/o GCE

VMAT3   -secondary w. GCE

VMAT4   -tertiary

VMAT5   Mother not living in the household

           Father's highest educational attainment dummies

VOTE1   -primary or less (excluded base)

VOTE2   -secondary w/o GCE

VOTE3   -secondary w. GCE

VOTE4   -tertiary

VOTE5   Father not living in the household

Variables in Z only

edu23   Proportion of district population with at least full secondary education

Table 4: Various Models Explaining SAT Score

	OLS						IV		2SLS			
	(I) Pooled		(IIa) Grammar		(IIb) Vocational		(III) Pooled		(IV) Grammar		Vocational	
	Coef.	P>|t|	Coef.	P>|t|	Coef.	P>|t|	Coef.	P>|t|	Coef.	P>|t|	Coef.	P>|t|
female	-6.91	0.000	-6.22	0.000	-7.33	0.000	-6.93	0.000	-6.33	0.000	-7.33	0.000
edu23	10.96	0.005	12.11	0.000	10.27	0.021	10.35	0.000	9.53	0.010	10.35	0.022
CJ5	-2.42	0.000	-2.54	0.000	-2.37	0.000	-2.68	0.000	-3.66	0.000	-2.33	0.000
MA5	-5.31	0.000	-5.12	0.000	-5.38	0.000	-5.52	0.000	-6.05	0.000	-5.35	0.000
VMAT2	-0.41	0.104	-0.29	0.625	-0.44	0.113	-0.41	0.114	-0.25	0.673	-0.44	0.111
VMAT3	0.92	0.001	1.55	0.009	0.77	0.013	1.06	0.000	2.21	0.001	0.75	0.028
VMAT4	2.57	0.000	3.44	0.000	1.83	0.000	2.98	0.000	4.90	0.000	1.77	0.002
VMAT5	-1.83	0.204	1.89	0.483	-2.76	0.062	-1.88	0.098	2.05	0.452	-2.76	0.063
VOTE2	-0.19	0.650	0.37	0.686	-0.42	0.373	-0.27	0.560	0.13	0.894	-0.41	0.399
VOTE3	1.00	0.032	1.59	0.111	0.80	0.106	1.00	0.031	1.71	0.082	0.80	0.105
VOTE4	1.80	0.000	2.70	0.011	1.24	0.008	2.02	0.000	3.54	0.001	1.20	0.014
VOTE5	-3.98	0.000	-4.99	0.067	-3.66	0.003	-4.00	0.000	-5.20	0.057	-3.66	0.003
GRAM	9.11	0.000	-	-	-	-	7.48	0.000	-	-	-	-
lambda	-	-	-	-	-	-	-	-	3.24	0.033	-0.16	0.874
Const	55.35	0.000	62.29	0.000	56.28	0.000	56.81	0.00	62.48	0.000	56.07	0.000
Nobs	43318		15336		27982		43318		15336		27982	
R^2	0.37		0.18		0.22		0.37		0.18		0.22	

Variables described on the next page

Variables definitions

female	dummy = 1 if women, = 0 othervise
edu23	Year-to-year change in the size of district specific cohort of 13 years old (in 1992)
CJ5	Native (Czech) language grade in the 5th year at the primary school. It ranges in 1 to 5, from best to poor.
MA5	Math grade in the 5th year at the primary school. It ranges in 1 to 5, from best to poor.
	Mother's highest educational attainment dummies
VMAT1	-primary or less (excluded base)
VMAT2	-secondary w/o GCE
VMAT3	-secondary w. GCE
VMAT4	-tertiary
VMAT5	Mother not living in the household
	Father's highest educational attainment dummies
VOTE1	-primary or less (excluded base)
VOTE2	-secondary w/o GCE
VOTE3	-secondary w. GCE
VOTE4	-tertiary
VOTE5	Father not living in the household

Variables in Z only

edu23	Proportion of district population with at least full secondary education
GRAM	dummy = 1 if grammar school, = 0 othervise (vocational school)

Table 5: Estimates of Marginal Effects
from Probit Model of Grammar School Enrolment

	dF/dx	P>|z|
Dvek	0.0002	0.025
BORN_F	0.040	0.000
r2SOS	-0.590	0.000
r2GYM	1.390	0.000
Lvel	-0.063	0.000
female	-0.018	0.039
CJ5	-0.195	0.000
MA5	-0.163	0.000
VMAT2	0.015	0.232
VMAT3	0.120	0.000
VMAT4	0.309	0.000
VMAT5	-0.052	0.327
VOTE2	-0.057	0.005
VOTE3	0.007	0.724
VOTE4	0.155	0.000
VOTE5	-0.001	0.988
Nobs	43324	
PseudoR^2	0.225	

Variables

Dvek   Year-to-year change in the size of district specific cohort of 13 years old (in 1992)
BORN_F dummy = 1 if pupil born during September-December period, = 0 othervise
r2SOS   Share of 1st year slots in vocational schools on the population of 15 years old
r2GYM   Share of 1st year slots in grammar schools on the population of 15 years old
Lvel   Log of municipality population
female dummy = 1 if women, = 0 othervise
CJ5   Native (Czech) language grade in the 5th year at the primary school. It ranges in 1 to 5, from best to poor.
MA5   Math grade in the 5th year at the primary school. It ranges in 1 to 5, from best to poor.
          Mother's highest educational attainment dummies
VMAT1   -primary or less (excluded base)
VMAT2   -secondary w/o GCE
VMAT3   -secondary w. GCE
VMAT4   -tertiary
VMAT5   Mother not living in the household
          Father's highest educational attainment dummies
VOTE1   -primary or less (excluded base)
VOTE2   -secondary w/o GCE
VOTE3   -secondary w. GCE
VOTE4   -tertiary
VOTE5   Father not living in the household

Table 6: Decomposition of 2nd Stage Estimates

| Variable | Panel A: Estimates | | | | | | | Panel B: Decomposition | | | | | | |
| | Grammar | | | Vocational | | | Pooled | Absolute | | | | Relative | | |
	Coef.	Mean	Pred.	Coef.	Mean	Pred.	Coef.	Diff	E[1]	C[1]	CE[1]	Diff[%]	E[%]	S[%]
female	-6.326	0.591	**-3.738**	-7.333	0.611	**-4.478**	-6.997	**0.74**	0.144	0.615	-0.02	5.4	3.1	4.6
CJ5	-3.656	1.51	**-5.52**	-2.333	2.005	**-4.678**	-3.899	**-0.842**	1.155	-2.651	0.655	6.2	24.7	-19.9
MA5	-6.055	1.437	**-8.701**	-5.349	1.893	**-10.125**	-6.497	**1.424**	2.438	-1.336	0.322	10.4	52.2	-10.0
VMAT2	-0.255	0.162	**-0.041**	-0.444	0.348	**-0.154**	-0.362	**0.113**	0.083	0.066	-0.035	0.8	1.8	0.5
VMAT3	2.214	0.495	**1.097**	0.751	0.48	**0.36**	1.696	**0.737**	0.012	0.701	0.023	5.4	0.3	5.3
VMAT4	4.904	0.309	**1.513**	1.767	0.094	**0.166**	4.866	**1.347**	0.379	0.295	0.673	9.9	8.1	2.2
VMAT5	2.05	0.003	**0.005**	-2.756	0.008	**-0.022**	-1.77	**0.027**	0.015	0.039	-0.026	0.2	0.3	0.3
VOTE2	0.126	0.259	**0.033**	-0.409	0.477	**-0.195**	-0.534	**0.228**	0.089	0.255	-0.117	1.7	1.9	1.9
VOTE3	1.713	0.308	**0.528**	0.801	0.324	**0.26**	1.095	**0.268**	-0.013	0.295	-0.014	2.0	0.3	2.2
VOTE4	3.539	0.419	**1.481**	1.205	0.172	**0.207**	3.12	**1.274**	0.297	0.401	0.576	9.3	6.4	3.0
VOTE5	-5.199	0.003	**-0.018**	-3.661	0.009	**-0.033**	-4.07	**0.015**	0.021	-0.014	0.009	0.1	0.4	-0.1
edu23	9.533	0.314	**2.995**	10.349	0.312	**3.225**	7.548	**-0.23**	0.027	-0.254	-0.002	1.7	0.6	-1.9
const	62.478	1	**62.478**	56.067	1	**56.067**	63.435	**6.411**	0	6.411	0	46.9	0.0	48.1
Panel C: Aggregate decomposition														
Subtotal			**52.112**			**40.6**		**11.512**	**4.646**	**4.823**	**2.043**	**84.3**	**99.4**	**36.2**
Selection	3.237	0.802	**2.596**	-0.161	-0.44	**0.071**	5.383	**2.525**						
TOTAL			**54.708**			**40.671**		**14.037**			-1.588 Subtotal w/constant			

1) E: endowment effect; C: coefficient effect; CE: interaction term

Variables in X and Z

female dummy = 1 if women, = 0 othervise
CJ5 Native (Czech) language grade in the 5th year at the primary school. It ranges in 1 to 5, from best to poor.
MA5 Math grade in the 5th year at the primary school. It ranges in 1 to 5, from best to poor.
  Mother's highest educational attainment dummies
VMAT1 -primary or less (excluded base)
VMAT2 -secondary w/o GCE
VMAT3 -secondary w. GCE
VMAT4 -tertiary
VMAT5 Mother not living in the household
  Father's highest educational attainment dummies
VOTE1 -primary or less (excluded base)
VOTE2 -secondary w/o GCE
VOTE3 -secondary w. GCE
VOTE4 -tertiary
VOTE5 Father not living in the household
Variables in Z only
edu23 Proportion of district population with at least full secondary education

Table 7: Aggregate Components of the Raw SAT Score Gap Between Vocational and Grammar Schools Students

Component	Gap		
	Absolute	**% of the raw gap**	**% of avg. score in vocational schools**
Raw gap	14.0	100.0	34.6
Selection	2.5	18.0	6.2
Endowment	4.6	33.1	11.4
Intercepts	6.4	45.7	15.8
Coefficients w/o intercepts	-1.6	-11.3	-3.9
Interaction	2.0	14.6	5.0

Table 8: Estimated Treatment Parameters

OLS (1)	9.11	Coefficient on grammar school dummy in model (I)
OLS (2)	6.01	Difference in intercepts of models (IIa) and (IIb)
IV	7.48	Coefficient on grammar school dummy in model (III)
Average Treatment on Treated	9.6	$ATE^1 = E(Y^1-Y^0|D=1)$
Average Treatment on Untreated	3.33	$ATE^0 = E(Y^1-Y^0|D=0)$
Average Treatment Effect	5.55	$ATE = E(Y^1-Y^0)$
Sorting Gain	2.73	$E(U^1-U^0|D=1)$
Local Average Treatment Effects		$LATE[D(Z)=0,D(Z')=1]$
Supply effect	7.12	
Demographic effect	7.18	