Essays in Economics of Education

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Preface

This dissertation was written in the period from January 2011 to March 2014, while I was enrolled as a PhD student at CSER, Centre for Strategic Research in Education, at Aarhus University and had an office in Copenhagen at KORA, Danish Institute for Local and Regional Government Research. I am grateful for the financial support from the Danish Strategic Research Council through CSER and Aarhus University.

I would like to thank my advisor Helena Skyt Nielsen for helpful guidance and suggestions for improving my dissertation in countless ways. I would also like to thank my co-advisor Niels Egelund and the rest of the staff affiliated with CSER for fruitful comments and inspiration. Special thanks go to my co-authors Eskil Heinesen, Kristin J. Kleinjans, Anthony Dukes, Jacob Ladenburg and Camilla Dalsgaard for seamless and productive collaboration. In addition, my colleagues at KORA have been of invaluable help in the writing of this dissertation; both with regard to ongoing discussions of academic subjects and by creating a pleasant work environment. Here, my changing office colleagues, Signe Frederiksen, Lene Back Kjærsgaard, Kenneth Lykke Sørensen and Henrik Lindegaard Andersen, all deserve gratitude.

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Karl Fritjof Krassel

Copenhagen, March 2014

Summary

The present dissertation consists of four self-contained studies all relating to topics in economics of education. Chapter 1 is divided into two subchapters, both of which are about class size in compulsory school (primary and lower secondary school). Chapter 2 presents a study on determinants of enrolment in and completion of upper secondary education, while Chapter 3 presents a study on occupational aspirations, and hence the related final specialising step in the education system.

The study presented in Chapter 1.1 is named “Class-size effects in secondary school” and is a joint study with Eskil Heinesen. Using Danish register data and data from the Ministry of Education, we analyze class-size effects on academic achievement in the tenth grade. The optional tenth grade of lower secondary school is designed to give academically weak students an opportunity to catch up before proceeding to upper secondary education. Investigating whether class size is important for the academic achievement of this group, who are more at risk of dropping out of the educational system, is of particular political interest. We exploit an institutional setting, where pupils cannot predict class size prior to enrollment and where post-enrollment responses aimed at affecting realized class size are unlikely. We identify class-size effects by combining a regression discontinuity design with control for lagged achievement and school fixed effects. We find statistically significant negative effects of class size on academic achievement, but we do not find significant effect heterogeneity with respect to gender, immigrant status, lagged achievement or parental characteristics.

A study entitled “Balancing the risk of ‘lazearian’ interrupters and the benefits of educational and social peers: Tracing parental preferences for class-size reduction” (joint study with Jacob

Ladenburg and Camilla Dalsgaard) is presented in Chapter 1.2. The study uses Danish survey data from a choice experiment to estimate parental preferences for class-size reduction. The preferences are estimated in terms of willingness to pay for a class-size reduction. While parents with children in large classes are willing to pay for class-size reduction, parents with children in small classes are reluctant and even express negative utility for further class-size reduction. We interpret this as parents balancing the risk of potential interrupters and benefits of educational and social peers, when forming their preferences for class size.

Chapter 2 presents a study entitled “Completion of upper secondary education: The roles of cognitive and noncognitive skills”. The study uses OECD PISA survey data matched with Danish registry data to estimate enrolment in and completion of upper secondary education. The primary focus of the paper is to investigate whether cognitive and noncognitive skills differ in importance across general upper secondary education (high school) and vocational upper secondary education. The measures of cognitive and noncognitive skills are formed using factor analysis. Academic achievement and self-confidence are found to be important for enrolment in high school, while academic achievement and perseverance are important for completion of high school. With respect to completion of vocational education, neither academic achievement nor self-confidence and perseverance predict completion. Basic attendance measures (measured during compulsory schooling), however, are strong predictors of completion of vocational education. The attendance measures also predict completion of high school, but to a lesser extent.

The final study, “Occupational Prestige and the Gender Wage Gap” (joint with Kristin J. Kleinjans and Anthony Dukes), is presented in Chapter 3 and lies in the intersection between economics of education and labour economics. The study uses the same data as used in the study presented in Chapter 2. In addition, survey data on occupational prestige and register data on occupational characteristics are added. The study seeks to explain the gender wage gap by

heterogeneous preferences across gender for wage and prestige. In a Danish context, occupational options are to a great extent determined by education, and hence the study relates to the final specialising step in the education system that takes place through either vocational education or higher education. In self-reports, women express a stronger preference than men for occupations that are more valuable to society, which we hypothesize leads women to place more importance than men on the occupational prestige of their occupation. Support is found for the hypothesis, and gender differences are most pronounced among individuals from lower socioeconomic backgrounds.

Dansk resume (summary in Danish)

Essays i Uddannelsesøkonomi

Denne afhandling består af fire selvstændige studier, der alle relaterer sig til emner inden for uddannelsesøkonomi. Kapitel 1 er delt i to delkapitler, der begge omhandler klassestørrelse i grundskolen. Kapitel 2 præsenter et studie af determinanter for påbegyndelse og gennemførelse af ungdomsuddannelse, mens kapitel 3 præsenterer et studie om beskæftigelsesmæssige ønsker og derved relaterer sig til det sidste specialiserende trin i uddannelsessystemet.

Studiet præsenteret i kapitel 1.1 har titlen "Class-size effects in secondary school" og er skrevet sammen med Eskil Heinesen. Ved brug af danske registerdata og data fra Undervisningsministeriet analyserer vi klassestørrelseseffekter på eksamenskarakterer i 10. klasse. Som afslutning på grundskolen er den frivillige 10. klasse en mulighed for bogligt svage elever for at forbedre deres niveau, før de fortsætter med en ungdomsuddannelse. At undersøge om klassestørrelse har en betydning for netop denne gruppe, som alt andet lige har højere risiko for at droppe ud af uddannelsessystemet, er af særlig politisk interesse. Vi udnytter en institutionel konstruktion, hvor elever ikke kan forudsige klassestørrelse før påbegyndelse af 10. klasse, og hvor handlinger i forhold til at påvirke realiseret klassestørrelse er mindre sandsynlige. Vi identificerer klassestørrelseseffekter ved at kombinere et regression discontinuity-design med kontrol for karakterer i 9. klasse og skole fixed-effects. Vi finder statistik signifikante negative effekter af klassestørrelse på eksamenskarakterer, mens vi ikke finder effektheterogenitet i forhold til køn, herkomst, karakterer i 9. klasse eller forældrebaggrund.

Et studie med titlen “Balancing the risk of ‘lazearian’ interrupters and the benefits of educational and social peers: Tracing parental preferences for class-size reduction” (skrevet sammen med Jacob Ladenburg og Camilla Dalsgaard) er præsenteret i kapitel 1.2. I studiet anvendes danske survey-data i form af data fra et valgeksperiment til at estimere forældres præferencer for klassestørrelsesreduktion. Præferencerne er estimeret i form af betalingsvillighed i forhold til en klassestørrelsesreduktion. Mens forældre med børn i store klasser er villige til at betale for klassestørrelsesreduktion, er forældre med børn i små klasser mere tilbageholdne og udtrykker tilmed negativ nytte af yderligere klassestørrelsesreduktion. Vi fortolker dette således, at forældre balancerer risikoen for potentielle forstyrrelser af undervisningen med fordelene ved uddannelsesmæssige og sociale kammeratskabseffekter, når de danner deres præferencer for klassestørrelse.

Kapitel 2 præsenterer et studie med titlen “Completion of upper secondary education: The roles of cognitive and noncognitive skills”. Studiet anvender OECD PISA-data koblet med danske registerdata til at estimere påbegyndelse og gennemførelse af ungdomsuddannelse. Det primære fokus i studiet er at undersøge, om kognitive og ikke-kognitive færdigheder har forskellig betydning på tværs af gymnasiale og erhvervsfaglige ungdomsuddannelser. Målene for kognitive og ikke-kognitive færdigheder er dannet ved faktoranalyse. Boglige færdigheder og selvtillid prædikterer påbegyndelse af gymnasial ungdomsuddannelse, mens boglige færdigheder og vedholdenhed prædikterer gennemførelse af gymnasial ungdomsuddannelse. I forhold til gennemførelse af erhvervsfaglige ungdomsuddannelse har hverken boglige færdigheder, selvtillid eller vedholdenhed prædikativ styrke. I stedet findes, at simple mål for fremmøde (målt i grundskolen) er stærke indikatorer for gennemførelse af erhvervsfaglige uddannelser. Målene for fremmøde prædikterer også gennemførelse for gymnasiale ungdomsuddannelser men med mindre styrke.

Det sidste studie, "Occupational Prestige and the Gender Wage Gap" (skrevet sammen med Kristin J. Kleinjans og Anthony Dukes), er præsenteret i kapitel 3 og ligger i krydsfeltet mellem uddannelsesøkonomi og arbejdsmarkedsøkonomi. I studiet anvendes de samme data, som blev brugt i studiet præsenteret i kapitel 2. Derudover er der tilføjet survey-data på jobmæssig prestige og registerdata på andre jobmæssige karakteristika. Studiet søger at forklare lønforskellen mellem mænd og kvinder gennem heterogene præferencer for løn og prestige. Beskæftigelsesmæssige muligheder er i en dansk kontekst stærkt determineret af uddannelse, og studiet relaterer sig derfor til det sidste specialiserende trin i uddannelsessystemet, der finder sted gennem erhvervsfaglige eller videregående uddannelser. Gennem selvrapporterede præferencer udtrykker kvinder stærkere præferencer end mænd for jobs, der har værdi for samfundet. Vi fremsætter hypotesen, at denne præferenceforskel medfører, at kvinder lægger relativt større vægt end mænd på beskæftigelsesmæssig prestige i deres job. Vi finder støtte for denne hypotese og finder, at præferenceforskellen er mest udtalt for individer med lav socioøkonomisk baggrund.

Introduction

Among the choices an individual makes in the course of his or her life, the choices regarding human capital investments through education are some of the most important and far-reaching with respect to future consequences. The education investment decision often has very high alternative costs, and the gains are uncertain. In addition, undertaking education is highly time consuming, and the investment is irreversible. Hence, knowledge about all aspects of the human capital accumulation process through education is relevant – both from the perspective of the individual and from the perspective of the society as a whole. The present PhD dissertation is a collection of four self-contained studies covering different aspects of education. The studies all employ quantitative methods on various Danish data. The first two studies are presented in Chapter 1 and both concern the importance of class size in primary school and lower secondary school. Chapter 2 presents a study on the determinants of enrolment in and completion of upper secondary education, while Chapter 3 presents a study on the expected choice of occupation, and hence the associated expected further education.

1. Theoretical and methodological approach

The studies presented in this dissertation were conducted based on the tradition of microeconomics. More precisely, the studies can be classified as applied microeconomic studies, primarily within the fields of economics of education and secondarily labour economics. All studies have an empirical focus where data are used to answer empirical questions using microeconometric methods. The present section provides a brief introduction to the theoretical and methodological approach of the dissertation.

Two related theoretical concepts are key elements in this dissertation and in the economics of education generally. The first is human capital accumulation through education, and the second is the education production function. Both concepts can be thought of as the offspring of classical microeconomic production theory. Production is the process of transforming inputs to outputs, and the technology employed determines the result (Jehle & Reny 2001, Chapter 3). In the simplest form, firms seek to maximise profits by minimising production costs choosing the optimum quantities of labour and capital inputs in their production function to achieve a given level of output. To think of labour as only having a quantitative dimension is clearly an oversimplification. Skilled labour is more valuable than non-skilled labour, as the productivity is higher. But at the same time skilled labour is more costly than non-skilled labour, and this represents a trade-off for firms. Given the qualitative dimension of labour inputs, economics has a clear interest in the human capital accumulation process.

1.1 Human capital accumulation through education

Given the wage premium offered for skilled labour, the individual is faced with a decision of whether to invest in education. The concept of education as an investment asset found its way into economics through the works of, especially, Mincer (1958, 1974) and Becker (1964). Mincer sought to estimate the empirical return to schooling, while Becker formalised the analysis of human capital accumulation. An individual chooses to invest in education, if the rate of return of the investment is high enough, i.e. if the discounted sum of future gains exceeds the costs. It is important to notice that the analysis of human capital accumulation is highly general. Neither cost nor returns are limited to the monetary aspects of the investments. Undertaking education requires 'costly' effort, for instance, and the gains also include non-pecuniary gains (Wolfe & Haveman 2003).

As education requires effort, ability clearly plays a decisive role in the education investment decision. Given this, a clear purpose of compulsory education arises, namely to strengthen ability, inducing individuals to invest in further education after compulsory schooling. As discussed in Blaug (1985), early economics of education was criticised for having too narrow a perspective on the function of schools. Bowles and Gintis (1976) advocated the view that schools have a socialising function in that they affect noncognitive personality traits, and that these traits are highly valuable and rewarded both in the classroom and on the labour market. As Blaug phrase it, Bowles and Gintis find the 'widely observed association between personal earnings and schooling [is] usually attributed to the influence of education on the levels of cognitive knowledge in the working population' to be misleading.

Recent progress in economics of education has embraced some of the old critique by Bowles and Gintis. The investment perspective proposed by Becker is still relevant, but the understanding of the importance of multiple skills or personality traits has increased. In addition, an understanding has evolved that these skills are also formed by education, which is the 'socialising function' of schools that Bowles and Gintis hint at. An important contribution to the literature in recent years is the paper by Cunha & Heckman (2007). In the paper, a formal model of skill formation capturing recent findings in the literature is developed. Especially important is one inclusion in the model: '… abilities are created, not solely inherited, and are multiple in variety'. In other words, an individual possesses both cognitive and noncognitive skills and both are malleable. Cunha and Heckman introduced the term 'dynamic complementarity' to describe the situation in which investment in the stock of skills in period $t-1$ makes the investment in period t more productive. The stock of skills comprises all skills, both cognitive and noncognitive. Hence, in a framework like this early socialising in school, affecting noncognitive skills such as patience and self-control, increases the beneficial effects of later human capital investments.

1.2 The education production function

Inspired by the classical production function, a framework for understanding human capital accumulation is the theoretical construct of an education production function transforming inputs to educational outcomes. The model described by Cunha and Heckman (2007) can be considered as an education production function in the sense that it describes a technology that forms skills. An earlier description of the education production function was given by Bowles (1970). He considers the education production function to be given by

$$A = f(X_a, \ldots, X_m, X_n, \ldots, X_v, X_w, \ldots X_z),$$

where A is a measure of some school output, $X_a, \ldots, X_m$ are measures of the school environment, $X_n, \ldots, X_v$ are measures of environmental influences outside the school, including parental inputs, and $X_w, \ldots, X_z$ represents students' ability and initial level of learning prior to enrolment.

The theoretical framework of a production function is quite simple. Inputs are transformed by technology, resulting in outputs, and hence researchers are interested in uncovering the structural parameters of the education production function (or the partial effect of an input on a given output). The education production function framework is also an attractive approach to evaluating initiatives in the schooling sector. By using measures of the outcome variable at two points in time, the value-added effect of a given event can be estimated. For instance, testing student reading proficiency at two points in time can used to assess the value added by a reading course. In addition, as discussed by Todd & Wolpin (2003), the full set of relevant input variables are often not observed in the data, and therefore it is often more feasible to estimate value-added effects.

1.3 Methodological issues

Unlike in natural sciences, conducting experiments in social sciences are often difficult for both practical and ethical reasons. Hence, it is often necessary to settle for using observational data.

Fortunately, the availability of excellent micro-level data has increased in recent years. Examples are the availability of the OECD PISA data (from the PISA 2000 survey) and Danish data on exam marks in lower secondary school (from 2002). In addition, data often include unique person identifiers, through which data can be linked to official registers. The present dissertation takes advantage of this and uses both survey and registry data for the empirical analyses.

A major concern that is always present when using observational data is representability, i.e. whether the available sample is representative of the population of interest. Often, some sort of selection occurs on both observables and unobservables, and hence naïve estimates failing to take the selection into account would be biased. If the selection only occurs on observables, controlling for observables is sufficient to gain conditional independence. If the selection occurs on unobservables, the methodological approach required is often more complicated. Here, mimicking the experimental approach in natural sciences using a quasi-experimental approach can be fruitful. The pivotal point is then to find an empirical phenomenon resulting in randomisation at the margin of interest. A classic example of a quasi-experimental setting from economics of education is the analysis of class-size effects. See Chapter 1.1 for a thorough discussion. In some cases, it is not possible when using observational data to claim identification through exploiting a quasi-experimental setting or conditional independence given the richness of the data. In such cases, studies can still be relevant as they might uncover interesting (conditional) associations among observables. This is the case in the study presented in Chapter 2, for instance, showing how basic attendance measures (measured in compulsory school) can predict dropout from upper secondary education. Despite not necessarily being a finding of a causal relationship, the finding is useful from a screening and helping perspective, as the information is easily observed.

2. Introduction to the individual chapters

In the following, the individual chapters are briefly introduced with reference to the key concepts introduced in Section 1. The chapters are ordered so as to follow a student's progression through the education system. Note that Chapter 1 consists of two subchapters, Chapters 1.1 and 1.2, both of which present studies on class size.

2.1 Chapter 1.1 – Class-size effects in secondary school

The first study presented in the dissertation is a study on the effect of class size on academic achievement in the tenth grade. Hence, the study is an evaluation of an input in the education production function with respect to a certain school outcome. Tenth grade is offered as an optional additional year of schooling after compulsory education, targeted especially at academically weak students to prepare them for enrolment in upper secondary education. The study takes advantage of a *de facto* functioning class-size rule determining number of students per class in the tenth grade to identify the effect of class size in a quasi-experimental setting. Tenth grade is a rather unique feature of the Danish education system and lies in between lower and upper secondary education. Hence, we have entitled the study 'Class-size effects in secondary school', without being specific as to whether lower or upper secondary education is in question.

The study is a joint work with Eskil Heinesen, and the chapter has been accepted for publication and is forthcoming in Education Economics, Special issue: International Workshop on the Applied Economics of Education 2013.

2.2 Chapter 1.2 – Balancing the risk of 'lazearian' interrupters and the benefits of educational and social peers: Tracing parental preferences for class-size reduction

Chapter 1.1 illustrates that the school resource class size is important for the output in the education production function. As suggested by Bowles (1970), this also applies to parental inputs.

In addition, parental behaviour is likely to be influenced by perceived school resources. Parents can choose where to enrol their children, but can also choose the amount of time they want to spend assisting their children with homework, for instance. The study presented in Chapter 1.2 is a study on how parents react with regard to perceived school resources. More precisely, parental willingness to pay for class-size reduction is estimated in the study using data from a choice experiment. Thus, the study relates to the interplay between inputs in the education production function. A thorough understanding of such interplay is important as, for instance, politically induced changes in school resources might influence other inputs in the education production function too.

The study is a joint work with the KORA researchers Jacob Ladenburg and Camilla Dalsgaard and arose as a possibility late in the course of writing the dissertation. Therefore, the study has not yet been presented. Chapter 1.2 is relatively short, as the article is aimed at journals such as Economics Letters or similar.

2.3 Chapter 2 – Completion of upper secondary education: The roles of cognitive and noncognitive skills

Chapter 2 presents a study on the choice of enrolment in and completion of upper secondary education in Denmark. The transition from lower secondary to upper secondary education is a critical transition, and the official goal of a 95% completion rate of upper secondary education is currently not being fulfilled. The study divides upper secondary education into two branches: General purpose upper secondary education (high school) and vocational education. Compared to the high school branch of the education system, the vocational branch is especially plagued by low completion rates. The study investigates whether cognitive and noncognitive skills differ in their importance with respect to completion across the academically oriented high school and the more practically oriented vocational education. In relation to the discussion of human capital accumulation and inputs into the education production function, the study illustrates the importance of both cognitive and noncognitive skills with regard to educational outcomes.

The study has been presented at various workshops, but has not yet been submitted to any journal.

2.4 Chapter 3 – Prestige and the gender wage gap

Chapter 3 presents a study using detailed data on students' occupational aspirations from the OECD PISA data. In a Danish context, occupational options are closely determined by earlier educational choices, and hence that last study relates to the final specializing step through the education system. As documented in the economic literature, a wage gap continues to exist between men and women. We suggest an explanation for the wage gap by considering jobs to offer two kinds of payoffs to the jobholder: Wage payoff and prestige payoff. Given a compensating differentials framework, the gender wage gap might be explained by women choosing jobs with higher preference for prestige compared to men (and hence accepting lower wages). Going back to the human capital accumulation process described by Becker (1964), the study is an illustration of the generality of the theory. By considering jobs to give both wage and prestige payoffs, we explicitly think of both pecuniary and non-pecuniary gains as being relevant in the education investment decision facing the individual. In addition, we think (and indeed find support for this) that nonmonetary gains associated with educational investments can explain the empirical finding of the gender wage gap.

The study is a joint work with Kristin J. Kleinjans and Anthony Dukes. The study has been presented at various workshops, and the chapter has been submitted but not yet accepted.

References

Becker, G. S. 1964. "*Human capital: A theoretical and empirical Analysis with special reference to education.*" New York: Columbia University.

Blaug, M. 1985. "Where are We Now in the Economics of Educaton?" *Economics of Education Review* 4 (1): 17–28.

Bowles, S. 1970. "Towards and educational production function." In *Education, Income, and Human Capital*, W. L. Hansen (ed.), 9–70. NBER Book Series Studies in Income and Wealth, NBER.

Bowles, S., and H. Gintis. 1976. "*Schooling in Capitalist America.*" New York: Basic Books.

Jehle, G. A., and P. J. Reny. 2001. "*Advanced Microeconomic Theory.*" 2nd ed. Boston: Adison-Wesley.

Mincer, J. 1958. "Investment in Human Capital and Personal Income Distribution." *Journal of Political Economy* 66 (4): 281–302.

Mincer, J. 1974. "*Schooling, experience and earnings.*" New York: Columbia University Press.

Todd, P. E., and K. I. Wolpin. 2003. "On the Specification and Estimation of the Production Function for Cognitive Achievement." *The Economic Journal* 113 (485): F3–F33.

Wolfe, B. L., and R. H. Haveman. 2003. "Social and Nonmarket Benefits from Education in an Advanced Economy." In *Education in the 21st Century: Meeting the Challenges of a Changing World*, Y. Kodrzycki (ed.), 96–131. Boston: Federal Reserve Bank of Boston.

Chapter 1.1

Class-size effects in secondary school

Class-size effects in secondary school[1]

Karl Fritjof Krassel

Eskil Heinesen

Abstract

We analyze class-size effects on academic achievement in secondary school in Denmark exploiting an institutional setting where pupils cannot predict class size prior to enrollment, and where post-enrollment responses aimed at affecting realized class size are unlikely. We identify class-size effects combining a regression discontinuity design with control for lagged achievement and school fixed effects. Using administrative registry data, we find statistically significant negative effects of class size on academic achievement.

Keywords: School quality, human capital investment, regression discontinuity design, value-added models, school fixed effects, maximum-class-size rule

JEL codes: C23, I2, I21

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1. Introduction

The importance of school resources in the education production function remains a topic of great interest. When evaluating the effects of school resources in general and the effects of class size in particular various endogeneity issues are likely to arise. If parents tend to take their children out of poor performing classes and enroll them in well performing classes at other schools, the poor performing classes will become smaller while the well performing classes will grow larger. This implies that parameter estimates from a naive estimation of e.g. achievement on class size would be biased if this selection is not controlled for. In addition to parental responses, school administrators' behavior is likely to be influenced by performance also leading to biased estimates. For instance, less able pupils may often be placed in smaller classes; see Wössmann and West (2006). This identification problem is recognized in the existing literature and a number of studies have evaluated class-size effects on academic achievement in experimental or quasi-experimental settings. However, the evidence is often mixed. Based on the STAR experiment in the US, Krueger (1999) finds that a reduction of 8 pupils per class in the first four grades increases average test scores by 0.2-0.3 standard deviations in the distribution of pupils' individual test scores. Similar effect sizes are found for fifth graders in Israel in the analysis of Angrist and Lavy (1999) based on Maimonides' maximum class-size rule, and for ninth graders in Denmark in the analysis of Heinesen (2010) using within-school variation in subject-specific classes. However, Angrist and Lavy (1999) do not find significant effects for third and fourth graders, and Hoxby (2000) using maximum class-size rules and random population variation does not find significant class-size effects for Connecticut elementary schools.[2] For Sweden, Fredriksson et al. (2013) find that average class size in grades 4-6, instrumented by predicted class size based on a maximum class-size rule and enrollment in grade 4, has a negative effect on cognitive ability at age 13 and academic achievement at age 16, while Leuven et al. (2008) using similar methods (instrumenting average class size in grades 7-9 by predicted class size in grade 7) find no significant class-size effect on student achievement at the end of ninth grade in Norway.

Using panel data for Texas, Rivkin et al. (2005) estimate class-size effects on test score gains. They find clearly significant effects for fourth and fifth grades, some significant effects for sixth grade, but insignificant effects for seventh grade. Reducing class size by 8 pupils, the estimated effect sizes for fourth and fifth grades are in the range 0.04-0.12. These estimates are much smaller than the corresponding effect size estimates in Krueger (1999), Angrist and Lavy (1999) and Heinesen (2010), but this is to be expected since the dependent variable is test score gains from one grade to the next.

The mixed results in the literature across countries and grades mean that more evidence is informative. This paper aims at adding to this area of research by exploring the effect of class size on pupils' academic achievement, measured by examination marks, in an optional tenth grade of lower secondary school in Denmark which is offered after compulsory schooling (i.e., after ninth grade) and chosen by about 50% of a cohort. This voluntary extra year at lower secondary school is primarily aimed at adolescents who are academically weak or who have not yet decided which type of vocational or academic upper secondary education they want to pursue. About 20% of a cohort in

[2] Positive effects of reducing class size on years of schooling and other long-term outcomes are found in Krueger (2003) and Chetty et al. (2011) based on the STAR experiment, and in Browning and Heinesen (2007) and Fredriksson et al. (2013) based on analyses using maximum class-size rules and Danish and Swedish administrative data, respectively.

Denmark never finishes an upper secondary education in spite of the fact that the political goal for decades has been to reduce this share to about 5%. Since the tenth grade is an offer aimed especially at adolescents who are at risk of not obtaining an upper secondary education, it is of particular interest to investigate the importance of school quality at this grade. Class size is a meaningful measure of school resources in the Danish tenth grade since teaching occurs largely within a given 'class'. The group of pupils choosing tenth grade is highly selective, as explained, but we identify class-size effects by exploiting an institutional setting where pupils cannot predict class size prior to enrollment, and where post-enrollment responses aimed at affecting realized class size are unlikely. Furthermore, we use administrative register data which enables us to condition on a wide range of background variables, including lagged academic achievement, and we combine a value-added model with a regression discontinuity design and control for school fixed effects. Our results indicate positive effects of reducing class size on average exam marks. The estimated effect when class size is reduced by 10 pupils is about 0.08 standard deviations in the distribution of pupils' individual marks, which is in line with estimates for fifth graders in the value-added model of Rivkin et al. (2005).

2. Institutional features

In Denmark compulsory schooling is ten years, from preschool class to ninth grade, and in addition the lower secondary school system offers an optional tenth grade. After ninth grade pupils have the options to enroll into upper secondary education, either academic or vocational, enter the labor force, or enroll into the optional tenth grade of lower secondary school. Our focus in this paper is on the effect of class size in this optional tenth grade.[3]

The tenth grade class exists as an option for pupils both to improve their academic skills and to get more mature before continuing in the education system. From ninth grade around half of a cohort enrolls into tenth grade. Around half of these enroll into boarding schools, around ten percent enroll into other private schools and the rest enroll into public schools (Nielsen, 2010). The public tenth grade is either placed at normal public schools or located at special tenth grade schools. Tenth grade at a boarding school has the same curriculum as ordinary tenth grades but in addition they often provide other more topical courses, e.g. in music or sports. Given the nature and purpose of tenth grade, enrollment is highly selective. Although private schools (including boarding schools) are heavily subsidized by the municipalities and the state, parents pay on average a tuition fee of about 15% of costs (and boarding schools are more expensive). This is reflected in the selection into different types of schools for tenth grade: Pupils at private schools have more advantaged backgrounds (e.g., about 20% higher parental income and 1 year longer parental education) and they have higher GPA from ninth grade (about 0.3 standard deviations of the individual marks distribution).

Compulsory schooling in Denmark ends with a formal examination after ninth grade. The content of the exam is the same in all schools (whether public or private). Pupils are highly encouraged to take the exam, but it is not strictly mandatory. At the end of tenth grade pupils may either (re)take the ordinary (ninth grade) exit exam or they may choose to take the more advanced (tenth grade) exit exam. The decision which exam to take is at course level and hence pupils can

[3] This optional tenth grade is a rather unique feature of the Danish school system. To our knowledge only Finland has a similar optional tenth grade, but enrollment is only around 2 percent (own calculation on data from Statistics Finland).

end up with very different exam portfolios. Marks are given by the teacher and an external examiner. Pupils also receive marks for the year's work which are assessed by the teacher alone.

In traditional tenth grade classes at either private or public schools, the class as a unit of teaching is very important (as it is in earlier grades). Typically, the majority of lessons will be conducted within the class. This is especially true for the three mandatory subjects, Danish, math and English, which are the focus of this paper, since the outcome in the main analysis is the GPA of exam marks in these subjects (see below). However, boarding schools and specialized public tenth grade schools use only to some extend the traditional class structure, and these schools are therefore excluded from the analysis of this paper (see Section 4).

3. Empirical methods

We estimate class-size effects on exam marks GPA applying a regression discontinuity design (RDD) with a maximum-class-size rule as an instrumental variable for class size (as in Angrist and Lavy, 1999). This RDD is combined with control for school fixed effects, lagged GPA and a rich set of parental background variables. Our model which is estimated by 2SLS is given by:

$$T10_{ist} = \beta_{CS} CS_{st} + T9_{ist}\beta_{T9} + X_{ist}\beta_X + \varepsilon_s + \eta_{ist}. \qquad (1)$$

$$CS_{st} = \gamma_M M_{st} + T9_{ist}\gamma_{T9} + X_{ist}\gamma_X + \mu_s + \upsilon_{ist}. \qquad (2)$$

where indices i, s and t denote individuals, schools and years, respectively, $T10$ is tenth grade GPA, CS class size, $T9$ ninth grade GPA, X a vector of covariates (including individual, parental and school level covariates and cohort dummies), ε and μ are school fixed effects, η and υ idiosyncratic error terms, and M is predicted class size based on the maximum-class-size rule:

$$M_{st} = e_{ist} / (\text{int}((e_{ist} - 1)/m) + 1) \qquad (3)$$

with e denoting enrollment, m the maximum class size, and int(z) the largest integer smaller than or equal to z. Hence, small changes in enrollment around threshold values of the maximum class size rule have substantial influence on predicted class sizes. In the estimations we set $m = 28$. By national law, the maximum class size is 28 for grades 1–9 in Denmark. Although there is no binding rule for grade 10, 28 seems to function as a de facto maximum-class-size rule as illustrated in Figure 1, which shows M (with $m = 28$) and average class size for each value of enrollment. Although the RDD is 'fuzzy', the probability of a small class size is higher when enrollment is just above a discontinuity point compared to just below (especially for values of enrollment below about 100 where the density of enrollment is high), and the correlation between class size and M is high.

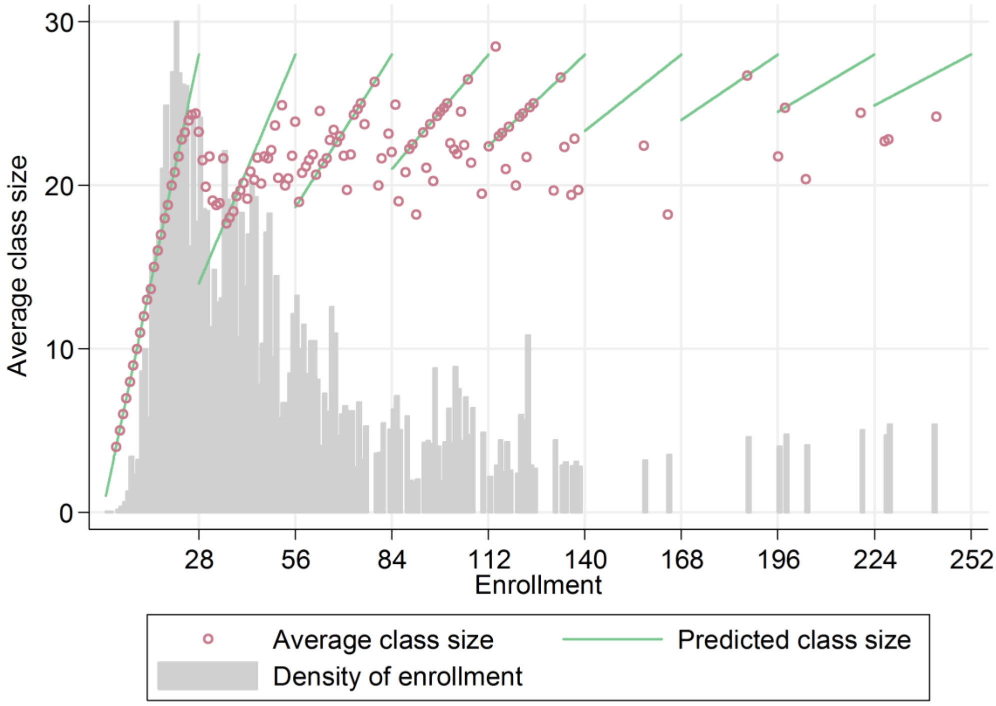

Figure 1: Average and predicted class size for each value of enrollment, and density of enrollment

The 2SLS estimator of the parameter of interest, β_{CS}, may be interpreted as a weighted average causal effect of changing class size in a more general model where class-size effects are heterogeneous and non-linear, given independence and monotonicity assumptions (Angrist and

Imbens, 1995): After control for other variables, the instrument should be independent of individuals' potential outcomes (potential GPA given class size); and an increase in enrollment may not reduce the number of classes.

The independence assumption is crucial. Since *M* is a (discontinuous) function of enrollment and enrollment may be correlated with educational outcomes for other reasons than class size, it is essential to control for these other channels of correlation between enrollment and outcomes. We use a rich set of control variables (for parental background and other student specific characteristics, especially lagged academic achievement) and we also control for school fixed effects. In addition, we control for a smooth function of enrollment in the regressions. Thus, essentially the identifying assumption is that the discontinuities in the relation between predicted class size and enrollment may be excluded from the outcome equation (1). In the main analysis we include in all regressions a second-order polynomial in enrollment. As a robustness check we replace this polynomial by a continuous piecewise linear trend in enrollment with slope equal to the slope of *M* between discontinuity points (the trend is defined by: e for $e \in [0, 28]$; $e/2 + 14$ for $e \in [29, 56]$; $e/3 + 70/3$ for $e \in [57, 84]$; etc.; see Angrist and Lavy, 1999). Results do not change in any significant way using this alternative specification.

The independence assumption also requires that students do not selectively exploit the class-size rule to obtain a small class size, which should hold in this case. First, compulsory schooling ends after ninth grade. This makes enrollment and class size in tenth grade rather unpredictable prior to enrollment since pupils choose different paths after ninth grade.[4] Second, post-enrollment

[4] This hypothesis is somewhat supported by the findings that the correlation between class size in tenth grade and class size in ninth grade the year before is only 0.20 while the within-school correlation between class sizes in tenth grade across years is 0.40.

selection responses to observed school quality are likely to be limited, since it is costly to change school and it only affects schooling in one year.

If pupils selectively exploited the class-size rule, we would expect observable characteristics of pupils at enrollment counts just above a discontinuity point to be different from those at enrollment counts just below this point. We test this using a restricted sample of observations with enrollment within intervals of ±4 around discontinuity points, and running regressions of a dummy for being to the right of discontinuity points on all explanatory variables (see Section 4.3). The p-value of an F-test that the coefficients of all individual specific variables of this regression are zero is 0.580 for OLS, and 0.923 controlling for school fixed effects. Thus, there is no indication of selection with respect to these observables, including lagged achievement and parental background, which are very important for academic outcomes. Therefore, selection in terms of unobservables is unlikely.

Using the RDD, class-size effects are identified by the discontinuous variation in predicted class size around cut-off values of enrollment where the predicted number of classes changes. However, schools may differ in terms of unobservables, e.g. the quality of tenth grade teachers, which might be correlated with (predicted) class size. To the extent that such unobservables are constant over time, our school fixed effects approach (in combination with RDD) controls for this. Time-varying unobservables might pose more problems. For instance, teacher quality in lower secondary school may differ between cohorts at a given school and it may also affect the share of pupils choosing upper secondary school after ninth grade, and therefore the share choosing to continue in tenth grade at the school. Thus, if pupils were exposed to high quality teachers in ninth and earlier grades a smaller fraction of ninth graders might choose tenth grade. These pupils may be academically weaker because they are more selected, or they may be stronger because they had good teachers. Most often these pupils will be exposed to a smaller class in tenth grade in which case the RDD takes account of this continuous variation, but in some cases the reduction in tenth grade enrollment may trigger a reduction in the (predicted) number of classes and therefore an increase in (predicted) class size. In either case it is important to take account of pupil academic skills at the beginning of tenth grade, and we do that by combining the RDD and school fixed effects approaches with a value added model, i.e. by controlling for ninth grade GPA. To sum up, the F-tests reported in the previous paragraph indicate that pupil characteristics are similar above and below discontinuity points, and control for school fixed effects and lagged GPA further guard against potential endogeneity issues.

4. Data

We combine administrative registry data on pupils and their parents from Statistics Denmark with administrative registry data from the Ministry of Education on individual exam results and the number of pupils and classes in tenth grade at each school. Examination results are from May and June each year (the end of the school year), while data on the number of pupils and classes are recorded in September the year before (the beginning of the school year). Data on individual examination results in ninth and tenth grade are available from 2002 (i.e. the school year 2001/02) and hence 2002 is the beginning of our data window. In principle we could obtain register data up to 2012, but in 2007 a new grading scale was introduced and in 2007-2008 a change in both subjects up of examination and the content of examinations changed. Hence our data window closes in 2006. Since we estimate value-added models we drop observations on pupils not observed in both ninth and tenth grade and the estimation period is 2003-2006.[5]

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[5] In the case of a school change during the school year of tenth grade, we use data on class size at the school where the exit exam is taken.

4.1 Explanatory variables

The variable of primary interest is class size. We do not have data for the size of individual classes, but we construct the average class size at each school in a given year by dividing the number of tenth grade pupils at the school by the number of tenth grade classes. This is not a serious limitation since it eliminates possible bias due to within-school sorting (for a given school and year, the size of classes may vary for non-random reasons). Also, in our RDD approach the instrument predicts average class size at the school given enrollment. As explained in Section 2, we limit our sample to consist of only traditional tenth grade classes in either private or public schools.[6] In addition we drop a few observations with unreasonable large class sizes.[7] While data on enrollment is of very high quality, data on the number of classes is not quite so reliable, although they are in general of high quality for traditional schools. When observed class size is unusually large, this is probably due to underreporting of the number of classes, and this is the reason why we exclude these observations. Measurement error in class size will tend to bias OLS estimates of class-size effects towards zero, but the IV estimator removes this measurement error since predicted class size is a function of enrollment, but not of the reported number of classes.

The most important pupil-specific explanatory variables are the marks obtained in ninth grade. We use two different averages (GPAs), one of examination marks and one of marks for the year's work. Other pupil-specific explanatory variables are gender, immigrant status, number of

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[6] Hence we exclude boarding schools and public tenth grade schools. The reason for this is that they only to some extend use the traditional class structure. The average class size is not a meaningful measure for these schools and in addition the reported number of classes is imprecise (typically much too low) for these institutions.

[7] We drop observations with class size above 35. In total we drop 1,746 observations corresponding to 3.6% of the sample. Our estimation results are robust to this restriction; see Section 5.2.

siblings, and whether the pupil lives with his or her parents. In addition we have information on parents in terms of employment status, education, income, etc.

4.2. Outcome variables and estimation sample

In our main estimations we use as the outcome a GPA of exams taken at the end of tenth grade. As discussed above, at the end of tenth grade pupils can either choose to take the ordinary exit exam or the advanced exit exam or a combination of the two. Table 1 shows a cross tabulation of the number of ordinary and advanced exit exams taken at the end of tenth grade, and it is clear that pupils in fact utilize all three options.[8] For instance, among the 46,267 tenth grade pupils in the dataset 28,796 take no ordinary exit exams and six advanced exit exams; 2,017 take six ordinary exit exams and no advanced exit exams; and 2,553 take two ordinary exit exams and four advanced exit exams. In addition, the table shows that some pupils only take a few exams. This reflects the possibility that pupils can choose (with the school's consent) not to take an exam. Such a situation can arise if a pupil has severe learning difficulties in a specific topic and hence has skills far below the minimum exam requirements in that topic.

[8] The ordinary exams which we include in the analysis are in Danish (written and oral), spelling (Danish, written), math (written and oral), and English (oral). The advanced exams included in the analysis are in the mandatory subjects: Danish (written and oral), math (written and oral), and English (written and oral).

Table 1: Pupils' combinations of ordinary and advanced exams

		# of ordinary exit exams							Total
		0	1	2	3	4	5	6	
# of advanced exit exams	0	412	51	77	138	195	691	2,017	3,581
	1	69	41	56	83	43	100	3	395
	2	234	104	287	1,224	504	242	0	2,595
	3	413	190	361	109	6	0	0	1,079
	4	1,191	2,394	2,553	176	0	0	0	6,314
	5	2,997	120	2	0	0	0	0	3,119
	6	28,796	388	0	0	0	0	0	29,184
Total		34,112	3,288	3,336	1,730	748	1,033	2,020	46,267

This self-selection implies a missing data problem for pupils choosing not to take a given exam. It is unreasonable to compare grade point averages across pupils who do not choose to attend the same number of exams or who take exams at different levels (since content of and requirements for the ordinary and the advanced exit exams differ). Our solution to these complications is to define our outcome variable as the GPA based on the six advanced exams for the three mandatory subjects (i.e. written and oral exams for Danish, math, and English), and to restrict the basic estimation sample to pupils who have taken all these exams. However, we also show results for the effect of class size on the probability of taking all these six advanced exams using the full sample of 46,267 pupils.

4.3. Summary statistics

Table 2 shows summary statistics of the outcome variables used in the estimations. Grades have been standardized to have mean zero and standard deviation unity in order to ease interpretation of the estimation results. The standardization was carried out on basis of all observations on marks for each exam/subject. The standard deviation of the GPA is below unity because of the averaging over several individual marks. Table 2 shows that 63% (29,184 pupils) of the entire sample (of 46,267 pupils) take all six advanced exams. The GPA of exam marks (for pupils taking all six advanced exams) has a mean of 0.072 and a standard deviation of a 0.644. It is not surprising that the mean is above zero since pupils taking all six advanced exams are a selected high-ability group.

Table 2: Summary statistics of outcomes variables

Variable	Mean	SD	N
Choosing advanced exams in all mandatory subjects	0.631		46,267
GPA, based on advanced exam marks in mandatory subjects	0.072	0.644	29,184

The main estimations use the GPA based on advanced exam marks for those taking all six exams. Hence, Table 3 shows summary statistics of explanatory variables for this sample. In addition to the summary statistics, the table shows estimation results for OLS and school fixed effects (SFE) regressions of class size on all explanatory variables. As expected, larger enrollment is associated with larger class size, and private schools have smaller classes. The hypothesis that all parameters of the individual specific variables are zero is clearly rejected ($p<0.001$) in the regression without school fixed effects; in the model with school fixed effects it is rejected at the 10% level ($p=0.093$). In the model without school fixed effects ninth grade GPAs for exam marks and marks for the year's work are significant (but have opposite signs) and so is the dummy for no register information on the mother, which has a large negative coefficient. Missing information on the mother (because she is dead or living abroad) occurs for 1.4% of the children. By construction, when the mother is not in the registers, she does not receive social assistance, she is not in the workforce, and she has missing information on unemployment, education and wage income. So the coefficient on this variable is difficult to interpret. There is some indication that class size is smaller for disadvantaged pupils: In the OLS regression without school fixed effects, the point estimates of variables for parents receiving social assistance or being out of the workforce are negative, and parental education and father's wage income tend to have a positive relation with class size. It is perhaps surprising that these parameters are not more significant since the distribution of pupils on schools is affected by various selection mechanisms and school resources are affected by socioeconomic conditions. However, although schools in areas with low socioeconomic status will often receive more resources per pupil from the municipality, there is a counteracting mechanism, since richer municipalities will often decide to spend more on schools in spite of extensive grants and equalization schemes which eliminate most financial inequalities between municipalities (Heinesen, 2004). Also, extra resources to schools with many disadvantaged pupils are presumably primarily targeted at younger children. Anyway, the regressions in Table 3 indicate that class size is not random, at least not without control for school fixed effects. As discussed above, we use a RDD as our main identification strategy to tackle this problem.

Table 3: Summary statistics of explanatory variables and OLS and school fixed effects regressions of class size on controls

	Mean	SD	(1) OLS Coeff.	(1) OLS SE	(2) SFE Coeff.	(2) SFE SE
Class size	20.914	4.498	-		-	
GPA 9th grade (exam marks)	0.135	0.574	-0.182+	(0.108)	-0.035	(0.063)
GPA 9th grade (year marks)	0.159	0.622	0.324**	(0.103)	0.112+	(0.059)
Enrollment/100	0.571	0.454	8.025***	(1.038)	19.255***	(2.269)
Enrollment squared/10,000	0.532	0.962	-2.560***	(0.480)	-7.410***	(1.113)
Female	0.490	0.500	0.004	(0.063)	0.036	(0.038)
Immigrant (1st or 2nd generation)	0.076	0.265	0.070	(0.237)	-0.072	(0.088)
Child lives with both parents	0.678	0.467	-0.113	(0.083)	-0.006	(0.041)
Number of siblings	0.806	0.903	-0.043	(0.034)	-0.001	(0.020)
Private school	0.278	0.448	-0.887*	(0.353)	-	
Mother social assistance beneficiary	0.046	0.210	-0.039	(0.167)	0.027	(0.113)
Father social assistance beneficiary	0.025	0.157	-0.011	(0.207)	0.074	(0.122)
Mother's level of unemployment	0.016	0.067	-0.480	(0.440)	-0.130	(0.253)
Missing: Mother's unemployment	0.167	0.373	-0.024	(0.138)	-0.008	(0.087)
Father's level of unemployment	0.012	0.056	0.066	(0.473)	0.076	(0.326)
Missing: Father's unemployment	0.166	0.372	-0.178	(0.159)	-0.086	(0.088)
Mother not in workforce	0.049	0.215	-0.087	(0.176)	-0.019	(0.119)
Father not in workforce	0.081	0.273	-0.167	(0.222)	-0.286*	(0.131)
Mother not in registers	0.014	0.119	-0.696*	(0.299)	-0.237	(0.184)
Father not in registers	0.054	0.227	0.130	(0.247)	0.199	(0.156)
Mother's age ≤ 19 at child birth	0.033	0.179	0.001	(0.140)	-0.023	(0.097)
Mother: Years of schooling	11.929	2.388	0.010	(0.018)	0.006	(0.007)
Father: Years of schooling	11.823	2.386	0.026	(0.018)	0.000	(0.008)
Missing: Mother’s education	0.080	0.271	-0.105	(0.114)	-0.089	(0.080)
Missing: Father’s education	0.113	0.316	-0.004	(0.141)	-0.054	(0.071)
Log mother's wage income	2.732	1.314	-0.003	(0.055)	-0.026	(0.033)
Log father's wage income	2.756	1.597	0.052	(0.057)	-0.031	(0.032)
Mother has no wage income	0.150	0.357	-0.094	(0.167)	-0.092	(0.103)
Father has no wage income	0.224	0.417	0.320	(0.197)	0.013	(0.119)
Year 2003	0.267	0.442	-		-	
Year 2004	0.236	0.425	0.131	(0.271)	0.329	(0.249)
Year 2005	0.242	0.428	0.321	(0.319)	0.446	(0.300)
Year 2006	0.256	0.436	1.037***	(0.301)	0.959**	(0.307)
Constant	-		17.107***	(0.608)	13.553***	(0.835)
Observations	29,184		29,184		29,184	
R^2			0.149		0.607	
F-test, individual specific parameters jointly equal to zero (p-value)			0.000		0.093	

Robust standard errors clustered at schools in parentheses: + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. In (2) R^2 is from the regression using the within-school transformed variables.

5. Estimation results

5.1. Type of exit exam

Given the nature of examination after the tenth grade it is relevant to initially investigate the effect of class size on the choice of taking advanced exams (see Section 4.2). Hence, Table 4 presents estimates from five linear probability models of taking all six advanced exams in mandatory subjects. All five models include all the controls of Table 3 except that model (1) does not include lagged GPA (and the private school dummy is not included in school fixed effects models (3) and (5)). Comparing the two OLS models (1) and (2) we see that controlling for lagged GPA increases R^2 and the precision of the class-size estimate a lot, and so does inclusion of school fixed effects; see model (3). In (3) the class-size estimate is -0.024 and statistically significant, whereas it is smaller numerically and insignificant in (1) and (2). In the IV models the standard error of the class size estimate is larger, and in model (4) without school fixed effects it becomes insignificant, although the size of the point estimate is only slightly smaller (numerically) than in model (3). In the IV model (5) with school fixed effects, the estimated class size effect is 2-3 times larger than in (3) and (4) and it is marginally significant at the 10% level. For brevity, we do not show first-stage estimates, but the instrument (M) is highly significant with F-values of 138 and 58 in (4) and (5), respectively. Thus, there is no weak instrument problem. Estimating the IV-SFE model (5) for public and private schools separately, the class-size estimates become -0.062 and -0.091, respectively, but they are not significantly different.

The point estimate in (5) indicates that a reduction in class size by 10 pupils will increase the probability of taking the six advanced exams by 6.5 percentage points; the estimates in (1)-(4) indicate an effect of 1-2.5 percentage points. The sign of the estimated effect is as expected, since smaller class size gives the teacher more time with the individual pupil whereby achievement is likely to be higher and the cost of effort required for taking the advanced exam lower. As discussed above, in the main regressions of the effect of class size on GPA we restrict the sample to pupils who have taken all six advanced exams in the mandatory subjects. Hence, if the share of academically weak pupils taking the advanced exams tends to be higher in smaller classes, then the estimated class-size effect on GPA (on the restricted sample of exam-takers) tends to be biased towards zero, so (numerically) we are likely to estimate a lower bound of the effect of class size on GPA.[9]

Table 4: Linear probability models of choosing all six advanced exams in mandatory subjects

	(1) OLS	(2) OLS	(3) SFE	(4) IV	(5) IV, SFE
Class size / 10	-0.007	-0.016	-0.024*	-0.019	-0.065+
	(0.014)	(0.012)	(0.010)	(0.026)	(0.034)
GPA 9th grade (exam marks)		0.201***	0.192***	0.201***	0.192***
		(0.008)	(0.007)	(0.008)	(0.007)
GPA 9th grade (year marks)		0.152***	0.153***	0.152***	0.153***
		(0.006)	(0.006)	(0.006)	(0.006)
R^2	0.080	0.284	0.353	0.284	0.250
F-test, weak instrument				138.349	58.227
Schools	482	482	482	482	482
Observations	46,267	46,267	46,267	46,267	46,267

Robust standard errors clustered at schools in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. In (5) R^2 is from the regression using the within-school transformed variables. All regressions include the control variables of Table 3.

[9] It is beyond the scope of this paper to analyse dropout, but regressions using data at school by year level of the number of pupils who are at the schools at the end of the school year according to the exam register on class size and enrollment at the beginning of the school year (and year dummies) result in marginally significant negative coefficients of class size, indicating that a reduction in class size will tend to reduce dropout. This is in line with the indications of a positive effect of reducing class size on the probability of taking advanced exams in Table 4.

5.2. Class-size effects on GPA: Main results

Table 5 shows the main estimation results where the dependent variable is the GPA of the six advanced exams in mandatory subjects. The models are similar to those in Table 4, except for the dependent variable. Column (1) shows OLS estimates of the model without control for lagged GPA while columns (2)–(5) show estimates from value-added models where R^2 is much larger. In column (1) class size is clearly insignificant (with a small positive point estimate). Controlling for lagged GPA in (2) results in a negative point estimate of -0.012 which is however not significant either. Controlling for lagged marks tends to lead to numerically larger negative OLS estimates of class-size effects. One interpretation is that a large share of academically weak tenth grade pupils (who typically got low marks in ninth grade) tends to induce schools to reduce class size, which will bias the estimated class-size effect towards positive values in case controls for lagged achievement are not included, whereas this bias will be reduced if such controls are included. The class-size estimate of the school fixed effects model (3) is similar to the estimate in (2), and still not significant. Apart from non-random class-size variation, one reason why the class-size estimates in the OLS models (1)-(3) are small and insignificant may be measurement error in class size. Especially, some schools may tend to underreport the number of classes implying unusually large observed class size. The estimation sample has been restricted to observations with class size of 35 or less (as explained in footnote 6), but 35 is still a very large class size in the Danish context. If we exclude observations with class size above 30, the OLS estimate of (3) becomes larger numerically (about -0.025) and statistically significant at the 10% level.

In columns (4) and (5) we deploy our quasi-experimental RDD identification strategy and estimate IV models without and with school fixed effects, respectively. Again, the instrument is highly significant in the first-stage regression with F-values of 119 and 57, respectively. The IV estimate of the class-size effect in (4) is -0.035, but only marginally significant (the p-value is

0.102), whereas the school fixed effects-IV estimate in (5) is -0.08 and significant at the 5% level. The estimate in the preferred model (5) indicates that a reduction in class size by 10 pupils will increase GPA by about 0.08 standard deviations in the distribution of individual marks. This is about 40% of the estimates found in Krueger (1999) for grades 0-3 using the STAR experiment data, in Angrist and Lavy (1999) for grade 5 using a RDD (without control for school fixed effects or lagged achievement) and in Heinesen (2010) for grade 9 using variation in subject-specific class size, and of about the same magnitude as the estimates for fifth graders in the value-added model of Rivkin et al. (2005). Possible explanations for our relatively small estimates for tenth graders is that the 'treatment' of a given class size only lasts for one year, that class-size effects might be smaller in tenth grade compared to earlier grades, and that pupil characteristics are different because the choice of the optional tenth grade is highly selective. We have tried to include interaction terms between class size and background variables such as gender, ninth grade GPA, immigrant status and parental characteristics, but they are all insignificant, both in models of GPA and in models of choosing advanced exit exams.

Table 5: Regression models of GPA from advanced exams in mandatory subjects

	(1) OLS	(2) OLS	(3) SFE	(4) IV	(5) IV, SFE
Class size / 10	0.008	-0.012	-0.015	-0.035	-0.080*
	(0.013)	(0.010)	(0.012)	(0.021)	(0.035)
GPA 9th grade (exam marks)		0.660***	0.654***	0.660***	0.653***
		(0.008)	(0.008)	(0.008)	(0.008)
GPA 9th grade (year marks)		0.232***	0.250***	0.233***	0.251***
		(0.008)	(0.007)	(0.008)	(0.007)
R^2	0.086	0.637	0.657	0.637	0.633
F-test, weak instrument				119.474	56.622
Schools	471	471	471	471	471
Observations	29,184	29,184	29,184	29,184	29,184

Robust standard errors clustered at schools in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. In (5) R^2 is from the regression using the within-school transformed variables. All regressions include the control variables of Table 3.

For the preferred IV/SFE model, Table 6 shows results from five robustness checks. Model (1) is identical to the preferred model (5) of Table 5. Model (2) has the same specification except that the polynomial in enrollment is replaced by a continuous piecewise linear trend in enrollment with slope equal to the slope of M between discontinuity points (see Section 3). Model (3) is equivalent to (1) except that it is estimated on the full sample including observations with class size above 35. Models (4) and (5) are equivalent to (1) except that the sample is restricted to observations with enrollment counts not larger than 70 and 126 (which are the midpoints between the second and third, and the fourth and fifth discontinuity points, respectively). Model (6) is equivalent to (1) except that the sample includes only public schools. The five alternative specifications of model and sample produce about the same class-size coefficient as in (1). There are no statistically significant differences, although (numerically) the point estimate in (5) is about 15% larger than in (1), and that in (4) 15% lower. In model (6) with only public schools the class-size estimate is only marginally significant at the 10% level due to the smaller number of schools. The corresponding point estimate for private schools (not shown in the table) is about -0.05, but not significantly different from zero (or from -0.08).

Table 6: Robustness checks of the IV-SFE model of GPA of advanced exams

	(1)	(2)	(3)	(4)	(5)	(6)
Class size / 10	-0.080*	-0.079*	-0.077*	-0.068*	-0.093**	-0.082+
	(0.035)	(0.037)	(0.035)	(0.034)	(0.036)	(0.044)
Enrollment control:						
Polynomial	x		x	x	x	x
Piecewise linear trend		x				
Sample:						
Observed class size ≤ 35	x	x		x	x	x
Enrollment ≤ 70				x		
Enrollment ≤ 126					x	
Public schools only						x
R^2	0.633	0.633	0.632	0.634	0.631	0.629
F-test, weak instrument	56.622	47.825	38.900	53.403	54.297	36.509
Schools	471	471	474	445	464	348
Observations	29,184	29,184	30,253	21,899	27,375	21,058

Robust standard errors clustered at schools in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. R^2 is from the regression using the within-school transformed variables. All regressions include the control variables of Table 3.

6. Conclusion

The optional tenth grade at lower secondary school in Denmark is designed to give academically weak students an opportunity to catch up before proceeding to upper secondary school or vocational education. Investigating if class size is important for academic achievement of this group who are more at risk of dropping out of the educational system is of particular political interest.

We investigate class-size effects on GPA of exam marks in tenth grade, exploiting an institutional setting where pupils cannot predict class size prior to enrollment, and where post-enrollment responses aimed at affecting realized class size are unlikely. We combine a regression discontinuity design with control for lagged achievement and school fixed effects (to take account of unobserved time-constant differences between schools). Thus, controlling for lagged achievement, we identify class-size effects by within-school variation over time in class size caused by a maximum-class-size rule producing discontinuous variation in class size when the number of classes changes at critical values of enrollment. Using administrative registry data, we find statistically significant (but rather small) class-size effects indicating that reducing class size has beneficial effects. We do not find significant effect heterogeneity with respect to gender, immigrant status, lagged achievement or parental characteristics.

References

Angrist, J. D., and G. W. Imbens. 1995. “Two-stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity.” *Journal of the American Statistical Association* 90 (430): 431–442.

Angrist, J. D., and V. Lavy. 1999. “Using maimonides’ rule to estimate the effect of class size on scholastic achievement.” *The Quarterly Journal of Economics* 114 (2): 533–575.

Browning, M., and E. Heinesen. 2007. “Class size, teacher hours and educational attainment.” *Scandinavian Journal of Economics* 109 (2): 415–438.

Chetty, R., J. N. Friedman, N. Hilger, E. Saez, D. W. Schanzenbach, and D. Yagan. 2011. “How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star.” *The Quarterly Journal of Economics* 126 (4): 1593–1660.

Fredriksson, P., B. Öckert, and H. Oosterbeek. 2013. “Long-Term Effects of Class Size.” *The Quarterly Journal of Economics* 128 (1): 249–285.

Heinesen, E. 2004. “Determinants of local public school expenditure: A dynamic panel data model.” *Regional Science and Urban Economics* 34 (4): 229-253.

Heinesen, E. 2010. “Estimating class-size effects using within-school variation in subject-specific classes.” *Economic Journal* 120 (545): 737–760.

Hoxby, C. M. 2000. “The effects of class size on student achievement: New evidence from population variation.” *The Quarterly Journal of Economics* 115 (4): 1239–1285.

Krueger, A. B. 1999. “Experimental estimates of education production functions.” *The Quarterly Journal of Economics* 114 (2): 497–532.

Krueger, A. B. 2003. “Economic considerations and class size.” *Economic Journal* 113 (485): F34–F63.

Leuven, E., H Oosterbeek and M. Rønning (2008): Quasi-experimental estimates of the effect of class size on achievement in Norway. *Scandinavian Journal of Economics* 110 (4): 663–693.

Nielsen, S. I. 2010. “9. og 10. klasseelevernes tilmelding til ungdomsuddannelserne” (Transition to upper secondary school from 9th and 10th grade). Memorandum, UNI·C Statistik & Analyse, Copenhagen.

Rivkin, S. G., E. A. Hanushek, and J. F. Kain. 2005. “Teachers, schools and academic achievement.” *Econometrica* 73 (2): 417–458.

Wössmann, L., and M. West. 2006. “Class-size effects in school systems around the world: Evidence from between-grade variation in TIMSS.” *European Economic Review* 50 (3): 695–736.

Chapter 1.2

Balancing the risk of ‘lazearian’ interrupters and the benefits of educational and social peers: Tracing parental preferences for class-size reduction

Balancing the risk of 'lazearian' interrupters and the benefits of educational and social peers: Tracing parental preferences for class-size reduction[1]

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Camilla Dalsgaard

Abstract

Using Danish survey data from a choice experiment, parental preferences for class-size reduction are estimated in terms of willingness to pay. While parents with children in large classes are willing to pay for class-size reduction parents with children in small classes are reluctant and even express negative utility for further class-size reduction. We interpret this as parents balancing the risk of 'lazearian' interrupters and the benefits of educational and social peers, when forming their preferences for class size.

Keywords: willingness to pay; class-size reduction; parental preferences

JEL codes: C25, I2, I22

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1. Introduction

Among the numerous inputs to the education production function (Bowles 1970), class size has the virtue of being both easily observable and highly malleable. School administrators can sort pupils into classes, while parents can choose school based on perceived school quality. In the class-size-effect literature, these sources of selection are recognized, and class-size effects are estimated in experimental or quasi-experimental settings (e.g. Chetty et. al 2011, Angrist and Lavy 1999). The parental choice of school is a multi-parameter optimization problem, where (in addition to perceived school quality) proximity, costs, and peers are likely to influence the choice. Hence, parents most likely compromise between their preference for class size and other factors. The purpose of this paper is to investigate whether there is a discrepancy between demand for and supply of preferred class size. This is done by investigating the parental willingness to pay (WTP) for a smaller class size using a choice experiment (Adamowicz et al. 1994, Carlsson et al. 2005).

In the framework of Lazear (1999), increasing the class size increases the risk of disruption and hence reduces educational production. In contrast, recent literature has found positive peer effects, in the sense that other pupils' background (e.g. Ammermüller and Pischke 2009) and that the number of friends in the pupils' network (e.g. Calvó-Armengol et al. 2009) have positive bearings on the individual pupils' achievement. From this perspective, parental preferences for class size are ambiguous. On the one hand, a large class is detrimental to achievement, as the risk of disruption is higher. On the other hand, all else equal, a large class implies better odds of finding good peers. Though this has not been given as much attention as the education peer effect, the social benefits (beyond the educational effects) might also influence preferences for class sizes. Hence, being in a large class with many educational and social peers might be better than being in a small class with fewer peers.

Parental inputs are also important in the education production function and hence, parents are more than merely choice-making consumers. They are also suppliers of education, for instance when they help their children with their homework. Parents can hence adjust their own supply of education to help their children reach the desired level of educational achievement. Bonesrønning (2004) and Datar and Mason (2008) have found some evidence on complementarity between class size and parental involvement in the educational production. Reducing class size results in more involved parents, which can possibly be explained by the teachers having more time to communicate with the parents (Datar and Mason 2008). In contract, a recent study (Fredriksson et al. 2014) has fund that high-income parents are more likely to help their child with homework if the child is placed in a large class. In addition, Fredriksson et al. (2014) find that parents with children placed in large classes are more likely to change school. The effect is most pronounced for low income parents but the difference between high and low income parents is not significant.

The rest of the paper is organised as follows: Section 2 discusses the data and the empirical method. In Section 3 the estimation results are presented, while Section 4 Concludes.

2. Data and empirical method

Parental preferences for class-size reduction were estimated using data from a web-based survey collected during October and November of 2009. The survey was conducted among 1,436 parents with at least one child in compulsory school (public or private) across 12 Danish municipalities. In the survey, parents were asked to state their preferences for class-size reduction, the number of physical education (PE) lessons and whether the school should have a lunch program. In order to control for the preferences for higher educational production, an increase in the number of Danish lessons was also included as an attribute. To facilitate an estimation of WTP[2], a

[2] The WTP for attribute j is estimated the traditional way by $\beta_{service_j} / \beta_{cost}$.

cost attribute represented by a school fee was included. The options were bundled together, and the parents could choose among two alternatives (A and B) and the status quo situation (i.e. an opt-out alternative). Status quo implied no change in school fees, while options A and B implied increased fees.[3] The choice of attributes and their levels were based partly on a literature review and partly on initial qualitative surveys. A simple D-efficient fractional factorial main effect with 36 alternatives was applied (Kuhfeld 2004). The 36 alternatives were divided among 6 blocks, and hence each respondent evaluated three different choice sets. The attributes and the levels are presented in Table 1. The estimation was carried out using a Random Parameter Logit (RPL) model framework (Train 2003). All service attributes are specified as being randomly and normally distributed and the cost attribute as fixed. The off-diagonal elements in the covariances matrix of the randomly distributed variables were estimated. The estimations were carried out in Stata using the programme coding by Hole (2007) and using 500 Halton draws.

[3] In Denmark public education is fully tax financed, while private education is partly taxed financed and partly tuition financed.

Table 1: Attributes and attribute levels

Attributes	Levels of attribute changes in survey
Number of Danish lessons per week	As today (ref.)
	One more lesson
	Two more lessons
Number of physical education (PE) lessons per week	As today (ref.)
	One more lesson
	Two more lessons
Lunch at school	Not offered (ref.)
	Non-organic food offered
	Organic food offered
Students per class	As today (ref.)
	2 fewer pupils per class
	4 fewer pupils per class
Additional cost (€) per child per year/month	0 €/year
	13 €/year (1 €/month)
	67 €/year (6 €/month)
	133 €/year (11 €/month)
	267 €/year (22 €/month)
	667 €/year (56 €/month)
	1333 €/year (111 €/month)

The survey also uncovered the respondents' present service level with regard to the four specific services in question and some individual background information. All explanatory variables and summary statistics are provided in Appendix A, Table A1.

As suggested in the introduction, both an educational and a social peer effect might weaken the preferences for smaller classes. Accordingly, we would expect parents' preferences for class size reductions to be lower the fewer students there were in their child's class. Hence, to test the potential effect the respondents were divided into four groups based on their response to the number of pupils in their child's class question. In the following, parents whose child is in a class with more than 24 pupils, 21-24 pupils, 17-20 pupils or less than 17 pupils will be referred to as $\text{Parents}_{>24}$, $\text{Parents}_{21\text{-}24}$, $\text{Parents}_{17\text{-}20}$ and $\text{Parents}_{<17}$, respectively. Three models were estimated. A main effect model (MEM), a Limited Class-Size Model (LCSM) and a Full Class-Size Model (FCSM). In the LCSM, the number of pupils in the class effect was estimated by interacting the $\text{Parents}_{21\text{-}24}$,

$Parents_{17-20}$ and $Parents_{<17}$ variables with the two class-size-reduction variables. In the FCSM model, preference relations among all explanatory variables were added to test the robustness of the LCSM. In Denmark, the level of service in the public (free for all) schools is determined by the municipalities.[4] To account for municipality-induced heterogeneity in the provided school service, the FCSM also include variables coding for the municipality the respondents are living in.

3. Results

The preferences are presented in Table 2. Only the main effects and the estimated relations between the number of students in the class and the preferences for class-size reductions are shown. All estimated interaction effects between socio-demographic variables and preferences variables can be seen in Table A2. For the variance-covariance matrix of the estimated random parameters, see Table A3.

[4] Under the conditions given by the Primary Education Act named "LBK nr 521 af 27/05/2013 (folkeskoleloven)" (https://www.retsinformation.dk/Forms/r0710.aspx?id=145631&exp=1, last accessed March 25, 2014).

Table 2: Estimation results. Mixed logit estimations with choices as outcome

	(1) MEM	(2) LCSM	(3) FCSM
Cost (€/month)	-0.0000463***	-0.0000505***	-0.000475*
	(0.00000388)	(0.00000460)	(0.000212)
One more Danish lesson per week	1.163***	1.347***	1.173***
	(0.181)	(0.192)	(0.187)
Two more Danish lessons per week	1.325***	1.532***	1.378***
	(0.182)	(0.203)	(0.196)
One more PE lesson per week	1.540***	1.588***	1.532***
	(0.217)	(0.221)	(0.205)
Two more PE lessons per week	1.537***	1.570***	1.521***
	(0.214)	(0.217)	(0.206)
Non-organic lunch	0.755***	0.779***	0.755***
	(0.151)	(0.160)	(0.148)
Organic lunch	0.766***	0.838***	0.755***
	(0.162)	(0.175)	(0.163)
Two fewer pupils per class	0.556***	1.731***	2.166
	(0.168)	(0.358)	(1.523)
Four fewer pupils per class	0.768***	2.215***	1.574
	(0.160)	(0.341)	(1.360)
$\text{Parents}_{<17}$ × two fewer pupils per class		-2.915***	-2.782***
		(0.560)	(0.588)
$\text{Parents}_{<17}$ × four fewer pupils per class		-3.527***	-3.387***
		(0.537)	(0.558)
$\text{Parents}_{17\text{-}20}$ × two fewer pupils per class		-1.654***	-1.679***
		(0.436)	(0.443)
$\text{Parents}_{17\text{-}20}$ × four fewer pupils per class		-2.260***	-2.185***
		(0.417)	(0.415)
$\text{Parents}_{21\text{-}24}$ × two fewer pupils per class		-0.774*	-0.782*
		(0.385)	(0.374)
$\text{Parents}_{21\text{-}24}$ × four fewer pupils per class		-0.614+	-0.669+
		(0.345)	(0.345)
Alternative specific constant for the status quo alternative	0.941*** (0.228)	1.053*** (0.240)	-0.801 (1.233)
Remaining explanatory variables	*no*	*no*	*yes*
No. of respondents		1.436	
No. of choices		4.308	
LL(0)		-4732.8	
LL(β)	-3879.3	-3824.0	-3738.9
McFadden R^2	0.180	0.192	0.210

Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. See Table A2 for the remaining estimates of FCSM.

Overall, the preferences are as expected. As shown in column (1), on average parents prefer fewer pupils in the classes, a higher number of Danish and PE lessons per week and a lunch programme (organic or non-organic) and have negative preferences for higher costs. Moving on to the LCSM and the FCSM in columns (2) and (3), the estimated preference relations show that the fewer pupils in the class, the weaker the preference for class-size reduction, when estimated relative to the preferences of Parents$_{>24}$. This suggests that parents are aware of the possible peer effects. The inclusion of the many control variables in the FCSM does not alter the conclusion, but increases the standard error of the main effect estimates $\beta_{\text{Four fewer pupils per class}}$ and $\beta_{\text{Two fewer pupils per class.}}$ The class-size related preferences and estimated WTP levels are shown in Figure 1.

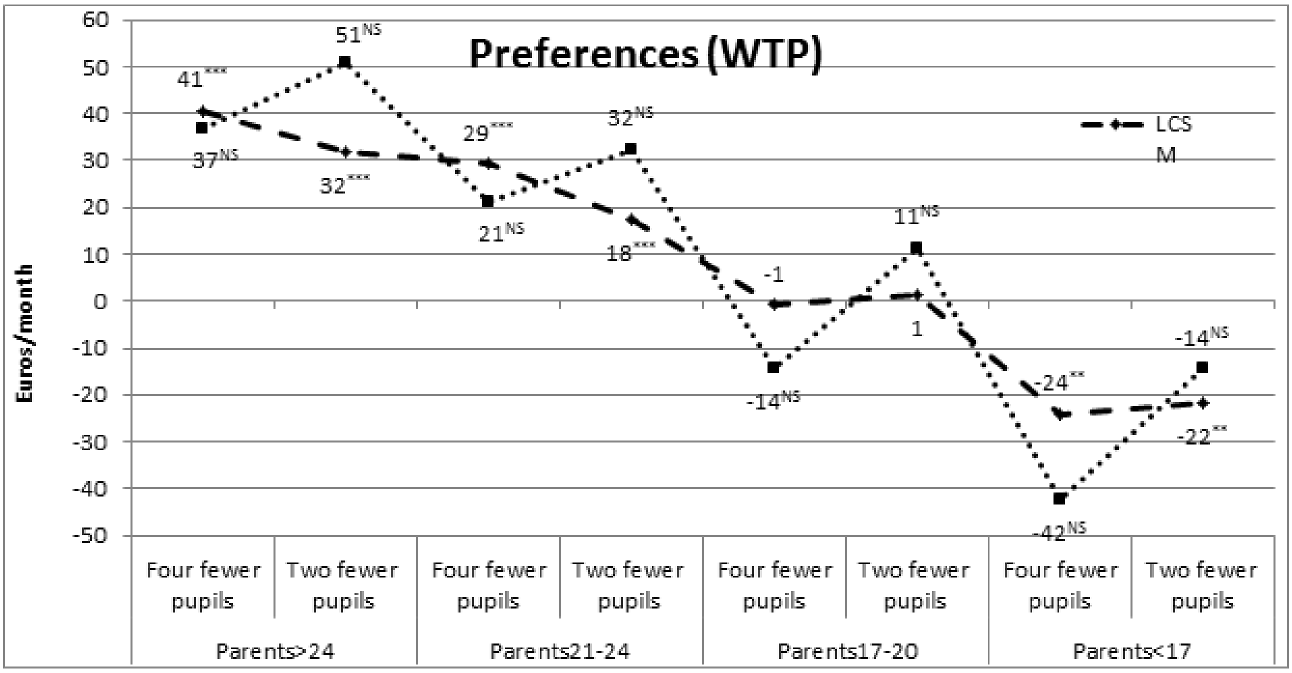

Figure 1: LCSM and FCSM results – Willingness to pay given number of pupils (** p < 0.01, *** p < 0.001, NS not significant)

Based on the LCSM, the optimal number of pupils per class from the perspective of the parents seems to be in the interval of 17-20 pupils per class, as WTP is not significantly different from zero. This suggests, again from the perspective of the parents, that the positive effect of a small class size and vis-à-vis negative effect of few educational and social peers cancel each other out in that interval. For larger class sizes, WTP for reducing the number of pupil per class by two or four pupils increases to 18€ and 29€ for $\text{Parents}_{21\text{-}24}$ and 32€ and 41€ for $\text{Parents}_{>24}$, respectively. Perhaps most interestingly, the evaluation of educational and social peer effects relative to the direct educational effect from class size seem to be particularly strong among $\text{Parents}_{<17}$ who have significantly negative preferences and WTP of –22€ and –24€ for reducing the number of pupils per class by two or four pupils. For groups of parents the differences in WTP for reducing the number of pupils by two or four pupils are insignificant, except for $\text{Parents}_{21\text{-}24}$. Among groups, WTPs are significantly different for all parent groups, i.e.

$$\text{WTP}_{\text{Parents}_{<17}} < \text{WTP}_{\text{Parents}_{17\text{-}20}} < \text{WTP}_{\text{Parents}_{21\text{-}24}} < \text{WTP}_{\text{Parents}_{>24}},$$

for reducing the number of pupils with by and four pupils, respectively. The same tendency in preferences seems to be evident in the FSCM. However, due to the large variation in the main effect parameter estimate for the reduction in the number of pupils per class with two and four the joined preferences (main effect and interaction effect) are insignificant. Nevertheless, the relative preferences prevail with regard to the point estimates.

4. Conclusion

Traditional quasi-experimental valuations of class-size effects indicate that increasing the class size reduces educational achievement. Accordingly, we will expect parents to have preferences for smaller class size. However, we show that this might only be part of the truth and that peer effects might weaken the parental preferences for smaller class size. Based on a choice experiment, the preferences for class-size reduction weakens the fewer pupils there are in the class, and utility may even be negative, when the number of pupils in the class is below 17.

References

Adamowicz, W., J. Louviere, and M. Williams. 1994. "Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities". *Journal of Environmental Economics and Management* 26 (3): 271–292.

Ammermüller, A., and J. S. Pischke. 2009. "Peer effects in European primary schools: Evidence from the Progress in International Reading Literacy Study." *Journal of Labor Economics* 27 (3): 315–348.

Angrist, J. D., and V. Lavy. 1999. "Using Maimondides' rule to estimate the effect of class size on scholastic achievement." *Quarterly Journal of Economics* 114 (2): 533–575.

Bonesrønning, H. 2004. "The determinants of parental effort in education production: do parents respond to changes in class size?" *Economics of Education Review* 23 (1): 1–9.

Calvó-Armengol, A., E. Patacchini, and Yves Zenou. 2009. "Peer Effects and Social Networks in Education." *The Review of Economic Studies* 76 (4): 1239–1267.

Carlsson, F., P. Frykblom, and C. J. Lagerkvist. 2005. "Using cheap talk as a test of validity in choice experiments." *Economics Letters* 89 (2): 147–152.

Chetty, R., J. N. Friedman, N. Hilger, E. Saez, D. W. Schanzenbach, and D. Yagan. 2011. "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star". *The Quarterly Journal of Economics* 126 (4): 1593–1660.

Datar, A., and B. Mason. 2008. "Do reductions in class size 'crowd out' parental investment in education?". *Economics of Education Review* 27 (6): 712–723.

Fredriksson, P., B. Öckert, and H. Oosterbeek. 2014. "Inside the Black Box of Class Size: Mechanisms, Behavioral Responses, and Social Background." IZA Discussion Paper No. 8019.

Hole, A. R. 2007. "Fitting mixed logit models by using maximum simulated likelihood". *Stata Journal* 7 (3): 388–401.

Kuhfeld, W. 2004. “*Marketing research methods in SAS. Experimental design, choice, conjoint and graphical techniques*”. SAS Institute Inc.

Lazear, E. P. 2001. “Educational Production”. *The Quarterly Journal of Economics* 116 (3): 777–803

Train, K. 2003. “*Discrete choice methods with simulation”*. Cambridge: Cambridge University Press.

Appendix A

Table A1: Explanatory variables and summary statistics

Explanatory variables	Mean	Coding
Gender of parent		
Female	0.624	=1 if female, else = 0
Male	0.376	Reference group
Age of parent		
Age: 23-34 years	0.121	=1 if age=23-34 years, else = 0
Age: 35-44 years	0.291	=1 if age=35-44 years, else = 0
Age: 45-54 years	0.558	=1 if age=45-54 years, else = 0
Age: 55-65 years	0.030	Reference group
Civil status of parent		
Married or living with another person	0.861	=1 if married or living with another person, else =0
Living alone	0.139	Reference group
Educational level of parent		
Long term	0.123	=1 if long term, else = 0
Medium term	0.382	=1 if medium term, else = 0
Short term	0.122	=1 if short term, else = 0
Vocational	0.238	Reference group
High school	0.072	Reference group
Compulsory school	0.053	Reference group
Other education	0.010	Reference group
Annual household income (DKK)		
0-199.999	0.037	
200.000-399.999	0.160	
400.000-599.999	0.261	Continuous[a]
600.000-799.999	0.241	
800.000-999.999	0.112	
1.000.000 or more	0.079	
Don't know / refuse	0.106	=1 if don't know/refuse, else = 0
Number of children that is or has been in school		
1 (the child in focus, the first child)	0.403	=1 if first child, else = 0
2	0.463	Reference group
3	0.110	Reference group
> 3	0.024	Reference group
Number of pupils in the class of the child in focus		
16 or less	0.133	= 1 if 16 or less, else = 0
17-20	0.267	= 1 if 17-20, else = 0
21-24	0.430	= 1 if 21-24, else = 0
25-28	0.171	Reference group

Explanatory variables	Mean	Coding
Grade attended of child in focus		
0th-3rd grade	0.455	=1 if 0^{th}-3^{rd} grade, else = 0
4th-6th grade	0.249	=1 if 4^{th}-6^{th} grade, else = 0
7th -9th grade	0.271	=1 if 7^{th}-9^{th} grade, else = 0
10th grade (optional)	0.025	Reference group
Child in focus attends public or private school		
Private school	0.233	=1 if private school, else =0
Public school	0.767	Reference group
Political orientation from left to right		
Very left	0.087	
Left	0.202	
Neutral	0.301	Continuous[b]
Right	0.185	
Very right	0.058	
Don't know	0.166	=1 if Don't know, else = 0
Municipality the parent live in		
Bornholm	0.068	= 1 if Bornholm, else = 0
Brøndby	0.106	= 1 if Brøndby, else = 0
Gentofte	0.070	= 1 if Gentofte, else = 0
Lolland	0.084	= 1 if Lolland, else = 0
Norddjurs	0.075	= 1 if Norddjurs, else = 0
Nyborg	0.072	= 1 if Nyborg, else = 0
Odsherred	0.090	= 1 if Odsherred, else = 0
Ringkøbing-Skjern	0.066	= 1 if Ringkøbing-Skjern, else = 0
Stevns	0.088	= 1 if Stevns, else = 0
Sønderborg	0.088	= 1 if Sønderborg, else = 0
Vesthimmerland	0.095	Reference group
Aarhus	0.100	=1 if Aarhus, else = 0
Observations	1,436	

[a)] Respondents who do not know their income or refuse to state it are coded as 0. These respondents are controlled for by an indicator variable, see table. [b)] the scale goes from 1 to 5, where 1 is equal to "very left" and 5 is equal to "very right". Respondents who do not know their political orientation are coded as 0. These respondents are controlled for by an indicator variable, see table.

Table A2: Estimation results of FCSM continued from Table 2

Mixed logit estimations with choices as outcome

	(3) FCSM continued	
Gender of the parent		
Female × two fewer pupils per class	0.995**	(0.349)
Female × four fewer pupils per class	0.820*	(0.323)
Female × alternative specific constant for the status quo alternative	0.147	(0.273)
Female × cost	-0.000173***	(0.0000499)
Age of parent		
Age ≤34 years × two fewer pupils per class	-2.000+	(1.127)
Age ≤34 years × four fewer pupils per class	-1.079	(0.987)
Age ≤34 years × alternative specific constant for the status quo alternative	-2.236*	(0.900)
Age ≤34 years × cost	-0.000153	(0.000155)
Age 35-44 years × two fewer pupils per class	-1.822+	(1.014)
Age 35-44 years × four fewer pupils per class	-0.768	(0.882)
Age 35-44 years × alternative specific constant for the status quo alternative	-1.829*	(0.804)
Age 35-44 years × cost	0.00000709	(0.000136)
Age 45-54 years × two fewer pupils per class	-1.044	(0.984)
Age 45-54 years × four fewer pupils per class	-0.382	(0.861)
Age 45-54 years × alternative specific constant for the status quo alternative	-1.484+	(0.784)
Age 45-54 years × cost	-0.0000601	(0.000132)
Civil Status of parent		
Married or living with other person × two fewer pupils per class	-0.529	(0.474)
Married or living with other person × four fewer pupils per class	0.966*	(0.470)
Married or living with other person × alternative specific constant for the status quo alternative	0.00915	(0.403)
Married or living with other person × cost	-0.0000117	(0.0000720)
Educational level of parent		
Long term × two fewer pupils per class	-0.344	(0.549)
Long term × four fewer pupils per class	-0.301	(0.507)
Long term × alternative specific constant for the status quo alternative	0.0489	(0.452)
Long term × cost	0.000136+	(0.0000776)
Medium term × two fewer pupils per class	-0.188	(0.364)
Medium term × four fewer pupils per class	0.150	(0.339)
Medium term × alternative specific constant for the status quo alternative	-0.284	(0.299)
Medium term × cost	0.0000854	(0.0000542)
Short term × two fewer pupils per class	-0.575	(0.499)
Short term × four fewer pupils per class	-0.174	(0.462)
Short term × alternative specific constant for the status quo alternative	0.481	(0.397)
Short term × cost	0.000141+	(0.0000733)
Annual household income (DKK)		
Household income (1000 DKK) × two fewer pupils per class	0.188*	(0.0814)
Household income (1000 DKK) × four fewer pupils per class	0.0522	(0.0753)
Household income (1000 DKK) × alternative specific constant for the status quo alternative	0.0917	(0.0675)
Household income (1000 DKK) × cost	-0.0000209+	(0.0000120)
Grade attended of child in focus		
0th-3rd grade × two fewer pupils per class	0.436	(0.969)
0th-3rd grade × four fewer pupils per class	0.0673	(0.872)
0th-3rd grade × alternative specific constant for the status quo alternative	1.666*	(0.838)
0th-3rd grade × cost	-0.0000113	(0.000138)
4th-6th grade × two fewer pupils per class	-0.176	(0.960)
4th-6th grade × four fewer pupils per class	-0.222	(0.869)
4th-6th grade × alternative specific constant for the status quo alternative	1.340	(0.835)

	(3) FCSM continued	
4th-6th grade × cost	-0.00000683	(0.000137)
7th-9th grade × two fewer pupils per class	-0.352	(0.950)
7th-9th grade × four fewer pupils per class	-0.294	(0.862)
7th-9th grade × alternative specific constant for the status quo alternative	1.571+	(0.832)
7th-9th grade × cost	0.0000482	(0.000136)
Number of children that is or has been in school		
First child in school × two fewer pupils per class	0.284	(0.318)
First child in school × four fewer pupils per class	0.525+	(0.305)
First child in school × alternative specific constant for the status quo alternative	0.0308	(0.264)
First child in school × cost	-0.0000964*	(0.0000477)
Child in focus attends public or private school		
Private school × two fewer pupils per class	-0.0122	(0.369)
Private school × four fewer pupils per class	-0.345	(0.352)
Private school × alternative specific constant for the status quo alternative	1.179***	(0.297)
Private school × cost	0.0000917+	(0.0000544)
Political orientation from left to right		
Political orientation × two fewer pupils per class	0.0298	(0.0643)
Political orientation × four fewer pupils per class	-0.0167	(0.0616)
Political orientation × alternative specific constant for the status quo alternative	0.177**	(0.0555)
Political orientation × cost	0.00000478	(0.00000974)
Municipality the parent live in		
Brøndby × two fewer pupils per class	-1.471*	(0.604)
Brøndby × four fewer pupils per class	-0.587	(0.563)
Brøndby × alternative specific constant for the status quo alternative	0.119	(0.445)
Brøndby × cost	0.000149	(0.0000908)
Gentofte × two fewer pupils per class	0.498	(0.667)
Gentofte × two fewer pupils per class	0.0810	(0.634)
Gentofte × alternative specific constant for the status quo alternative	-0.387	(0.544)
Gentofte × cost	0.0000392	(0.0000984)
Lolland × two fewer pupils per class	0.421	(0.624)
Lolland × four fewer pupils per class	-0.336	(0.595)
Lolland × alternative specific constant for the status quo alternative	0.951+	(0.502)
Lolland × cost	0.000211*	(0.0000933)
Norddjurs × two fewer pupils per class	-0.175	(0.664)
Norddjurs × four fewer pupils per class	-0.183	(0.620)
Norddjurs × alternative specific constant for the status quo alternative	0.886+	(0.519)
Norddjurs × cost	0.000106	(0.0000984)
Nyborg × two fewer pupils per class	-0.488	(0.677)
Nyborg × four fewer pupils per class	-0.909	(0.628)
Nyborg × alternative specific constant for the status quo alternative	-0.740	(0.522)
Nyborg × cost	0.000265**	(0.0000971)
Odsherred × two fewer pupils per class	-0.308	(0.623)
Odsherred × four fewer pupils per class	-0.125	(0.574)
Odsherred × alternative specific constant for the status quo alternative	0.225	(0.490)
Odsherred × cost	-0.00000920	(0.0000973)
RingkøbingSkjern × two fewer pupils per class	-0.0596	(0.667)
RingkøbingSkjern × four fewer pupils per class	-0.410	(0.644)
RingkøbingSkjern × alternative specific constant for the status quo alternative	-0.239	(0.555)
RingkøbingSkjern × cost	0.000103	(0.0000981)
Stevns × two fewer pupils per class	0.181	(0.594)
Stevns × four fewer pupils per class	-0.0468	(0.531)
Stevns × cost	0.0000387	(0.0000938)
Sønderborg × two fewer pupils per class	-0.241	(0.632)
Sønderborg × four fewer pupils per class	-0.409	(0.595)
Sønderborg × alternative specific constant for the status quo alternative	-0.654	(0.481)

	(3) FCSM continued	
Sønderborg × cost	-0.000133	(0.000102)
Aarhus × two fewer pupils per class	-1.412*	(0.641)
Aarhus × four fewer pupils per class	-1.222*	(0.600)
Aarhus × alternative specific constant for the status quo alternative	-0.316	(0.506)
Aarhus × cost	0.000209*	(0.0000922)
Missing information/refuse/don't know variables		
Household income refuse/don't know × two fewer pupils per class	0.538	(0.700)
Household income refuse/don't know × four fewer pupils per class	-0.218	(0.662)
Household income refuse/don't know × alternative specific constant for the status quo alternative	-0.187	(0.579)
Household income refuse/don't know × cost	0.0000412	(0.000104)
Political orientation don't know × two fewer pupils per class	0.617	(0.559)
Political orientation don't know × four fewer pupils per class	0.187	(0.526)
Political orientation don't know × alternative specific constant for the status quo alternative	1.487**	(0.470)
Political orientation don't know × cost	-0.0000141	(0.0000838)

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table is a continuation of Table 2.

Table A3: Variance-covariance matrix of the estimated random parameters

	(1) MEM	(2) LCSM	(3) FCSM
Alternative specific constant for the status quo alternative × alternative specific constant for the status quo alternative	5,391**	6,027**	4,424*
	(1,961)	(1,899)	(1,786)
Alternative specific constant for the status quo alternative × one more Danish lesson per week	-1,740*	-1,356*	-2,076***
	(0,765)	(0,677)	(0,634)
Alternative specific constant for the status quo alternative × two more Danish lessons per week	-2,350*	-1,596*	-2,511
	(1,009)	(0,787)	(0,770)
Alternative specific constant for the status quo alternative × one more PE lesson per week	1,826	0,684	0,531
	(1,453)	(1,214)	(0,998)
Alternative specific constant for the status quo alternative × two more PE lessons per week	3,009*	2,074+	2,246*
	(1,504)	(1,201)	(1,117)
Alternative specific constant for the status quo alternative × non-organic lunch	-1,055	-2,119**	-0,935
	(0,843)	(0,731)	(0,794)
Alternative specific constant for the status quo alternative × organic lunch	-0,936	-1,773**	-1,482
	(1,065)	(0,837)	(0,911)
Alternative specific constant for the status quo alternative × two fewer pupils per class	0,221	0,711	0,547
	(1,071)	(0,948)	(0,785)
Alternative specific constant for the status quo alternative × four fewer pupils per class	-0,545	0,209	-0,183
	(0,786)	(0,939)	(0,723)
One more Danish lesson per week × one more Danish lesson per week	2,562***	3,957***	2,653**
	(0,787)	(1,175)	(0,898)
One more Danish lesson per week × two more Danish lessons per week	2,689***	4,077***	2,948**
	(0,767)	(1,088)	(0,932)
One more Danish lesson per week × one more PE lesson per week	-2,335***	-2,426**	-2,356**
	(0,698)	(0,853)	(0,831)
One more Danish lesson per week × two more PE lessons per week	-3,176***	-3,480***	-3,444***
	(0,780)	(0,950)	(0,952)
One more Danish lesson per week × non-organic lunch	0,078	-0,611	-0,077
	(0,535)	(0,653)	(0,500)
One more Danish lesson per week × organic lunch	0,601	0,507	0,326
	(0,564)	(0,644)	(0,557)
One more Danish lesson per week × two fewer pupils per class	-2,355**	-2,744**	-1,712**
	(0,787)	(0,984)	(0,649)
One more Danish lesson per week × four fewer pupils per class	-0,152	0,193	0,040
	(0,472)	(0,644)	(0,500)
Two more Danish lessons per week × two more Danish lessons per week	2,894**	4,572***	3,292**
	(0,956)	(1,347)	(1,149)
Two more Danish lessons per week × one more PE lesson per week	-2,319*	-2,213**	-2,460**
	(0,932)	(0,907)	(0,982)
Two more Danish lessons per week × two more PE lessons per week	-3,375***	-3,945***	-3,758***
	(0,898)	(1,078)	(1,081)
Two more Danish lessons per week × non-organic lunch	0,205	-0,778	-0,025
	(0,556)	(0,729)	(0,547)
Two more Danish lessons per week × organic lunch	0,647	0,083	0,424
	(0,594)	(0,705)	(0,619)
Two more Danish lessons per week × two fewer pupils per class	-2,267**	-2,070*	-1,830**
	(0,797)	(0,897)	(0,709)
Two more Danish lessons per week × four fewer pupils per class	-0,087	0,554	0,057
	(0,507)	(0,664)	(0,548)
One more PE lesson per week × one more PE lesson per week	10,275***	10,193***	8,105***
	(2,540)	(2,615)	(2,047)
One more PE lesson per week × two more PE lessons per week	7,951***	7,023***	6,585***
	(2,060)	(1,908)	(1,681)
One more PE lesson per week × non-organic lunch	-0,490	-0,580	-0,004
	(0,919)	(0,952)	(0,812)

	(1) MEM	(2) LCSM	(3) FCSM
One more PE lesson per week ×	-1,384	-1,794+	-1,592
organic lunch	(1,138)	(1,030)	(1,029)
One more PE lesson per week ×	3,022*	2,282+	2,301*
two fewer pupils per class	(1,248)	(1,314)	(1,084)
One more PE lesson per week ×	-0,351	-0,688	-0,749
four fewer pupils per class	(0,916)	(1,076)	(0,869)
Two more PE lessons per week ×	7,824***	6,754***	7,057***
two more PE lessons per week	(2,195)	(1,895)	(1,888)
Two more PE lessons per week ×	-0,181	-0,097	-0,320
non-organic lunch	(0,777)	(0,778)	(0,786)
Two more PE lessons per week ×	-0,323	-0,477	-0,973
organic lunch	(1,090)	(0,876)	(0,963)
Two more PE lessons per week ×	2,538*	1,742	2,217*
two fewer pupils per class	(1,097)	(1,100)	(0,909)
Two more PE lessons per week ×	-0,699	-1,088	-0,745
four fewer pupils per class	(0,816)	(0,846)	(0,824)
Non-organic lunch ×	4,482***	6,092***	5,364***
non-organic lunch	(1,187)	(1,620)	(1,340)
Non-organic lunch ×	4,550***	5,222***	5,229***
organic lunch	(1,207)	(1,366)	(1,233)
Non-organic lunch ×	-2,785**	-2,911**	-2,954**
two fewer pupils per class	(0,921)	(1,059)	(1,002)
Non-organic lunch ×	-3,098***	-4,128***	-3,246**
four fewer pupils per class	(0,880)	(1,108)	(1,051)
Organic lunch ×	6,452***	7,552***	6,973***
organic lunch	(1,692)	(1,899)	(1,669)
Organic lunch ×	-3,004**	-3,362**	-3,249**
two fewer pupils per class	(1,048)	(1,211)	(1,050)
Organic lunch ×	-2,481**	-3,321**	-2,580**
four fewer pupils per class	(0,949)	(1,136)	(1,004)
Two fewer pupils per class ×	6,734***	8,082***	6,349***
two fewer pupils per class	(1,821)	(2,165)	(1,778)
Two fewer pupils per class ×	4,172***	4,833***	4,136***
four fewer pupils per class	(1,152)	(1,374)	(1,143)
Four fewer pupils per class ×	4,956***	5,654***	4,746**
four fewer pupils per class	(1,355)	(1,585)	(1,568)

Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Chapter 2

Completion of upper secondary education: The roles of cognitive and noncognitive skills

Completion of upper secondary education:

The roles of cognitive and noncognitive skills[1]

Karl Fritjof Krassel

Abstract

Both cognitive and noncognitive skills have been found to be important for educational outcomes. This paper adds to the area of research by investigating the importance of cognitive and noncognitive skills for enrolment in and completion of upper secondary education. Measures of cognitive and noncognitive skills were constructed using factor analysis on OECD PISA survey data matched with Danish registry data. Academic achievement and self-confidence are found to be important for enrolment in high school, while academic achievement and perseverance are important for completion of high school. With respect to completion of vocational education, neither academic achievement nor self-confidence and perseverance predict completion. Basic attendance measures (measured during compulsory schooling), however, are strong predictors of completion of vocational education. The attendance measures also predict completion of high school, but to a lesser extent.

Keywords: Cognitive and noncognitive skills, factor analysis, upper secondary education

JEL codes: C25, I2, I21

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1. Introduction

Within the field of economics, extensive research has established that cognitive and noncognitive skills[2] are important for a range of outcomes. The purpose of this paper is to shed light on the roles of cognitive and noncognitive skills with respect to educational outcomes. Specifically, the importance of cognitive and noncognitive skills for enrolment in and (especially) completion of upper secondary education in Denmark is analysed. The motivation behind this study is illustrated in Figure 1 (Statistics Denmark 2011). While completion of high school is around 85%, vocational students are more often delayed in their studies and drop out more often. This empirical observation is in striking contract to the Danish Government's official goal, stating that 95% of a youth cohort should complete upper secondary education. Hence, the question is whether lack of cognitive and noncognitive skills can explain the discrepancy between reality and the political goal, and whether cognitive and noncognitive skills differ in importance between the more academically oriented high school and the more practically oriented vocational education.

[2] In the following I solely use the term 'skills' for consistency but I do not consider it to have other denotations nor connotations than abilities or traits.

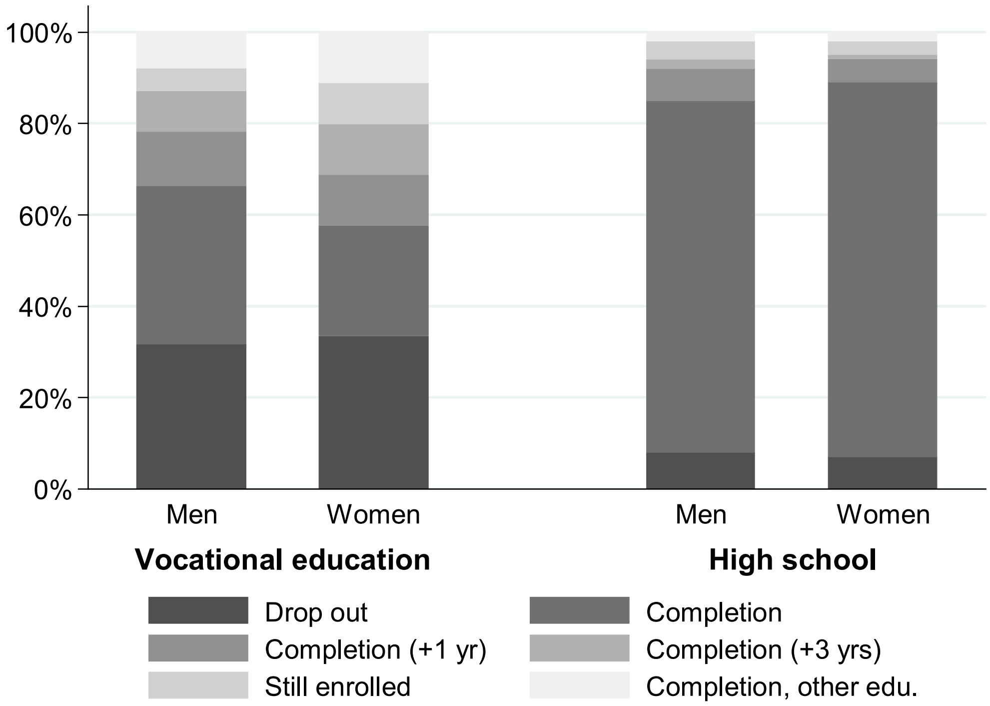

Figure 1: Completion of upper secondary education.
Status of the 2002/2003 cohort in 2010

In the literature, cognitive and noncognitive skills have been found to be important for labour market outcomes (DellaVigna and Paserman 2005, Antecol and Cobb-Clark 2010, Cobb-Clark and Tan 2011), health outcomes (Carneiro et al. 2007, Heckman et al. 2006), social outcomes (Falch et al. 2012, Coneus and Laucht 2014) and educational outcomes (see below).[3] While cognitive skills are typically measured using IQ tests, grades or similar, the methods for measuring noncognitive skills are much more diverse. DellaVigna and Paserman (2005) use information on having a bank account and smoking behaviour as measures of the noncognitive skill 'patience', while Jacob (2002) uses information on grade retention and behaviour as measures of noncognitive skills. Other studies take a more direct approach and use information on self-reported noncognitive skills. An

[3] Some of the papers analyze multiple outcomes.

example of such a study is Heckman et al. (2006), in which information on respondents' self-reported loss of control and self-esteem is used. Yet another branch of the literature has adopted methodology from psychology and employs models of personality traits to capture information on noncognitive skills. An example of such a model is the *Big Five* model of personality traits, which has been used in, for instance, Cobb-Clark and Tan (2011). See Digman (1990) for a thorough discussion of the Big Five model. Another personality trait model is the *Consideration of Future Consequences* (CFC) scale, which measures the degree of orientation towards future outcomes when choosing current behaviour (see Strathman et al. 1994) and is used in, for instance, Delaney et al. (2013).

The various approaches to measuring noncognitive skills illustrate their intangible and diverse nature. Borghans et al. (2008) consider the difference between cognitive and noncognitive skills to be difficult to define with precision, due to the presence of 'quasicognitive' skills such as creativity and practical intelligence. One approach is to regard noncognitive skills as those not related to abstract problem solving. Using the terminology of Cunha and Heckman (2007), noncognitive skills can refer to patience, self-control, temperament, risk aversion and time preference. In this paper, explorative factor analysis is conducted, and thereby measures of cognitive and noncognitive skills are constructed. Academic achievement and self-confidence are found to be important for enrolment in high school, while academic achievement and perseverance are found to be important for completion of high school. With respect to completion of vocational education, neither academic achievement nor self-confidence and perseverance predict completion. Rather, basic attendance measures (measured during compulsory schooling) are found to be strong predictors of completion of vocational education. The attendance measures also predict completion of high school, but to a lesser extent.

The rest of the paper is organized as follows: Section 2 discusses the existing literature on the roles of cognitive and especially noncognitive skills for educational outcomes, while Section 3 describes the institutional setting of upper secondary education in Denmark. Section 4 is devoted to a description of the empirical method, and Section 5 presents the data. Estimation results are presented in Section 6, while Section 7 provides conclusions.

2. Skills and educational outcomes

Both cognitive and noncognitive skills have been found to have a bearing on educational outcomes. With respect to enrolment in college, Jacob (2002) finds that noncognitive skills explain 42% of the attendance gap between men and women, while Aucejo (2012) finds that noncognitive skills fully explain the gender attendance gap. Cornwell et al. (2013) study the gender achievement gap and find that boys are graded lower than girls by their teachers, when controlling for the results of reading, math and science tests. Interestingly, the finding is neutralized (or even reversed in some specifications) when controlling for noncognitive skills.[4] Cornwell et al. suggest that teachers reward girls' "developed attitude toward learning".

Heckman et al. (2006) investigate the roles of cognitive and noncognitive skills in explaining a range of outcomes. With respect to schooling outcomes, they find that noncognitive skills affect the probability of being a 4-year-college graduate at age 30 positively. For instance, going from the fifth to the ninth decile of noncognitive skills raises the conditional probability from approx. 0.15 to approx. 0.45.[5] Interestingly, Heckman et al. (2006) also find that schooling affects tested cognitive

[4] The children's noncognitive skills are measured using teachers' responses to a range of questions transformed by a "Social Rating Scale" developed by the US National Center of Educational Statistics, who also provide the data.

[5] Heckman et al. (2006) Figure 21, Panel iii.

and noncognitive skills and hence suggest that early childhood interventions are important, as there are dynamic complementarities (using the terminology of Cunha and Heckman 2007).

Another study focusing on completion is Munk (2013). Using the same data as the present study, Munk finds that adding variables relating to noncognitive skills accounts for around 9.5% of the increase in log-likelihood score, when comparing an estimation with only an intercept and an estimation with individual, family and school-specific variables added.[6]

Poor study behaviour has been found to have adverse effects on achievement (Dobkin et al. 2010, Arulampalam et al. 2012). Delaney et al. (2013) study determinants of study behaviour and use noncognitive skills as explanatory variables in their analysis. Specifically they use the Big Five personality traits (openness, conscientiousness, extraversion, agreeableness and neuroticism), a measure of willingness to take risks and a measure of future orientation[7] to predict student behaviour along with traditional covariates. Overall they find that especially conscientiousness and future orientation are important determinants, predicting lecture attendance and additional study positively. Hence, the study by Delaney et al. (2013) suggests a likely pathway through which noncognitive skills have a bearing on schooling outcomes.

As the discussed literature suggests, noncognitive skills are important for – but not limited to – a range of schooling outcomes. With respect to the importance of both cognitive and noncognitive skills, Heckman and Rubinstein (2001) make an interesting observation. *General Educational*

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[6] Munk (2013) and the present study vary in multiple dimensions. Most significantly, Munk (2013) does not employ a factor analysis but uses the survey items directly in the regressions. This is not preferable, as it adds a lot of noise to the estimates. Factor analysis reduces the number of variables, back tracking the co-variation between the items and discarding the random variation across the items.

[7] Using the mentioned CFC scale.

Development (GED) recipients and high school graduates who do not attend college are comparable with respect to A*rmed Forces Qualifying Test* (AFQT) scores, though GED recipients do not get higher wages than high school dropouts. This difference can be attributed to differences in noncognitive skills. Hence, not only are noncognitive skills important from a statistical point of view, but their importance is of such magnitude that they are directly valued in the labour market.

It should be noted that the usage of cognitive and noncognitive skills to explain outcomes can be problematic for two reasons. Junker et al. (2012) point out the first problem. As Junker et al. note, test scores are often used as measures of cognitive skills in analyses of labour market outcomes. This can be problematic, as cognitive skill is a latent construct and test scores are hence prone to measurement error. The same argument can be raised against the usage of measures of noncognitive skills. Another problem is the limitation of skill to cognitive skill. Cunha and Heckman (2007, 2008) consider human capital as given by some function of cognitive and noncognitive skills, both of which are formed by recursive technologies affected by the stock of each other, investment in both and parental skills. Hence, if we believe the formation of human capital takes place as described by Cunha and Heckman we must include measures of noncognitive skills as proxies for human capital. It should be noted that if cognitive and noncognitive skills are functions of each other, one should be careful when assessing their relative importance with respect to a given outcome, as they might affect the outcome through one and another.

In this study, explorative factor analyses are conducted, and factors proxying both latent cognitive and noncognitive skills are retained. Hence, measures of both cognitive and noncognitive skills are included, as suggested by Cunha and Heckman's description of human capital. The issue of cognitive and noncognitive skills being latent constructs is further discussed in Section 4.

3. Upper secondary education in Denmark

Compulsory education in Denmark consists of ten years of schooling from the zeroth to the ninth grade. The free-for-all *Folkeskole* is a comprehensive school covering both primary education (zeroth to sixth grade) and lower secondary education (seventh to ninth grade). In addition, an optional tenth grade is provided at some, but not all, free schools. In the private sector, there are both day schools and boarding schools. Some private schools cover all grades, while others merely cover a subset of grades. It is especially popular to finish lower secondary education with a stay at a boarding school in the ninth or tenth grade (or both). After finishing lower secondary school, students choose either to enrol in upper secondary education or enter the labour force.

Upper secondary education can be divided into vocational and general purpose upper secondary education. The former will henceforth be denoted vocational education, while the latter will be denoted high school. Vocational educations are rather diverse and include technical, mercantile and health-related educations. A typical education consists of both formal schooling and apprenticeship. The length of a vocational education is typically four years, but some are of a shorter duration. High school education can take place at ordinary high schools or at technical or mercantile high schools. The duration is generally three years, but there are other options of shorter duration. Unlike vocational educations, high school educations are intended to be followed by additional higher education.

In general, the admission ‘costs’ for both types of upper secondary education are rather low. High schools’ admission requirements differ a little across different types of high school, but the main requirement is approval from the sending institution. If the student lacks approval, the high school can make enrolment contingent on passing a matriculation exam. With regard to vocational educations, most educations have no entry requirements, while some have restricted admission due to popularity. For certain educations, students are only admitted if they have an apprenticeship contract at the time of enrolment, for instance.

4. Empirical method

The focus of this paper is to determine the importance of cognitive and noncognitive skills with respect to enrolment in and completion of upper secondary education. Hence, with regard to completion I am interested in estimating

$$Y_i = 1\left[\gamma_{\theta^C}\theta_i^C + \gamma_{\theta^{NC}}\theta_i^{NC} + X_i'\beta + u_i > 0\right], \tag{1}$$

where θ^C and θ^{NC} are latent cognitive and noncognitive skills, respectively. X contains traditional covariates, while Y is an indicator variable for completion. Unfortunately, I do not observe the latent cognitive and noncognitive skills θ^C and θ^{NC}. Instead I use the proxies T^C and T^{NC} and estimate

$$Y_i = 1\left[\gamma_{T^C}T_i^C + \gamma_{T^{NC}}T_i^{NC} + X_i'\beta + u_i > 0\right]. \tag{2}$$

Using proxies implies a problem of finding appropriate measures, and in general $\gamma_{\theta^C} \neq \gamma_{T^C}$ and $\gamma_{\theta^{NC}} \neq \gamma_{T^{NC}}$. As discussed below, I use factor analysis to find T^C and T^{NC} and retain one cognitive factor and three noncognitive factors. On the one hand, it would be preferable to be able to backtrack θ^C and θ^{NC}, and hence be able to estimate γ_{θ^C} and $\gamma_{\theta^{NC}}$ directly. On the other hand, knowing γ_{θ^C} and $\gamma_{\theta^{NC}}$ would be of little help with respect to screening and helping at-risk students, if the latent cognitive and noncognitive skills are unobserved and not easily measured. From a screening and helping perspective, easily observed and estimated proxies T^C and T^{NC}, and corresponding estimates γ_{T^C} and $\gamma_{T^{NC}}$, are more useful.

I run two types of estimations. The first type is multinomial logit estimation used to estimate enrolment, while the second type is standard logit estimation used to estimate completion.[8] To allow for heterogeneous importance of the explanatory variables with respect to completion of high school and vocational education, the main explanatory variables are interacted with an indicator for vocational education. As pointed out by Ai and Norton (2003), presenting marginal effects might be misleading for logit models if interaction terms are included, as the marginal effects of the interaction terms are not necessarily equal to the marginal interaction effects. Hence, I present the estimation results as exponentiated coefficients. Note that the exponentiated parameter estimates for the interactions must be interpreted as multiplicative effects in relation to some baseline odds (Buis 2010). With regard to completion, I ended up estimating

$$Y_i = 1\left[\alpha_0 + \alpha_1 voc_i + \gamma_{T^C} T_i^C + \gamma_{T^C \times voc} T_i^C \times voc_i + \gamma_{T^{NC}} T_i^{NC} + \gamma_{T^{NC} \times voc} T_i^{NC} \times voc_i + X_i'\beta + u_i > 0\right], \quad (3)$$

where voc_i is an indicator of vocational education. Note that α_0 is the constant, while α_1 is the parameter to the vocational education indicator. Hence, the baseline odds are $\exp(\alpha_0)$ and $\exp(\alpha_0 + \alpha_1)$ for high school and vocational education, respectively.

5. Data

The data were constructed by matching rich survey data from OECD's *Programme for International Student Assessment* (PISA) for the year 2000 with registry data from Statistics Denmark. From the PISA 2000, I used data on Danish students' reading, math and science skills and additionally data from the associated *Student Questionnaire* and *Cross-Curricular Competencies Questionnaire*. Based on the PISA 2000 data, I was able to construct my measures of cognitive and noncognitive skills described in detail below and in Appendix A. From Statistics Denmark's registers, I obtained data on the PISA respondents and their parents. Specifically, I

[8] See Wooldridge (2002) for an introduction to estimation models.

obtained information on enrolment and completion, gender, ancestry, family composition and parental education. I followed the students in the registers from 1998 to 2009 and constructed background variables using 1999 data. Prior to the estimations, the data set was transformed into cross-section data. The data set contains 3,926 observations, out of which 3,599 entered upper secondary education.

Figure 2 shows the current or highest completed education for the PISA 2000 sample. Despite the long data window, it is worth noticing that a relatively large proportion of the sample was still without education above lower secondary level in 2009.

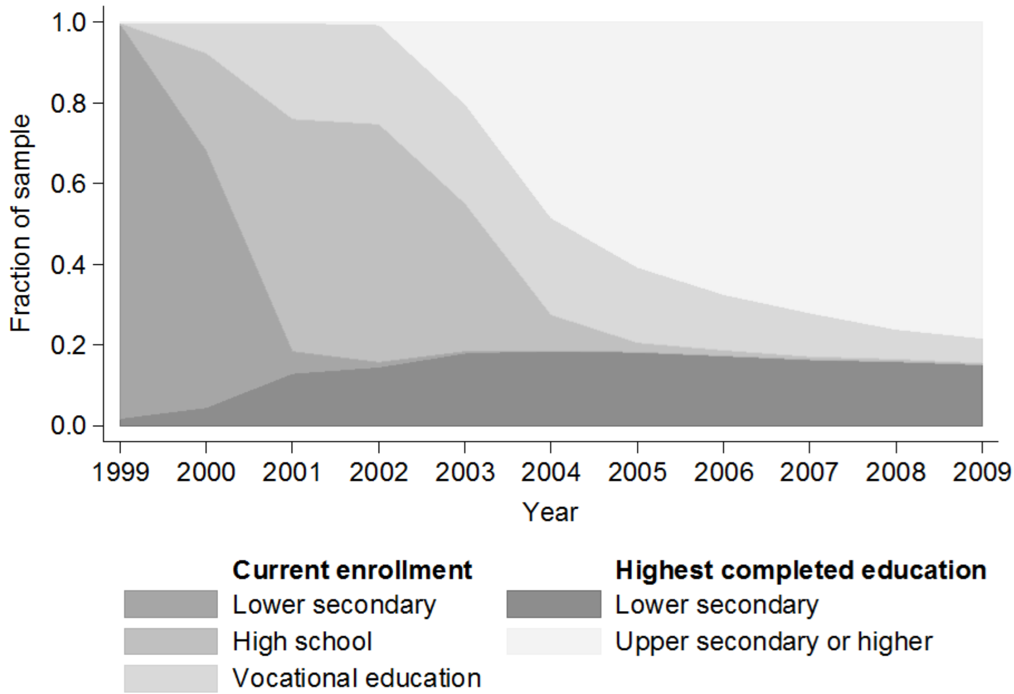

Figure 2: Upper secondary education: Enrolment and completion Status of the PISA respondents (1999 to 2009)

5.1 Outcome variables

I use two different but closely related outcome variables. The first outcome measures enrolment in upper secondary education. This variable takes three different values identifying the three states ‘nonparticipation’, ‘high school’ and ‘vocational education’. Nonparticipation is a residual state in the sense that it is defined if a student has not begun a high school or vocational education by the end of 2002, i.e. within two years of completing compulsory schooling (not including tenth grade). Note that the nonparticipation category includes both employed and unemployed individuals, and that the variable only measures the first enrolment. Hence, dropout and reenrolment were disregarded.

The second outcome variable measures completion of upper secondary education. This variable identifies completion of first enrolment within the designated time frame plus one year, where first enrolment must take place no later than 2002. Hence, vocational educations are considered to be completed if they are completed within five years, while high school educations are considered to be completed if completed within four years. The definition of the completion indicator allows dropout and immediate reenrolment to the same type of upper secondary education to still result in the education being considered as completed. For instance, an education involving a change from an ordinary high school to a technical high school or a change from one vocational education to another will be considered completed, if it takes place within the time frame. In contrast, an education involving a change from, for instance, high school to vocational education would be considered an incomplete high school education. The definitions of the two outcome variables are challenged in various robustness checks in Section 6.3.

Table 1 displays summary statistics for the two outcome variables. Around 61% choose a high school education, while around 30% choose a vocational education. The rest are considered to be in the residual group denoted nonparticipation. With respect to completion, a remarkable difference arises between high school and vocational students. While around 85% complete a high school education, less than 50% complete a vocational education. Hence, the sample displays approximately the same tendencies as the population described in Statistics Denmark (2011).

Table 1: Summary statistics of the dependent variables

	Share choosing / completing	Number of observations
Enrolment in upper secondary education		
Nonparticipation	0.083	327
High school	0.614	2,410
Vocational education	0.303	1,189
Completion of upper secondary education		
High school	0.845	2,410
Vocational education	0.474	1,189

5.2 Explanatory variables

The main explanatory variables are the measures of cognitive and noncognitive skills proxied using data from the PISA 2000 surveys. The factor analysis is described in detail in Appendix A. Cognitive skills are proxied using PISA reading, math, and science scores. The domain of PISA 2000 was reading, and hence a reading score for most of the sample was observed, while only math and science scores were observed for around half of the sample. All three scores were observed for around one fifth of the sample. The factor analysis resulted in one factor. An obvious name for this factor would be “cognitive skills”, but to stress the fact that the factor is only a proxy for latent cognitive skills it will be denoted “academic achievement”. As a robustness check, the different scores are also used individually, as the three scores are likely to capture different aspects of latent cognitive skills. Rangvid (2012) showed that the PISA math score is more important than the reading score for completion of the vocational education for immigrant boys, for instance.

Noncognitive skills were proxied using information from the CCC Questionnaire battery, one consisting of 28 questions (see Table A1) relating to study techniques (e.g. *"When I study, I start by figuring out exactly what I need to learn"* and *"When I study, I memorise as much as possible"*), confidence with respect to being able to understand the material (e.g. *"If I decide not to get any problems wrong, I can really do it"* and *"I'm certain I can master the skills being taught"*) and reasons for studying (e.g. *"I study to ensure that my future will be financially secure"* and *"I study to get a good job"*). The factor analysis results in two well-identified factors and one less well-identified factor. The two well-identified factors are denoted 'perseverance' and 'self-confidence' and are identified through some (but not all) of the questions relating to study techniques and confidence, respectively. The less well-identified factor is denoted "Future orientation" and is identified through the questions relating to reasons for studying. See Appendix A for details.

The OECD PISA data set comes with a set of variables based on the CCC Questionnaire question battery. Ideally, the factor analysis I conduct would result in the same factors as the ones provided. This is generally not the case, which is hardly surprising as I am only using the Danish branch of the PISA data and a somewhat different method. Specifically, eight factors are provided in the data set capturing (according to PISA): Instrumental motivation, control strategies, (index of) memorisation, (index of) elaboration, effort and perseverance, perceived self-efficacy, and control expectation. Instrumental motivation is based on the exact same items as the factor I denote future orientation, and the correlation is 0.989. Effort and perseverance and perceived self-efficacy clearly relate to the factors perseverance and self-confidence, respectively, but are both based on fewer items. The correlations are 0.875 and 0.902, respectively. If I only used the factors provided by PISA, a valid objection would be that they might not all be relevant in a Danish setting. To avoid such an objection, I re-estimated the noncognitive factors and used the original factors as a robustness check in Section 6.3. My denominations of the factors were deliberately chosen to be close the PISA names to recognise the close links. The estimation results show no practical differences between using the re-estimated factors and the original factors. See OECD (2002) for a detailed description of the PISA factors.

The last set of explanatory variables from the PISA questionnaires is variables derived from questions relating to school attendance. In the Student Questionnaire, the students were questioned on the frequency of missed school days, skipped classes or late arrivals in the last two weeks. They could answer "*none*", "*1 or 2*", "*3 or 4*" and "*5 or more*". For the analysis, the outcomes were collapsed into indicator variables taking the value 1 if the students report anything other than *none*. Note that the students were surveyed during compulsory schooling, and hence, the variables are not per construction indicators of a pending dropout from upper secondary education.

The last set of explanatory variables contains the previously mentioned variables derived from Statistics Denmark's registers on individual and family-specific characteristics. All explanatory variables are reported in Table 2 and discussed in detail in Section 5.3. As the estimation tables display exponentiated coefficients, the continuous variables (the variables for cognitive and noncognitive skills) were standardised prior to estimation to keep baseline odds stable across estimations. Finally, indicator variables for missing values were created. The estimates for these missing indicators are not shown in the estimation tables.

5.3 Descriptive differences between high school and vocational students

The main focus of the paper is on enrolment in and completion of upper secondary education. Hence, Table 2 shows summary statistics of the explanatory variable given type of upper secondary education. In addition, the table shows t-scores and corresponding significance levels for mean comparison tests. The table shows clear differences between students in high school and vocational education on a range of parameters. High school students have significantly higher academic achievement, self-confidence and perseverance, and show a higher degree of future orientation. In addition, a larger share of women enrols into high school, while there is no difference with respect to ancestry. With respect to family composition, vocational education enrollers are slightly more likely to come from atomized families, but the difference is numerically small. Finally, the students in the two samples differ in level of parental education, high school students tending to have higher-educated parents.

Table 2: Summary statistics of the explanatory variables

	Mean		Difference	t-score	Number of observations	
	High school	Voc. educ.			High school	Voc. educ.
Cognitive skill proxies						
Academic achievement	0.423	-0.710	1.133***	17.52	549	262
Reading score / 100	0.424	-0.668	1.092***	36.08	2,406	1,185
Math score / 100	0.353	-0.557	0.910***	21.31	1,362	662
Science score / 100	0.348	-0.500	0.849***	20.17	1,327	653
Noncognitive skill proxies						
Self-confidence	0.219	-0.358	0.577***	16.42	2,251	1,036
Perseverance	0.128	-0.220	0.348***	9.40	2,238	1,055
Future orientation	0.057	-0.064	0.121***	3.38	2,285	1,081
Female	0.554	0.366	0.189***	10.92	2,410	1,189
Non-western immigrants or descendants	0.042	0.057	-0.015	-1.88	2,410	1,189
Living with both parents (ref.)	0.720	0.660	0.060***	3.62	2,410	1,189
Living with one parent	0.170	0.188	-0.017	-1.27	2,410	1,189
Living with one parent and a new partner	0.100	0.137	-0.037**	-3.17	2,410	1,189
Living without parents	0.010	0.015	-0.005	-1.27	2,410	1,189
Father's education						
Basic (ref.)	0.209	0.356	-0.147***	-9.07	2,410	1,189
Vocational	0.388	0.463	-0.075***	-4.28	2,410	1,189
Short and medium term	0.218	0.102	0.116***	9.55	2,410	1,189
Long term	0.128	0.012	0.116***	15.53	2,410	1,189
Missing	0.056	0.067	-0.011	-1.25	2,410	1,189
Mother's education						
Basic (ref.)	0.279	0.466	-0.187***	-10.93	2,410	1,189
Vocational	0.298	0.347	-0.048**	-2.89	2,410	1,189
Short and medium term	0.337	0.135	0.202***	14.62	2,410	1,189
Long term	0.057	0.008	0.050***	9.27	2,410	1,189
Missing	0.029	0.045	-0.016*	-2.36	2,410	1,189
Study behaviour						
Late arrivals	0.441	0.491	-0.050**	-2.79	2,352	1,159
Missed school days	0.471	0.546	-0.074***	-4.15	2,368	1,149
Skipped classes	0.193	0.268	-0.075***	-4.87	2,333	1,137

Ref. indicates variables used as reference categories. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure A1 shows kernel density plots of the cognitive and noncognitive skill proxies (including future orientation used as a robustness check). With regard to academic achievement, self-confidence and perseverance, high school students have a right-shifted distribution compared to vocational students. With regard to future orientation, the distributions are more or less on top of each other. For all four sets of distributions, Kolmogorov-Smirnov tests result in p-values < 0.001.

6. Estimation results

6.1 Enrolment in upper secondary education

To illustrate the differences between the groups choosing high school and vocational education, enrolment is initially estimated. The results are presented in Table 3, which shows the results of multinomial logit estimations. Estimates are presented for the choices among (1) high school and nonparticipation, (2) vocational education and nonparticipation, and (3) high school and vocational education. For the sake of brevity, the table only shows the estimates for the main explanatory variables (academic achievement, self-confidence and perseverance), but the remaining individual and family specific explanatory variables are also controlled for in the estimations.

The results show that the primary predictor of enrolment is academic achievement. Higher academic achievement predicts enrolment in high school at the cost of both nonparticipation and vocational education. Interestingly, it does not predict vocational education enrolment at the cost of nonparticipation. The same pattern applies for self-confidence, but to a lesser degree (given the standardisation of the variables). In contrast, perseverance has no significant importance, despite the different endowments between high school and vocational students, as reported in Table 2 and Figure 3.c. The lack of significant estimates in column (2) may be due to the composition of the sample being coded as nonparticipation, as it consists of both students who never choose an education and able but late enrollers.

Table 3: Enrolment in upper secondary education. Multinomial logit estimations with the enrolment indicator as dependent variable

	(1) High school vs. nonparticipation	(2) Vocational education vs. nonparticipation	(3) High school vs. vocational education
Academic achievement†	3.184***	0.827	3.851***
	(0.672)	(0.151)	(0.558)
Self-confidence†	2.043***	1.066	1.918***
	(0.195)	(0.100)	(0.113)
Perseverance†	0.930	0.973	0.955
	(0.083)	(0.088)	(0.050)
Remaining explanatory variables		*yes*	
Pseudo R^2		0.173	
Log-likelihood		-2,818.61	
Observations		3,926	

Exponentiated coefficients and robust standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. † The standard errors are found by bootstrapping using 200 replications.

6.2 Completion of upper secondary education

Having illustrated the influence of the cognitive and noncognitive skill proxies on enrolment, the next step is to investigate their importance with respect to completion. The enrolment decision is a low-cost decision, while completion requires costly effort and is hence the most interesting event to investigate.

Table 4 shows exponentiated coefficients from logit estimations for the completion probability. Explanatory variables are gradually added across the columns. For each regression, baseline odds are presented for both vocational education and high school. The baseline odds for high school is simply the exponentiated constant, while the baseline odds for vocational education is the exponentiated sum of the constant and the coefficient of the indicator for vocational education. Standard errors and corresponding significance levels were deliberately neglected for the baseline odds, as they merely reflect descriptive statistics of the sample. In column (1), the unconditional baseline odds are presented for reference.[9] As discussed earlier, the completion rates differ considerably among types of upper secondary education. For high school, the odds of completion are around 5.5:1, while they are around 0.9:1 for vocational education.

Column (2) displays the results of a regression, where the proxy for cognitive skills academic achievement is included. To allow for heterogeneous importance across types of upper secondary education, the variable is included in both levels and interacted with an indicator variable for vocational education. The first thing to note is the change in baseline odds reflecting differences in (demeaned) academic achievement. On average, vocational education students have lower academic achievement than high school students, and hence the baseline odds for vocational education increase when controlling for academic achievement. The opposite is the case for high school students. The second thing to note is the exponentiated parameter estimates. While academic achievement is highly important (and significant) for completion of high school, the p-value of a joint test of academic achievement and the corresponding interaction with the vocational education indicator is 0.088. Thus, academic achievement is only marginally significant in predicting completion of vocational education.

Adding noncognitive skill proxies in column (3) shows that perseverance positively and significantly predicts completion of high school, while self-confidence is insignificant. The point estimate for academic achievement is reduced a little but is not significantly different compared to the estimate in column (2). The odds ratio of academic achievement and the noncognitive skill proxies combined is 1.143, indicating that cognitive skills are more important than noncognitive

[9] For instance, the baseline odds for vocational education correspond to a completion rate of $0.902/(1+0.902)=0.474$, which is the same as the completion rate reported in Table 1.

skills in predicting completion of high school.[10] A joint test of all interactions between the skill proxies and the indicator variable for vocational education gives a p-value of 0.188. In addition, the individual tests of the skill proxies and corresponding interactions all produce p-values above 0.10. Thus, neither the cognitive skill proxy nor the noncognitive skill proxies predict completion of vocational education. The odds ratio between academic achievement and noncognitive skill proxies is 1.154, but is of little relevance due to the insignificant parameter estimates.

In column (4), the remaining individual specific control variables and the family-specific control variables are added to the estimation. Overall, the addition of the variables does not change the parameter estimates significantly, but it does reduce the point estimate of academic achievement while it increases the point estimate for perseverance. This serves as an indication of how the cognitive and noncognitive skill proxies capture elements of the latent cognitive and noncognitive skills not manifested in the remaining covariates. The estimation results in column (4) are regarded as the baseline estimates, and the odds ratios between the academic achievement and the noncognitive skill proxies are 1.054 and 1.081 for high school and vocational education, respectively.

Comparing the estimation results in Tables 3 and 4, it is interesting to note that self-confidence has predictive power with respect to choice of education, while perseverance has predictive power with respect to completion. The choice of high school requires little effort but is made contingent on expected outcome. Self-confidence affects this decision (and might even lure students to make a too demanding decision). When enrolled (in high school), the skill of perseverance comes in handy when effort is required. Here self-confidence is of less use.

[10] Given by $1.549/(1.126 \cdot 1.204) = 1.143$. For comparison, the odds ratio between the significant academic achievement and perseverance is 1.287.

Table 4: Baseline estimations of completion probability. Logit estimations with the completion indicator as dependent variable

	(1) No explanatory variables	(2) + cognitive skill proxy	(3) + non-cognitive skill proxies	(4) + remaining explanatory variables
Academic achievement†		1.611**	1.549**	1.395*
		(0.256)	(0.247)	(0.232)
× vocational†		0.798	0.819	0.869
		(0.173)	(0.184)	(0.200)
Self-confidence†			1.126	1.055
			(0.086)	(0.084)
× vocational†			0.979	1.032
			(0.112)	(0.121)
Perseverance†			1.204*	1.254**
			(0.087)	(0.090)
× vocational†			0.828+	0.821+
			(0.086)	(0.087)
Baseline odds‡				
Vocational	0.902	0.977	1.015	1.078
High school	5.461	4.825	4.871	4.974
Remaining explanatory variables	*no*	*no*	*no*	*yes*
Interaction estimates jointly equal to zero (p-values)				
All interactions	–	0.296	0.072	0.159
Estimate and corresponding interaction estimate jointly equal to zero (p-values)				
Academic achievement	–	0.088	0.101	0.209
Self-confidence	–	–	0.271	0.341
Perseverance	–	–	0.961	0.687
Pseudo R^2	0.124	0.127	0.133	0.161
Log-likelihood	-1,861.05	-1,853.94	-1,842.02	-1,782.98
Observations	3,599	3,599	3,599	3,599

Exponentiated coefficients and robust standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. † The standard errors were found by bootstrapping using 200 replications. ‡ Baseline odds for continuous variables equal to their means, and indicator variables equal to zero.

The baseline estimation does a poor job of explaining completion of vocational education by the cognitive and noncognitive skill proxies. Most surprisingly, perseverance does not predict completion of vocational education. As described above, vocational education typically consists of both formal schooling and working as an apprentice. This requires the students to find apprenticeships which are scarce in supply. In addition, all else equal perseverant behaviour is most likely a skill valued by employers. One explanation of the missing predictability of perseverance might be that it does not capture all aspects of what learning requires. The current measure of perseverance is based on items relating to learning strategies and the learning situation. In other words, the measure is based on items related to the respondent's intended study behaviour, which might be divergent from actual behaviour. The survey does not include objective measures of behaviour, but it does include self-reported attendance measures. Hence, it might be the case that these attendance measures can explain completion for vocational education students. Before adding these measures, remember that Delaney et al. (2013) showed a relationship between study behaviour and conscientiousness (among other skills). Given the similarity between conscientiousness and the measure denoted perseverance, I would expect perseverance to have predictable power with respect to the attendance measures. This is indeed the case, as shown in Table B1 in Appendix B.

The attendance measures are added to the baseline completion model, and the estimation results are reported in Table 5. In columns (1), (2) and (3), the variables indicating missed school days, skipped classes and late arrivals are added in turn (including interactions with the vocational education indicator). In each regression, the indicator variables in levels are highly significant and negatively predict completion. For completion of vocational educations, the missed school days and late arrivals have significant predictable power with respect to completion. In column (4), all three attendance measures were added simultaneously. Missed school days and late arrivals remain significant, while skipped classes does not. The joint estimate of missed school days and the interaction with the vocational education indicator is significant and below 1, while the joint estimate of late arrivals and the vocational education indicator are below 1 but marginally significant with a p-value of 0.060.[11] The correlation between the attendance measures and perseverance is indicated by the reduced point estimate for perseverance and the corresponding increased standard error.

The attendance measures not only have statistical significance, but also practical significance with respect to predicting completion of upper secondary education. For instance, missed school days in the last two weeks of compulsory school decreases the baseline odds of completing vocational education from 1.402 to 0.957, corresponding to a change in probability from 58.4% to 48.9% (52.4% for late arrivals).[12] Among cognitive and noncognitive skill proxies and traditional control variables, simple measures of recent attendance have predictable power with respect to events taking place years later. It is certainly not the immediate absence which has long term impact, but from a screening and supporting perspective this is very useful, as attendance is easily observed. Hence, attendance information can be used to identify at-risk students.[13]

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[11] The estimate for skipped classes is significant in column (2) but not in column (4). The attendance measures are correlated, which might explain the significance in column (2), while the lack of significance in column (4) might be explained by the lower prevalence of skipped classes (see Table 2). Skipping classes is only allowed for valid reasons (e.g. illness), and hence committing truancy is easier done by arriving late or skipping the whole school day.

[12] For high school, the probability of completion changes from 87.8% to 84.8% and 82.2% for skipped school days and late arrivals respectively.

[13] With respect to enrolment, attendance measures missed school days, and skipped classes predict enrolment in vocational education at the cost of high school (results not shown).

Table 5: Behavioural measures added to the baseline completion model.

Logit estimations with the completion indicator as dependent variable

	(1) Baseline + missed school days	(2) Baseline + skipped classes	(3) Baseline + late arrivals	(4) Baseline + all three measures
Academic achievement†	1.373+	1.374+	1.385*	1.389*
	(0.232)	(0.231)	(0.218)	(0.223)
× vocational†	0.883	0.874	0.878	0.878
	(0.202)	(0.208)	(0.190)	(0.208)
Self-confidence†	1.079	1.063	1.061	1.078
	(0.082)	(0.092)	(0.084)	(0.085)
× vocational†	0.976	1.010	1.036	0.993
	(0.116)	(0.126)	(0.122)	(0.116)
Perseverance†	1.214*	1.230**	1.189*	1.179*
	(0.091)	(0.090)	(0.085)	(0.096)
× vocational†	0.862	0.836+	0.839	0.856
	(0.097)	(0.089)	(0.097)	(0.094)
Missed school days	0.682**			0.776*
	(0.080)			(0.098)
× vocational	1.014			0.880
	(0.173)			(0.161)
Skipped classes		0.672**		0.810
		(0.094)		(0.124)
× vocational		1.340		1.299
		(0.266)		(0.281)
Late arrivals			0.581***	0.643***
			(0.071)	(0.083)
× vocational			1.277	1.219
			(0.219)	(0.221)
Baseline odds‡				
Vocational	1.251	1.097	1.230	1.402
High school	5.986	5.803	6.275	7.176
Remaining explanatory variables	*yes*	*yes*	*yes*	*yes*
Interaction estimates jointly equal to zero (p-values)				
All interactions	0.474	0.091	0.192	0.176
Estimate and corresponding interaction estimate jointly equal to zero (p-values)				
Academic achievement	0.195	0.272	0.117	0.212
Self-confidence	0.554	0.489	0.284	0.418
Perseverance	0.606	0.700	0.975	0.919
Missed school days	0.003	–	–	0.004
Skipped classes	–	0.460	–	0.737
Late arrivals	–	–	0.015	0.060
Pseudo R^2	0.165	0.166	0.168	0.174
Log-likelihood	-1,724.21	-1,700.37	-1,724.01	-1,665.51
Observations	3,517	3,470	3,511	3,429

Exponentiated coefficients and robust standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. † The standard errors were found by bootstrapping using 200 replications. ‡ Baseline odds for continuous variables equal to their means, and indicator variables equal to zero.

Table 6 displays interaction effects. Column (1) shows the baseline estimation (to facilitate comparison), while column (2) adds interaction terms between gender and the skill proxies. In column (3), interactions between the skill proxies are added. Column (2) shows that especially women have a hard time completing vocational educations, most likely due to selection into specific competitive educations. In addition, column (2) shows that self-confidence is of significance for women, but only with respect to completing high school education. On the other hand, perseverance seems only to be of significance for men, but again only for high school educations. With respect to vocational educations, perseverance still plays no role in predicting completion.

As discussed earlier, assessing the importance of latent cognitive and noncognitive skills can be difficult, both because they are (most likely) imprecisely proxied, but also because of dynamic complementarities, as pointed out by Cunha and Heckman (2007). Cognitive and noncognitive skills might co-develop and form each other. Hence, stating that cognitive skills are more important than noncognitive skills with respect to a certain outcome, for instance, might be imprecise, if the stock of cognitive skills is affected by the earlier stock of noncognitive skills (which again was affected by the even earlier stock of cognitive skills, etc.). An approach to shedding light on whether dynamic complementarities are present is to add interactions between the cognitive and noncognitive skill proxies. This is done in column (3), but no significant results with respect to the interactions are found. It is worth noticing that the point estimate does suggest a positive interaction effect between perseverance and academic achievement for vocational education, but the estimate is not significant. In general, the standard errors of the interactions between the noncognitive skill proxies and academic achievement are considerable.

Table 6: Interactions. Logit estimations with the completion indicator as dependent variable

	(1) Baseline		(2) + interactions between skills proxies and an indicator for females		(3) + interactions between cognitive and noncognitive skill proxies	
Female	0.939	(0.083)	1.054	(0.279)	0.939	(0.083)
× vocational			0.403*	(0.181)		
Academic achievement†	1.395*	(0.232)	1.521+	(0.360)	1.419*	(0.248)
× vocational†	0.869	(0.200)	0.807	(0.244)	0.854	(0.204)
× female†			0.817	(0.292)		
× vocational × female†			1.213	(0.554)		
Self-confidence†	1.055	(0.084)	1.112	(0.124)	1.061	(0.084)
× vocational†	1.032	(0.121)	0.948	(0.154)	0.992	(0.121)
× female†			1.115	(0.177)		
× vocational × female†			0.840	(0.210)		
× academic achievement†					0.894	(0.210)
× academic achievement × vocational†					0.914	(0.285)
Perseverance†	1.254**	(0.090)	1.351**	(0.134)	1.261**	(0.091)
× vocational†	0.821+	(0.087)	0.848	(0.120)	0.840	(0.094)
× female†			0.760+	(0.111)		
× vocational × female†			1.087	(0.241)		
× academic achievement†					0.939	(0.232)
× academic achievement × vocational†					1.298	(0.404)
Baseline odds‡						
Vocational education	1.078		1.377		1.064	
High school	4.974		4.836		5.013	
Remaining explanatory variables	*yes*		*yes*		*yes*	
Estimate and corresponding interaction estimate jointly equal to zero (p-values)						
Acad. ac. / acad. ac. × voc.	0.209		0.331		0.262	
Acad. ac. / acad. ac. × female	–		0.442		–	
All estimates w. academic achievement	–		0.517		–	
Self-con. / self-con. × voc.	0.341		0.641		0.589	
Self-con. / self-con. × female	–		0.045		–	
Self-con. / academic achievement	–		–		0.826	
All estimates w. self-confidence	–		0.932		0.582	
Pers. / pers. × voc.	0.687		0.146		0.484	
Pers. / pers. × female	–		0.794		–	
Pers. / academic achievement	–		–		0.495	
All estimates w. perseverance	–		0.620		0.341	
Pseudo R^2	0.161		0.174		0.162	
Log-likelihood	-1,782.98		-1,755.11		-1,781.56	
Observations	3,599		3,599		3,599	

Exponentiated coefficients and robust standard errors in parentheses, + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. † The standard errors were found by bootstrapping using 200 replications. ‡ Baseline odds for continuous variables equal to their means, and indicator variables equal to zero.

6.3 Robustness checks

Table 7 presents robustness checks with alternative skill proxies. Again, column (1) shows the baseline results to facilitate comparison. In column (2) to (4), academic achievement has been replaced by the individual PISA reading, math, and science scores, while the third proxy for noncognitive skills, future orientation, has been added in column (5). Columns (2) to (4) inidicate that the importance of reading, math and science scores differ across types of upper secondary education. The point estimate for reading score in column (2) is higher compared to the point estimates in columns (3) and (4), indicating that reading skills are more important for completion than math and science skills. In addition, the point estimate is also larger compared to the estimate for overall academic achievement in column (1). Furthermore, reading skills (and math and science skills) only seems to be important for completion of high school education. All tests of joint significance between the scores and the scores interacted with the indicator for vocational education are larger than 0.10. Note, however, that the p-value for the joint test of the reading score and the reading score interacted with the vocational education indicator is around 0.82, while it is 0.14 and 0.12 in columns (3) and (4), respectively. Hence, a larger sample size might have shown math and science to significantly predict completion of vocational education. A last thing to notice in column (2) to (4) is that the estimates for the noncognitive skill proxies do not change markedly compared to the results in column (1).

In column (5), the third noncognitive skill proxy, future orientation, is added along with self-confidence and perseverance. Overall, the point estimates for the existing factors do not change considerably compared to the baseline results in column (1). Interestingly, a higher degree of future orientation predicts completion negatively for both high school and vocational education. The factor is based on questions relating to monetary reasons for studying ('*I study to increase my job opportunities*', '*I study to ensure my future will be financially secure*' and '*I study to get a good* *job'*). In light of this, the results are somewhat counterintuitive. An explanation could be that the factor also relates to impatience and hence predicts dropout for students chasing more immediate gains. The results might also be driven by the factor being poorly identified.

Table 7: Alternative measures of cognitive and noncognitive skills. Logit estimations with the completion indicator as dependent variable

	(1) Baseline	PISA scores (2) Reading score	PISA scores (3) Math score	PISA scores (4) Science score	(5) Future orientation
Academic achievement†	1.395+				1.369+
	(0.232)				(0.236)
× vocational†	0.869				0.887
	(0.200)				(0.204)
Reading score		1.657***			
		(0.138)			
× vocational		0.613***			
		(0.066)			
Math score			1.381***		
			(0.134)		
× vocational			0.827		
			(0.109)		
Science score				1.453***	
				(0.137)	
× vocational				0.800+	
				(0.108)	
Self-confidence†	1.055	0.943	1.020	1.013	1.085
	(0.084)	(0.079)	(0.085)	(0.083)	(0.082)
× vocational†	1.032	1.147	1.057	1.063	1.050
	(0.121)	(0.138)	(0.126)	(0.129)	(0.128)
Perseverance†	1.254**	1.291***	1.254**	1.270**	1.315***
	(0.090)	(0.096)	(0.090)	(0.091)	(0.105)
× vocational†	0.821+	0.805*	0.831+	0.817+	0.847
	(0.087)	(0.085)	(0.087)	(0.087)	(0.097)
Future orientation†					0.847*
					(0.059)
× vocational†					0.958
					(0.103)
Baseline odds‡					
Vocational education	1.078	1.066	1.021	1.025	1.128
High school	4.974	4.793	4.836	5.174	5.160
Remaining explanatory variables	*yes*	*yes*	*yes*	*yes*	*yes*
Interaction estimates jointly equal to zero (p-values)					
All interactions	0.159	0.000	0.116	0.068	0.471
Estimate and corresponding interaction estimate jointly equal to zero (p-values)					
Academic achievement	0.209	–	–	–	0.204
Reading score	–	0.823	–	–	–
Math score	–	–	0.138	–	–
Science score	–	–	–	0.121	–
Self-confidence	0.341	0.389	0.415	0.429	0.144
Perseverance	0.687	0.597	0.579	0.614	0.229
Future orientation	–	–	–	–	0.015
Pseudo R^2	0.161	0.169	0.163	0.164	0.164
Log-likelihood	-1,782.98	-1,766.29	-1,778.00	-1,775.53	-1,776.10
Observations	3,599	3,599	3,599	3,599	3,599

Exponentiated coefficients and robust standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. † The standard errors were found by bootstrapping using 200 replications. ‡ Baseline odds for continuous variables equal to their means, and indicator variables equal to zero.

The original factors based on question battery one of the CCC Questionnaire provided by PISA are used as noncognitive skill proxies in Table 8. In column (1) to (7), each factor is included one at a time along with academic achievement and the remaining individual and family specific variables, while all factors are included simultaneously in column (8). The overall finding is that the noncognitive skills proxies predict completion of high school, while they have no explanatory power with respect to completion of vocational education. The first exception is perceived self-efficacy, which does predict completion of vocational education but it only significant with a p-value of 0.092 in column (8). The second exception is instrumental motivation (based on the same items as future orientation), which negatively predicts completion of both high school and vocational education, but only in column (8). Compared to the baseline results, the results of the estimations using the PISA factors do not suggest an alternative interpretation of the importance of the noncognitive skill proxies. The PISA factors were standardised prior to the estimations, and hence it is in line with the baseline result that effort and perseverance is the most important noncognitive skill proxy.

Table 8: Completion estimations with PISA factors. Logit estimations with the completion indicator as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Academic achievement†	1.419*	1.420*	1.440*	1.407*	1.392*	1.368+	1.361+	1.382+
	(0.229)	(0.230)	(0.231)	(0.224)	(0.225)	(0.220)	(0.220)	(0.229)
× vocational†	0.884	0.878	0.871	0.877	0.884	0.890	0.913	0.918
	(0.201)	(0.199)	(0.197)	(0.198)	(0.200)	(0.201)	(0.206)	(0.212)
Instrumental motivation†	0.935							0.811***
	(0.049)							(0.047)
× vocational†	0.992							1.014
	(0.082)							(0.105)
Control strategies†		1.209**						1.028
		(0.076)						(0.111)
× vocational†		0.843*						0.833
		(0.068)						(0.121)
Index of memorisation†			1.177**					1.049
			(0.073)					(0.091)
× vocational†			0.955					1.117
			(0.083)					(0.146)
Index of elaboration†				1.094				0.892
				(0.065)				(0.076)
× vocational†				0.968				1.152
				(0.083)				(0.145)
Effort and perseverance†					1.357***			1.439***
					(0.085)			(0.129)
× vocational†					0.800**			0.787+
					(0.067)			(0.102)
Perceived self-efficacy†						1.125+		0.951
						(0.071)		(0.077)
× vocational†						1.030		1.220
						(0.093)		(0.149)
Control expectation†							1.222**	1.140
							(0.088)	(0.110)
× vocational†							0.863	0.844
							(0.082)	(0.112)
Baseline odds‡								
Vocational education	1.020	1.020	1.052	1.025	1.043	1.047	1.021	1.098
High school	4.959	4.913	4.890	4.907	4.990	4.877	4.856	5.128
Remaining exp. variables	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Interaction estimates jointly equal to zero (p-values)								
All interactions	0.853	0.133	0.718	0.776	0.033	0.839	0.254	0.136
Estimate and corresponding interaction estimate jointly equal to zero (p-values)								
Academic ach.	0.132	0.148	0.134	0.166	0.171	0.198	0.154	0.106
PISA index	0.229	0.749	0.042	0.332	0.183	0.025	0.404	††
Pseudo R^2	0.156	0.158	0.158	0.156	0.162	0.158	0.159	0.174
Log-likelihood	-1,792.87	-1,789.08	-1,788.85	-1,792.61	-1,780.37	-1,789.93	-1,787.97	-1,755.02
Observations	3,599	3,599	3,599	3,599	3,599	3,599	3,599	3,599

Exponentiated coefficients and robust standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. † The standard errors were found by bootstrapping using 200 replications. ‡ Baseline odds for continuous variables equal to their means, and indicator variables equal to zero. †† All p-values are above 0.10 except for instrumental motivation (0.006) and perceived self-efficacy (0.092).

The robustness checks in Table 9 use different definitions of the completion outcome variable to evaluate whether the chosen definition of completion is instrumental for the previous results. In panel A, the time frame in which the first enrolment must take place varies from 2000 to 2004. Overall, the estimation results are not sensitive to this change. In column (1), neither academic achievement nor perseverance is significant, most likely due to the reduced sample size. In panel B, the time given students to complete their education varies. Again the results are stable to this change overall. It is worth noticing that self-confidence becomes increasingly important for completion, as the time frame extends. A possible explanation for this could be that self-confidence helps students struggling to complete. The overall conclusion from Table 8 is that the results are not sensitive to exact definition of the outcome.

Table 9: Alternative definitions of the completion outcome variable. Logit estimations

	Panel A				
	First education begun no later than				
	(1) 2000	(2) 2001	(3) (2002)	(4) 2003	(5) 2004
Academic achievement†	1.390	1.364	1.395*	1.449*	1.460*
	(0.456)	(0.283)	(0.232)	(0.240)	(0.239)
× vocational†	0.905	0.904	0.869	0.852	0.830
	(0.400)	(0.240)	(0.200)	(0.197)	(0.174)
Self-confidence†	0.883	1.029	1.055	1.055	1.049
	(0.121)	(0.090)	(0.084)	(0.091)	(0.082)
× vocational†	1.157	1.047	1.032	1.051	1.072
	(0.272)	(0.136)	(0.121)	(0.136)	(0.129)
Perseverance†	1.316*	1.276***	1.254**	1.248**	1.250**
	(0.174)	(0.094)	(0.090)	(0.097)	(0.099)
× vocational†	0.797	0.817+	0.821+	0.828	0.814+
	(0.170)	(0.092)	(0.087)	(0.103)	(0.092)
Baseline odds‡					
Vocational education	1.050	1.054	1.078	1.176	1.158
High school	5.242	5.412	4.974	4.684	4.727
Remaining explanatory variables	*yes*	*yes*	*yes*	*yes*	*yes*
Pseudo R^2	0.197	0.172	0.161	0.159	0.159
Log-likelihood	-529.65	-1,568.93	-1,782.98	-1,848.49	-1,867.37
Observations	1,243	3,272	3,599	3,693	3,724
	Panel B				
	Completion within designated time frame plus				
	(1) 0 years	(2) (1 year)	(3) 2 years	(4) 3 years	(5) 4 years
Academic achievement†	1.499**	1.395*	1.359+	1.377*	1.312+
	(0.209)	(0.232)	(0.225)	(0.215)	(0.184)
× vocational†	0.772	0.869	0.888	0.845	0.911
	(0.169)	(0.200)	(0.196)	(0.182)	(0.185)
Self-confidence†	1.001	1.055	1.080	1.149+	1.163*
	(0.065)	(0.084)	(0.086)	(0.091)	(0.085)
× vocational†	1.084	1.032	0.987	0.871	0.838
	(0.118)	(0.121)	(0.123)	(0.109)	(0.106)
Perseverance†	1.113+	1.254**	1.168*	1.152*	1.136+
	(0.071)	(0.090)	(0.087)	(0.081)	(0.081)
× vocational†	0.914	0.821+	0.903	0.949	0.939
	(0.095)	(0.087)	(0.100)	(0.106)	(0.112)
Baseline odds‡					
Vocational education	0.439	1.078	1.450	1.638	1.260
High school	2.834	4.974	4.667	4.607	4.152
Remaining explanatory variables	*yes*	*yes*	*yes*	*yes*	*yes*
Pseudo R^2	0.185		0.135	0.117	0.137
Log-likelihood	-1,920.62		-1,745.18	-1,759.58	-1,817.81
Observations	3,599		3,599	3,599	3,599

The results in panel A, column (3) and panel B, column (2) are the baseline estimation and are included to ease comparisons to alternative models. Exponentiated coefficients and robust standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. † The standard errors were found by bootstrapping using 200 replications. ‡ Baseline odds for continuous variables equal to their means, and indicator variables equal to zero.

7. Conclusion

Motivated by a discrepancy between political ambitions and empirical realities, determinants for enrolment in and completion of upper secondary education in Denmark have been analysed. Focus has especially been on the roles of cognitive and noncognitive skills measured using PISA data from the OECD. The data were matched with Danish register data, and students were tracked from 1998 to 2009 to determine enrolment and completion. Measures of cognitive and noncognitive skills were formed using factor analysis.

The paper finds that academic achievement and self-confidence are important for enrolment in high school, while academic achievement and perseverance are important for completion of high school. With respect to completion of vocational education, neither academic achievement nor self-confidence and perseverance predict completion. Rather, basic attendance measures (measured during compulsory schooling) are strong predictors of completion of vocational education. The attendance measures also predict completion of high school, but to a lesser extent. Estimations of interaction effects indicate that self-confidence is of significance for women, while perseverance is of significance for men. Again, the estimates are only significant with respect to completion of high school. Various robustness checks were carried out to challenge the definition of a completed education. These showed that the specific definition of completion is not decisive for the results.

References

Ai, C., and E. C. Norton. 2003. "Interaction terms in logit and probit models." *Economics Letters* 80 (1): 123–129.

Antecol, H., and D. A. Cobb-Clark. 2010. "Do Non-Cognitive Skills Help Explain the Occupational Segregation of Young People?" IZA Discussion Paper No. 5093.

Arulampalam, W., R. A. Naylor, and J. Smith. 2012. "Am I missing something? The effects of absence from class on student performance." *Economics of Education Review* 31 (4): 363–375.

Aucejo, E. M. 2012. "Explaining Cross-Racial Differences in the Educational Gender Gap." Working Paper.

Borghans, L., A. Duckworth, J. J. Heckman, and B. T. Weel. 2008. "The Economics and Psychology of Personality Traits." *Journal of Human Resources* 43 (4): 972–1059.

Buis, M. 2010. "Stata tip 87: Interpretation of interactions in non-linear models." *The Stata Journal* 10 (2): 305–308.

Carneiro, P., C. Crawford, and A. Goodman. 2007. "The Impact of Early Cognitive and Non-Cognitive Skills on Later Outcomes." CEE DP 92.

Cobb-Clark, D. A, and M. Tan. 2011. "Noncognitive skills, occupational attachment, and relative wages." *Labour Economics* 18 (1): 1–13.

Coneus, K., and M. Laucht. 2014. "The effect of early noncognitive skills on social outcomes in adolescence." *Education Economics* 22 (2): 112–140.

Cornwell, C., D. B. Mustard, and J. van Parys. 2013. "Noncognitive Skills and the Gender Disparities in Test Scores and Teacher Assessments: Evidence from Primary School." *Journal of Human Resources* 48 (1): 236–264.

Cunha, F., and J. J. Heckman. 2007. "The Technology of Skill Formation." *The American Economic Review* 97 (2): 31–47.

Cunha, F., and J. J. Heckman. 2007. "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation." *Journal of Human Resources* 43 (4): 738–782.

Delaney, L., C. Harmon, and M. Ryan. 2013. "The role of noncognitive traits in undergraduate study behaviours." *Economics of Education Review* 32 (1): 181–195.

DellaVigna, S., and M. D. Paserman. 2005. "Job Search and Impatience." *Journal of Labor Economics* 23 (3): 527–588.

Digman, J. M. 1990. "Personality structure: Emergence of the five-factor model." *Annual Review of Psychology* 41 (1): 417–440.

Dobkin, C., R. Gil, and J. Marion. 2010. "Skipping class in college and exam performance: Evidence from a regression discontinuity classroom experiment." *Economics of Education Review* 29 (4): 566–575.

Falch, T., O. H. Nyhus, and B. Strøm. 2012. "Performance of young adults: The importance of cognitive and non-cognitive skills." Working paper.

Heckman, J. J., and Y. Rubinstein. 2001. "The Importance of Noncognitive Skills: Lessons from the GED Testing Program." *The American Economic Review* 91 (2): 145–149.

Heckman, J. J., J. Stixrud, and S. Urzua. 2006. "The Effect of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24 (3): 411–482.

Jacob, B. A. 2002. "Where the boys aren't: non-cognitive skills, returns to school and the gender gap in higher education." *Economics of Education Review* 21 (6): 589–598.

Junker, B., L. S. Schofield, and L. J. Taylor. 2012. "The use of cognitive ability measures as explanatory variables in regression analysis." *IZA Journal of Labor Economics* 1 (4).

Munk, M. D. 2013. "Completion of Upper Secondary Education: What Mechanisms Are at Stake?" *Comparative Social Research* 30: 255–291.

OECD. 2002. "*PISA 2000 Technical Report*." R. Adams and M. Wu (eds.). Paris: OECD.

Rangvid, B. S. 2012. "The Impact of Academic Preparedness of Immigrant Students on Completion of Commercial Vocational Education and Training." AKF Working Paper.

Statistics Denmark. 2011. Ungdomsuddannelser – gennemførelse og frafald 2010 (Youth education – completion and dropout 2010). *Nyt fra Danmarks Statistik* 352.

Strathman, A., F. Gleicher, D. S. Boninger, and C. S. Edwards. 1994. "The consideration of future consequences: Weighing immediate and distant outcomes of behavior." *Journal of Personality and Social Psychology* 66 (4): 742–752.

Truxillo. C. 2005. "Maximum likelihood parameter estimation with incomplete data." Proceedings of the Thirtieth Annual SAS(r) Users Group International Conference. (http://www2.sas.com/proceedings/sugi30/111-30.pdf)

Wooldridge, J. 2002. "*Econometric Analysis of Cross Section and Panel Data*." Cambridge, MA: MIT Press.

Appendix A: Factor analyses

Factor analyses were carried out to estimate proxies for the latent cognitive and noncognitive skills. Latent cognitive skills were proxied through factor analysis on the PISA WLE indices of reading (WLEREAD), math (WLEMATH) and science (WLESCIE) skills, while noncognitive skills were proxied through factor analysis on the first battery of questions from the PISA *Cross-Curricular Competencies Questionnaire* (CCCQ). The wordings of the CCCQ questions are displayed in Table A1. The data have missing observations for both the PISA WLE indices and the CCCQ questions. To avoid dropping most of the data, the factor analyses were carried out using the method described by Truxillo (2005). The idea is to use the expectation-maximization (EM) algorithm to obtain the EM covariance matrix. From this covariance matrix, the factors can then be estimated using maximum likelihood.[14]

Table A2 reports Cronbach's α and eigenvalue for the factor denoted academic achievement, based on the three WLE indices. In addition, rotated factor loadings are reported for the individual items. The factor clearly satisfies the Kaiser criterion with an eigenvalue larger than one. In addition, the internal validity is satisfactory with an α-value of 0.865. The factor primarily loads on the reading score and to a lesser extent the math and science scores.

The proxies for noncognitive skills were derived in two steps. Initially, a factor analysis was conducted using all 28 items from the CCC questionnaire listed in Table A1. The results are presented in Table A3. Three factors were identified. Two factors clearly satisfy the Kaiser criterion, while the last factor has an eigenvalue of just 1.000. For each retained factor, a new factor analysis was conducted including only items with high direct loadings and low cross loadings on other factors. Specifically, only items with direct (rotated) loadings above 0.5 and (rotated) cross

[14] The implementation of the method suggested by Truxillo (2005) in Stata is described at http://www.ats.ucla.edu/stat/stata/faq/factor_missing.htm (last visited: March 25, 2014).

loadings below 0.35 were included. The results of the three individual factor analyses are shown in Table A4. Based on the content of the included items, the factors are denoted self-confidence, perseverance and future orientation. Given the initial low eigenvalue of the future orientation factor combined with a Cronbach's α of just 0.779, the factor was only used in robustness checks. By construction, correlation between the factors is allowed. The correlation between perseverance and self-confidence is 0.604, while the correlation between academic achievement and perseverance and self-confidence, respectively, is 0.355 and 0.148.

Table A1: PISA 2000 Cross-curricular Competencies Questionnaire (CCCQ) question battery one

No.	Short names†	How often do these things apply to you?	Almost never	Some-times	Often	Almost always
1	Memorise	When I study, I try to memorise everything that might be covered	□	□	□	□
2	Understand	I'm certain I can understand the most difficult material presented in texts	□	□	□	□
3	Need to learn	When I study, I start by figuring out exactly what I need to learn	□	□	□	□
4	Difficult	When I sit down myself down to learn something really difficult, I can learn it	□	□	□	□
5	Much as possible	When I study, I memorise as much as possible	□	□	□	□
6	Job	I study to increase my job opportunities	□	□	□	□
7	Word as hard	When studying, I work as hard as possible	□	□	□	□
8	Most complex	I'm confident I can understand the most complex material presented by the teacher	□	□	□	□
9	Relate new	When I study, I try to relate new material to things I have learned in other subjects	□	□	□	□
10	Recite	When I study, I memorise all new material so that I can recite it	□	□	□	□
11	Bad grades	If I decide not to get any bad grades, I can really do it	□	□	□	□
12	Keep working	When studying, I keep working even if the material is difficult	□	□	□	□
13	Force myself	When I study, I force myself to check to see if I remember what I have learned	□	□	□	□
14	Future	I study to ensure my future will be financially secure	□	□	□	□
15	Over and over	When I study, I practice by saying the material to myself over and over	□	□	□	□
16	Problems wrong	If I decide not to get any problems wrong, I can really do it	□	□	□	□
17	Real world	When I study, I figure out how the information might be useful in the real world	□	□	□	□
18	Excellent	I'm confident I can do an excellent job on assignments and tests	□	□	□	□
19	Concepts	When I study, I try to figure out which concepts I still haven't really understood	□	□	□	□
20	Best to acquire	When studying, I try to do my best to acquire the knowledge and skill taught	□	□	□	□
21	Relating	When I study, I try to understand the material better by relating it to things I already know	□	□	□	□
22	Good job	I study to get a good job	□	□	□	□
23	Important	When I study, I make sure that I remember the most important things	□	□	□	□
24	Learn well	If I want to learn something well, I can	□	□	□	□
25	Fits in	When I study, I figure out how the material fits in with what I have already learned	□	□	□	□
26	Can master	I'm certain I can master the skills being taught	□	□	□	□
27	Additional info	When I study, and I don't understand something I look for additional information to clarify this	□	□	□	□
28	Best effort	When studying, I put forth my best effort	□	□	□	□

† The short name column was not present in the survey for the students.

Table A2: Factor analysis identifying the cognitive skill proxy

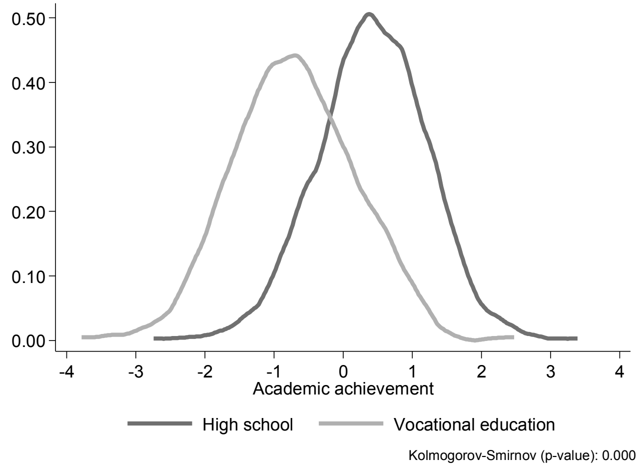
Variable (short names)	Item-test correlations	Item-rest correlations	Cronbach's α	Rotated factor loadings	Eigen-value
Academic achievement			*0.865*		2.005
Reading score	0.924	0.713	0.679	0.919	
Math score	0.887	0.698	0.840	0.748	
Science score	0.913	0.715	0.822	0.775	

Table A3: Initial factor analysis identifying noncognitive skill proxies

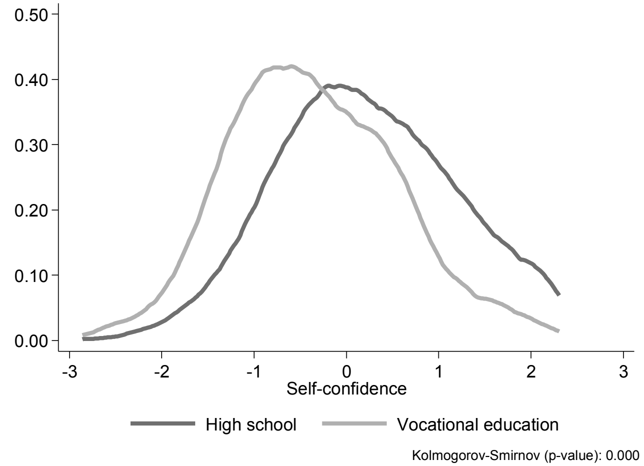
No.	Variable (short names)	N	Item-test correlations	Item-rest correlations	Cronbach's α	Rotated factor loadings		
						Factor 1	Factor 2	Factor 3
1	Memorise	3,836	0.512	0.464	0.924	0.267	0.338	0.214
2	Understand	3,818	0.569	0.523	0.924	0.622	0.172	0.098
3	Need to learn	3,817	0.464	0.411	0.925	0.218	0.322	0.183
4	Difficult	3,815	0.600	0.556	0.923	0.581	0.219	0.149
5	Much as possible	3,815	0.534	0.485	0.924	0.333	0.293	0.224
6	Job	3,802	0.521	0.468	0.924	0.171	0.179	0.641
7	Word as hard	3,812	0.637	0.596	0.922	0.394	0.396	0.265
8	Most complex	3,798	0.632	0.591	0.923	0.691	0.197	0.129
9	Relate new	3,770	0.635	0.596	0.922	0.434	0.433	0.154
10	Recite	3,774	0.552	0.509	0.924	0.287	0.406	0.185
11	Bad grades	3,781	0.562	0.515	0.924	0.547	0.177	0.170
12	Keep working	3,780	0.651	0.612	0.922	0.398	0.505	0.142
13	Force myself	3,806	0.590	0.545	0.923	0.139	0.652	0.164
14	Future	3,765	0.526	0.471	0.924	0.140	0.192	0.683
15	Over and over	3,771	0.532	0.484	0.924	0.057	0.603	0.207
16	Problems wrong	3,786	0.569	0.524	0.924	0.516	0.260	0.112
17	Real world	3,789	0.520	0.471	0.924	0.206	0.417	0.217
18	Excellent	3,781	0.548	0.504	0.924	0.633	0.105	0.142
19	Concepts	3,796	0.623	0.586	0.923	0.360	0.491	0.160
20	Best to acquire	3,779	0.657	0.621	0.922	0.343	0.523	0.224
21	Relating	3,760	0.618	0.579	0.923	0.325	0.509	0.171
22	Good job	3,732	0.501	0.448	0.925	0.122	0.124	0.781
23	Important	3,759	0.632	0.596	0.923	0.317	0.448	0.309
24	Learn well	3,764	0.612	0.573	0.923	0.531	0.253	0.220
25	Fits in	3,765	0.645	0.609	0.922	0.349	0.527	0.179
26	Can master	3,739	0.632	0.595	0.923	0.662	0.215	0.148
27	Additional info	3,758	0.567	0.521	0.924	0.249	0.506	0.150
28	Best effort	3,738	0.594	0.551	0.923	0.253	0.521	0.191
Average N		3,782	–	–	–	–	–	–
Minimum N		3,732	–	–	–	–	–	–
Test scale		–	–	–	0.926	–	–	–
Eigenvalues		–	–	–	–	8.887	1.228	1.000

Table A4: Factor analyses identifying noncognitive skill proxies in turn

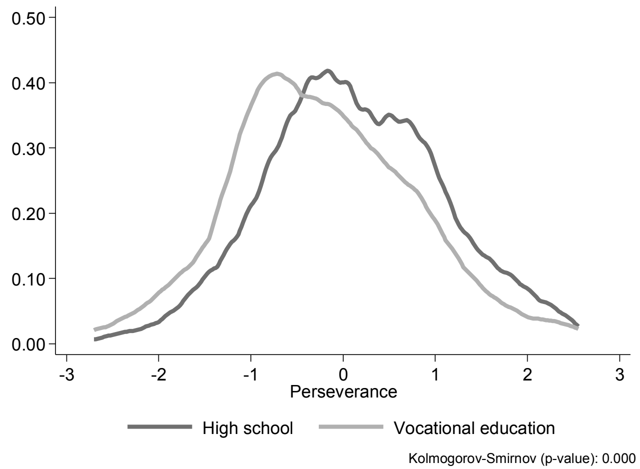
Variable (short name)		Item-test correlations	Item-rest correlations	Cronbach's α	Rotated factor loadings	Eigen-value
Self-confidence				*0.853*		3.387
2	Understand	0.685	0.569	0.838	0.637	
4	Difficult	0.697	0.578	0.837	0.630	
8	Most complex	0.747	0.648	0.829	0.721	
11	Bad grades	0.695	0.575	0.838	0.613	
16	Problems wrong	0.678	0.558	0.840	0.605	
18	Excellent	0.702	0.594	0.835	0.665	
24	Learn well	0.683	0.575	0.837	0.618	
26	Can master	0.741	0.646	0.829	0.716	
Perseverance				*0.841*		3.189
12	Keep working	0.706	0.588	0.820	0.653	
13	Force myself	0.721	0.605	0.817	0.663	
15	Over and over	0.655	0.526	0.827	0.580	
20	Best to acquire	0.708	0.601	0.818	0.667	
21	Relating	0.673	0.557	0.824	0.619	
25	Fits in	0.684	0.572	0.822	0.633	
27	Additional info	0.674	0.547	0.825	0.601	
28	Best effort	0.687	0.570	0.822	0.630	
Future orientation				*0.779*		1.629
6	Job	0.814	0.580	0.736	0.681	
14	Future	0.844	0.614	0.697	0.741	
22	Good job	0.845	0.642	0.671	0.785	



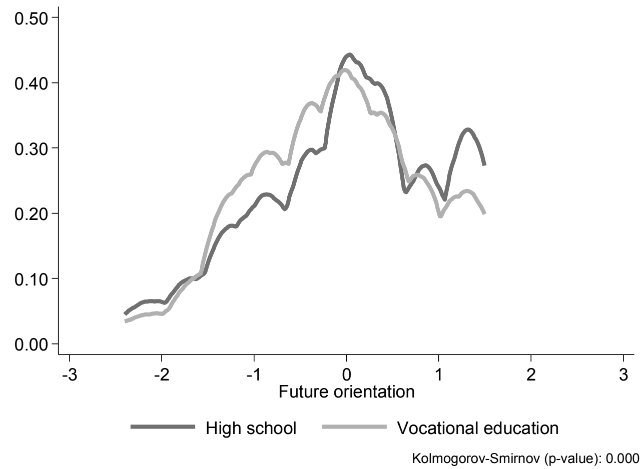
A: Academic achievement



B: Self-confidence



C: Perseverance



D: Future orientation

Figure A1: Kernel density plots of factors
by type of upper secondary education

Appendix B: Attendance and skill proxies

Table B1: Behavioural measures as outcomes. Logit estimations

	(1) Missed school days	(2) Skipped classes	(3) Late arrivals
Academic achievement†	0.830	0.840	1.019
	(0.096)	(0.127)	(0.117)
× vocational†	1.156	1.074	0.973
	(0.210)	(0.274)	(0.183)
Self-confidence†	1.009	0.987	0.987
	(0.052)	(0.070)	(0.056)
× vocational†	0.822+	0.996	1.097
	(0.083)	(0.128)	(0.126)
Perseverance†	0.881*	0.703***	0.722***
	(0.046)	(0.052)	(0.038)
× vocational†	1.115	0.954	0.954
	(0.113)	(0.120)	(0.105)
Baseline odds‡			
Vocational	0.804	0.240	0.950
High school	0.594	0.154	0.587
Remaining explanatory variables	*yes*	*yes*	*yes*
Interaction estimates jointly equal to zero (p-values)			
All interactions	0.241	0.959	0.885
Estimate and corresponding interaction estimate jointly equal to zero (p-values)			
Academic achievement	0.777	0.598	0.956
Self-confidence	0.028	0.878	0.440
Perseverance	0.832	0.000	0.000
Pseudo R^2	0.025	0.043	0.036
Log-likelihood	-2,376.17	-1,739.05	-2,332.56
Observations	3,517	3,470	3,511

Exponentiated coefficients and robust standard errors in parentheses, + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. † The standard errors were found by bootstrapping using 200 replications. ‡ Baseline odds for continuous variables equal to their means, and indicator variables equal to zero.

Chapter 3

Occupational prestige and the gender wage gap

Occupational Prestige and the Gender Wage Gap[1]

Kristin J. Kleinjans

Karl Fritjof Krassel

Anthony Dukes

Abstract

Occupational segregation by gender remains widespread and explains a significant part of the gender wage gap. We examine the explanation that heterogeneity in preferences for wages and occupational prestige leads to gender differences in occupational choices. In self-reports, women express a stronger preference than men for occupations that are more valuable to society, which we hypothesize leads women to place a relatively greater weight than men on the occupational prestige of their occupation. Using a unique data set from Denmark, we find support for this hypothesis. Gender differences are most pronounced among individuals from lower socioeconomic backgrounds.

Keywords: occupational choice, occupational prestige, social prestige, gender wage gap, gender roles

JEL Codes: D13, J16, J24

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1. Introduction

Women still earn less than men in most if not all countries (Anker, 1997; Blau, 2012). Up to one half of this gender pay gap can be explained by gender differences in occupational choice, commonly referred to as occupational segregation (Blau and Kahn, 2007; see also Hellerstein et al., 2008, and Bayard et al., 2003). Women's educational attainment has increased dramatically over the last decades, gender roles in society have changed and women's labor force attachment has increased in most industrialized countries (Blau, 2012, Blau and Kahn, 2000; Goldin et al., 2006). Young women today expect to be working throughout their lifetimes, albeit with intermittent absences for child bearing and rearing (Goldin, 2006), and women and men tend to choose different occupations even with the same level and type of education (Shauman 2006). This makes the traditional explanations of differences in human capital and expected labor force attachment less applicable, especially for young people.[2]

Our focus in this paper is on exploring whether young women and men choose different occupations because of heterogeneity in preferences over attributes of occupations. Up to now, research has mostly considered women's traditionally stronger preference for occupational attributes that make work more compatible with child rearing, such as shorter or more flexible work hours. In this paper, we consider a very different type of occupational attribute. We focus specifically on differences in how women and men trade off wage and occupational prestige, and how much wages differ as a result. Women express a stronger preference than men for occupations

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[2] In addition to the explanations of differences in human capital (Anker, 1997), expected labor force attachment (Polachek, 1981), and social roles (Eccles, 1994), recent studies have aimed at explaining occupational segregation with differences in non-cognitive skills (Cobb-Clark and Tan, 2011; Grove, Hussey, and Jetter, 2011) and differences in preferences for competition (Kleinjans, 2009), and found generally small but statistically significant effects.

that are deemed useful to society (see, for example, Fortin 2008; Grove, Hussey, and Jetter, 2011; Marini et al., 1996).[3] Hence, women likely place greater weight than men on the social value of their occupation.[4] If occupational prestige is related to the social value bestowed on an occupation, women should be more likely to choose occupations with higher prestige than men. Compensating variation leads to lower wages in occupations with higher prestige. Thus, if women sort into occupations with higher occupational prestige, their wages will be lower than those of men. To investigate this hypothesis, we analyze whether there are gender differences in the relative importance of occupational prestige for occupational choice, and whether this difference can explain part of the observed gender wage gap resulting from occupational segregation.[5]

Our results improve our understanding of reasons for occupational segregation. Furthermore, they shed light on the transmission mechanisms through which gender differences lead to differences in economic outcomes. In particular, if gender differences in preferences for wages and occupational prestige are the result of gender roles (and we find support for this interpretation), our findings can explain the mechanism by which gender roles lead to differences in occupational choices and, as a result, differences in wages.

In traditional economic models, occupational choice depends on expected wages and the cost of attaining an occupation. Sociologists – and, more recently, economists – have stressed

[3] For example, Marini et al. (1996) report that in a survey of high school seniors on the importance of job attributes women were 66% and 44% more likely than men to indicate as very important that a job is "helpful to others" and "worthwhile to society", respectively.

[4] Grove, Hussey, and Jetter (2011) find indeed that this is the case for a national sample of MBAs in the US and that it results in a wage penalty for women.

[5] This is also in line with the finding by Andreoni and Vesterlund (2001) that women are more altruistic than men when altruism is expensive.

the importance of other factors for occupational choice (Fershtman and Weiss, 1993 and 1998; Jacobs et al., 2006; Rothstein and Rouse, 2007). These include parental expectations and social norms, and non-monetary benefits, such as the social status of an occupation.

Occupational prestige (sometimes also referred to as social prestige) is defined as the social standing given to those holding a specific occupation (Hauser and Warren 1997). The occupational prestige assigned to an occupation is stable over time and similar across countries and different population subgroups, including gender (Anker, 1982; Treiman, 1977; Warren, Sheridan and Hauser, 1997). Although occupational prestige is highly correlated with wages, ability and educational requirements (Chartrand et al., 1987), occupational prestige measures cannot be explained solely by those variables. In some ways related to the notion of social status used by economists to proxy relative social standing (see, e.g., Dolton, Makepeace, and van der Klaauw, 1989; Fershtman and Weiss, 1998),[6] we think of the occupational prestige of an occupation as reflecting its perceived contribution to society (see also Anker, 1982). However, unlike social status, occupational prestige is non-rivalrous. Specifically, the contribution to society results from positive externalities of occupations or their contributions to public goods (e.g., teachers and nurses) and not from the number or type of workers in those occupations. Individuals benefit because contributing to society provides altruistic rewards (Fortin, 2008), that is, direct utility. Consequently, since women express stronger preferences for occupations that are deemed valuable to society women care more about occupational prestige than men.

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[6] Social status is generally a composite measure derived from occupational prestige, salaries, and sometimes the educational level of those holding the occupation (see Warren, Sheridan, and Hauser, 1998; and Hauser and Warren, 1997). Few economists consider occupational prestige – a notable exception is Zhang (2012), who uses prestige as a proxy for respect to analyze the effect of cultural attitudes on occupational choice.

In this paper, we are only able to speculate on the underlying reasons for these gender differences in preferences. Our findings are consistent with the explanation that they result directly or indirectly from gender role socialization. This could be through its effect on preferences (Eccles, 1994), discrimination by teachers or employers for non-traditional choices,[7] or the resulting lack of role models in non-traditional occupations (Blau, Ferber, and Winkler, 2010). It is also possible, however, that these preference differences result from gender differences in evolutionary advantages from altruistic behavior (Campbell, 2003), among other potential explanations. In this paper, we study how differences in preference for occupational prestige and wages affect occupational choice. Understanding the origins of the differences in preferences for occupational prestige and wages is beyond the scope of this paper.

In what follows, we present a simple equilibrium model of equalizing differences where occupational prestige is interpreted as an amenity. The model predicts, in particular, lower wages in occupations with higher occupational prestige for a given skill level if individuals care about occupational prestige. Hence, if women derive higher utility from occupational prestige, women will sort into lower paying but more prestigious occupations, resulting in a gender wage gap.[8] We then use a data set from Denmark to estimate a model of occupational choice in which the

[7] Compare, for example, public perception of female police officers and male receptionists or parents' and especially fathers' negative reaction to boys playing with dolls (Eliot, 2009; Fine, 2010).

[8] Such sorting could also explain why daughters have a lower intergenerational correlation of socioeconomic status than sons (Bowles and Gintis 2002), and why parental income affects men's but not women's expectations of educational achievement when parental education is controlled for (Kleinjans 2010). If more women opt for higher prestige but lower paying occupations than men, their wages have a lower correlation with parental income than men's.

probability of expecting to work in an occupation depends on occupational characteristics and individual measures of socioeconomic background and ability. [9] Our estimates indicate, indeed, that women expect to work in occupations with higher occupational prestige and lower average wages than men.

To examine the importance of these gender differences in preferences for the predicted wage gap, we study the counterfactual question of how much the gender wage gap would change if women had men's preferences for occupational prestige and wages. We find that these preference differences can explain about half of the gender gap resulting from occupational segregation. Furthermore, the gender differences are greater for individuals from lower socioeconomic backgrounds and for individuals with lower ability, in line with an interpretation that the gender differences in preferences are related to gender roles, which tend to be less traditional in higher SES families and among individuals with higher ability.

2. An Equilibrium Model of Wages and Occupational Prestige

In this section, we describe a simple equilibrium model of a labor market with occupational prestige. The objective of the model is to provide the formalization of the *theory of equalizing differences* (Rosen, 1986) as it regards the wage gap resulting from gender differences in preferences for occupational prestige (see also Hamermesh, 1999). These gender differences lead to gender segregation in occupations, which are accompanied by prestige and wage differences. We then show how this difference can be moderated by external factors, such as a worker's parental background, affecting occupational preferences.

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[9] In this paper, we cannot address gender wage differences resulting from differential sorting into firms within occupations (Blau, 2012).

There are two types of jobs, $j=0,1$, which correspond to an occupation with a low (0) and a high (1) exogenous level of occupational prestige. Workers' preferences are represented by the utility function $u(C,j)$, which is quasi-concave and increasing in C, the level of consumption purchased by wages. Occupational prestige can be considered an amenity, which provides additional utility for a given level of consumption for job $j=1$: $u(C,1)>u(C,0)$ for all C. For each worker, there exists a unique $z\geq 0$ such $u(C+z,0)=u(C,1)$, which represents the compensating variation for job $j=0$ compared with $j=1$. As discussed in the introduction, women may have a stronger relative preference for occupations with higher occupational prestige. We interpret this gender difference as follows. Let $i=F,M$ denote gender and suppose z_i uniquely solves $u_i(C+z_i,0)=u_i(C,1)$. Then $z_F>z_M$.

Using the above utility formulations, we can now derive the supply of workers. Suppose there is a set of workers with mass of one. Let $g_i(z)$ and $G_i(z)$ be the p.d.f. and c.d.f., respectively, corresponding to the distribution of workers' compensating variations, z, for each gender $i=F,M$. Assume genders have equal mass so that $G_M(\infty)=G_F(\infty)=\frac{1}{2}$. The gender differences in relative preferences over occupational prestige assumed above implies that:

$$G_F(z)<G_M(z) \text{ for all } z\in(0,\infty). \tag{1}$$

Let $\Delta w=w_0-w_1$ be the difference in wages across the two professions. Then worker i's occupational choice is $j=0$ if $\Delta w>z$ and $j=1$ otherwise. Note that any equilibrium with occupational segregation must have $\Delta w>0$ since otherwise all workers would choose occupation $j=1$. Furthermore, we shall also assume that $g_i(z)>0$ for all $z>0$ and some i so that some workers (even with very small z) have sufficiently little preference for occupational prestige and that an arbitrarily small wage differential makes occupation $j=0$ more attractive. The supply of workers N_j^S for each occupation $j=0,1$ is then expressed as

$$N_0^S = 1 - N_1^S = \int_{\Delta w}^{\infty} \left[g_F(z) + g_M(z) \right] dz = G_F(\Delta w) + G_M(\Delta w). \tag{2}$$

The number of women and men in the market for occupation j is $N_0^W = 1 - N_1^W = G_F(\Delta w)$ and $N_0^M = 1 - N_1^M = G_M(\Delta w)$, respectively.

To fully characterize the equilibrium we specify the demand side of the market. We assume that there are a set of employers that potentially hire in both occupations, $j=0$ or 1. They differ, however, in the marginal products of each type of occupation. Formally, suppose each employer's output technology is represented by linear functions: $x = a_j L_j$, where $L_j \geq 0$ is the number of workers hired in occupation j and a_j is the marginal product of labor for each occupation at a given employer. For instance, a hospital hires L_1 nurses (high occupational prestige) and L_0 janitors. Define $b \equiv a_0 - a_1$, which represents the relative marginal benefit of hiring in a low occupational prestige profession. We assume that each employer is characterized by its $b \in (-\infty, +\infty)$, whose distribution across employers is represented by the p.d.f. and c.d.f. $f(b)$ and $F(b)$. Employers hire in occupation $j=0$ if $b > \Delta w$ and $j=1$ otherwise. A necessary condition for some employers hiring in both occupations is that $F(0) < 1$. Then, the demand for workers in each profession is expressed as

$$N_1^D = 1 - N_0^D = \int_{-\infty}^{\Delta w} f(b)\, db = F(\Delta w). \tag{3}$$

The equilibrium condition is that the market clears in each occupation so that $N_j^S = N_j^D$ for $j=0,1$. Using (2) and (3), it is directly shown that any equilibrium wage differential Δw^* must satisfy $G_F\left(\Delta w^*\right)+G_M\left(\Delta w^*\right)=F\left(\Delta w^*\right)$. Workers are employed in both occupations as long as $G_i\left(\Delta w^*\right)\in\left(0,1/2\right)$ for some i. By the condition on g_i mentioned above, this is the case as long as $\Delta w^*>0$, which is implied by our assumption that $F\left(0\right)<1$.

We now establish that in equilibrium, there is gender segregation with a corresponding wage gap. Denote by N_j^i the equilibrium level of employment for gender i in occupation j. The assumption on gender preference differences in (1) implies $N_0^W<N_0^M$ and $N_1^W>N_1^M$, or that there is a greater portion of women (men) in the high (low) occupational prestige profession, $j=1$, than of men (women). The weighted wage differential across the population is

$$\bar{w}_F^*-\bar{w}_M^*=\frac{w_0^*N_0^W+w_1^*N_1^W}{N_0^W+N_1^W}-\frac{w_0^*N_0^M+w_1^*N_1^M}{N_0^M+N_1^M}<2w_1^*\left[\left(N_0^W+N_1^W\right)-\left(N_0^M+N_1^M\right)\right],$$

where the inequality holds because $\Delta w^*=w_0^*-w_1^*>0>N_0^W-N_0^M$. Since the RHS of the above inequality is zero ($N_0^i+N_1^i=1/2$, both i), we have $\bar{w}_F^*-\bar{w}_M^*<0$. Women earn less, on average, than men. This also implies that occupations with greater female shares have lower wages than those with greater male shares, in line with observed occupational pay differences (Blau, 2012).

Finally, we argue how external factors can affect worker preferences for occupations and ultimately the degree of gender segregation and wage differentials. Workers preferences for the degree of occupational prestige in an occupation may be affected by socioeconomic background (SES), for example, if gender roles are more traditional in lower SES families. This may also be reflected by ability if individuals with higher ability are more likely to challenge traditional gender roles. To implement this notion formally, rewrite the utility of a worker of type $i=F,M$ as $u_i\left(C,j;P\right)$, where P represents SES and ability and let $z_i\left(P\right)$ uniquely solve $u_i\left(C+z_i\left(P\right),0,P\right)=u_i\left(C,1,P\right)$. Since higher parental SES and ability may lead to less traditional gender roles, we interpret this by saying that $\kappa(P) = z_F(P) - z_M(P) > 0$ is a decreasing function of P for all C. It follows directly that gender segregation in occupations and the wage gap Δw decreases in P. If $\kappa(\bar{P}) = 0$ for sufficiently large $\bar{P}$, then gender segregation and the wage gap disappear.

3. The Gender Wage Gap in Denmark

In our empirical analysis, we use data from Denmark. Denmark is well-suited for our study because it has a gender wage gap that is similar to other countries and high levels of occupational segregation. At the same time, gender differences in labor force participation and part-time employment are relatively small, decreasing the importance of gender differences in expected labor force attachment for occupational choice. In what follows, we briefly describe these features.

The raw gender wage gap in Denmark is similar to many countries with about 16.4%.[10] As in many other countries, it cannot be explained by greater educational achievement by men since gender differences have narrowed over the past decades and are now reversed - women's average years of education are 13.2 compared to men's 12.3 years.[11] Despite women's increased educational achievement, occupational segregation in Denmark remains widespread. As an example, Figure 1 shows segregation by gender by industry; four of the ten industries have a 70% or higher share of one gender employed. Denmark differs, however, from other industrialized (non-Scandinavian)

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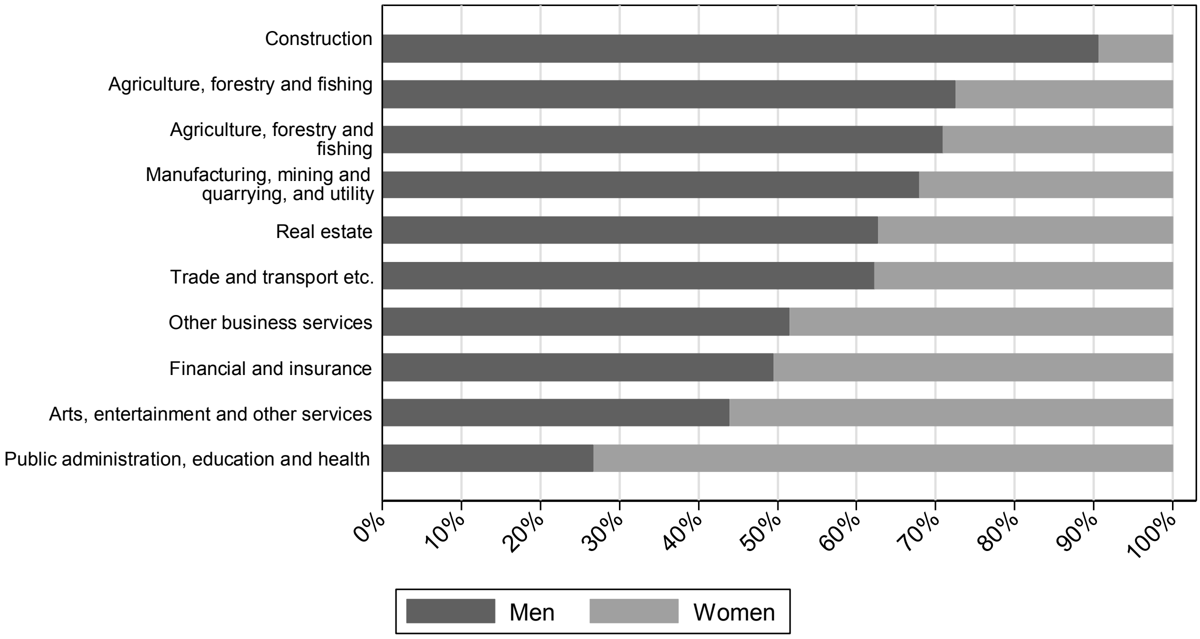
[10] Source: Eurostat, "Gender pay gap statistics" - Statistics Explained (http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Gender_pay_gap_statistics, accessed March 25, 2014). This is based on hourly earnings in 2007; the gap is about 4%-points smaller for performed work hours, and fluctuates with the business cycle (Larsen and Houlberg, 2013).

[11] Own calculations based on Statistics Denmark and ISCED97 for 2011 (www.statistikbanken.dk, KRHFU1, http://eng.uvm.dk/Uddannelse/Education%20system.aspx, accessed March 25, 2014).

countries in its relatively high labor force participation of both men and women and relatively low prevalence of female part-time employment. Denmark has strong dual-earner family policies with universal child care and paid parental leave (Lambert 2008), so, not surprisingly, the Danish gender gap in labor force participation of 7.0 percentage points is much smaller than in other countries, such as Germany (11.8 percentage points), the UK (14.4 percentage points), and the U.S. (13.5 percentage points).[12] This makes Denmark a good country to study occupational choice since differences in labor force attachment are smaller than in many other countries.

[12] Own calculations based on OECD Labour Force Statistics for 2010. Individuals in education are counted as being in the labor force. (http://stats.oecd.org/Index.aspx?DataSetCode=LFS_D, accessed March 25, 2014).



Source: Statistics Denmark.

Figure 1: Occupational Segregation by Gender in Denmark
(full time employed), 2008

The gender gap in part-time work is also smaller in Denmark than in other countries. In 2010, 24.1% of women worked part-time versus 12.0% of men – in contrast, for example, to Germany, where the share of women working part-time was 30.8% and that of men 8.4%.[13] Since part time workers tend to receive lower (hourly) wages, the tradeoff between wages and occupational prestige is different for people expecting to work part time from those who do not. As before, this makes Denmark a good country to study occupational choice since the smaller the gender gap the smaller is the potential impact of expected lower work hours. We come back to the role of preferences for short and flexible work hours for occupational choice in Section 5.

[13] Own calculations based on OECD Labour Force Statistics (http://stats.oecd.org Index.aspx?DataSetCode=FTPTC_D, accessed March 25, 2014). Part time is defined as working fewer than 30 work hours in the main job.

4. Data and Variables Used

We use a unique data set from Denmark that combines individual characteristics from survey and assessment data, occupational information drawn from population registries, and a measure of the occupational prestige of different occupations from a market research survey. A key advantage of this data set is that it allows us to distinguish the importance of occupational prestige from other correlated occupational and individual characteristics, such as wages and ability. Specifically, by using an exogenous source of occupational prestige we avoid the potential pitfall of endogeneity of expectations and occupational prestige.

We draw upon data from four sources, two of which come from the Danish PISA-Longitudinal data base.[14] The first is the 2000 OECD *Programme for International Students Assessment* (PISA) survey of nationally representative ninth graders. The second is a PISA follow-up survey entitled *Young people in job or education – values, choices and dreams for the future*, which re-interviewed the, by then, 19-years old PISA respondents in 2004. From the first survey, we draw the ability measure while we use occupational expectations from the latter (see more below). Parental income and education are drawn from matched Statistics Denmark registers for the year 2003. We use registry data from the entire Danish population in 2003 to derive the occupation-specific measures. The final source is a survey from 2006 conducted by *Ugebrevet A4*, a Danish news media owned by *LO, The Danish Confederation of Trade Unions*, in which a representative sample of 2,155 Danes was asked to score 99 occupations according to their occupational prestige by assigning a number from 0 (lowest) to 10 (highest)[15]. The survey was conducted in collaboration

[14] See Jensen and Andersen (2006) for more information on this data set.

[15] The exact wording the question asked was: ”How would you assess the prestige of the following occupations in Denmark? You can answer from 0 (no prestige at all) to 10 (very high prestige).

with *Analyse Danmark*, a Danish market research institute. The respondents were drawn from *Analyse Danmark's* multiple purpose web panel.

4.1 Outcome Variable

Occupational choice is derived from answers to a question in the PISA follow-up survey. Respondents were asked in which occupation they expect to work at age 30. Teenagers' expectations have been found to be predictive of outcomes (Fischhoff et al., 2000) and occupational expectations to be predictive for professionals (Schoon, 2001). Moreover, in Denmark the choice of occupation is closely related to educational choices, such as college major or type of educational training, mitigating the effect of the time difference between the age at the time of the survey and expected occupation. In addition, since occupational expectations reflect plans and intentions they are a good measure of the effect of occupational prestige and wages on occupational choice.

4.2 Occupation-Specific Variables

The occupational prestige scores are drawn from the above-mentioned survey conducted by *Analyse Danmark*. The occupational prestige of an occupation is measured as the mean score given by the respondents of the survey. Because there are some (albeit small) differences in the scores by age of the respondents, we use the scores of the youngest respondent category (ages 18-29). We match the expected occupation at age 30 to these scored occupations and link them to the occupation-specific variables extracted from the registry data for the entire Danish population. Occupation-specific variables include median annual wages of fulltime workers and their standard deviation.[16] Wages are divided by 50,000 to allow a rough comparison to $10,000 US dollars. Table A1 in the appendix shows the descriptive statistics by occupation, and the data appendix gives more information on the sample selection and matching.

[16] Fulltime is defined as working 30 hours or more.

The standard deviation of wages is included to proxy for risk to rule out the possibility that we erroneously attribute the effect of gender differences in risk aversion to gender differences in preferences for wages and occupational prestige. Women have been found to be more risk averse than men (see, for example, Powell and Ansic, 1997; and Croson and Gneezy, 2009, for experimental evidence) and studies have found that a small part of the gender pay gap can be explained by gender differences in attitudes towards economic risk (Le et al., 2011).

4.3 Individual-Specific Variables

The PISA reading test score is used as an objective measure of ability and skill. We transform the score into dummy variables for quartiles, calling the lowest quartile “low ability” and the highest quartile “high ability”. To control for socioeconomic status, we use parental income quartiles (labeled as before “low” if in the first quartile and “high” if in the highest) and parental education. For the latter, we use the highest education of the two parents, and label “low education” if it is vocational or below and “high” if one parent has a master degree (omitted level: short or medium, equivalent to an associate degree or higher but less than a master’s degree).

We also include the answers to a question in the follow-up survey about which of the three attributes are considered most important in a job: shorter/ convenient work hours, “That it is challenging”, or job safety (we exclude “don’t know” and missing answers in the respective estimation). It is possible that women expect to work fewer hours than men, at least during child bearing years. If this is the case then it likely affects occupational choice since part-time workers are paid less because they work fewer hours but also because hourly wages tend to be lower in part time positions (Manning and Petrongolo, 2008). We include these variables in a robustness check since it may be easier to work part time in occupations that have higher occupational prestige, for example, because they are in the public sector.

4.4 Descriptive Statistics

Table A2 in the appendix shows summary statistics by gender. In our working sample, women have 8.4% lower median wages in their expected occupation and 4.6% lower occupational prestige scores than men. As expected, wages and occupational prestige have a high correlation with 0.71. The joint distribution of wages and occupational prestige shows a pattern that is consistent with the hypothesis that women compared to men value occupational prestige relatively higher. Figure 2 shows a scatter plot of men's and women's occupational prestige and median hourly wages, including a fitted fractional polynomial curve. For any given wage, the predicted curve for women indicates a higher level of occupational prestige than for men. This comparison suggests that, for any wage, women's expected occupation tends to have higher occupational prestige. As a reference, Figure A1 in the appendix displays the distribution of wages sorted by occupational prestige for men and women combined; it also shows that there is no monotonic relationship between these two variables.

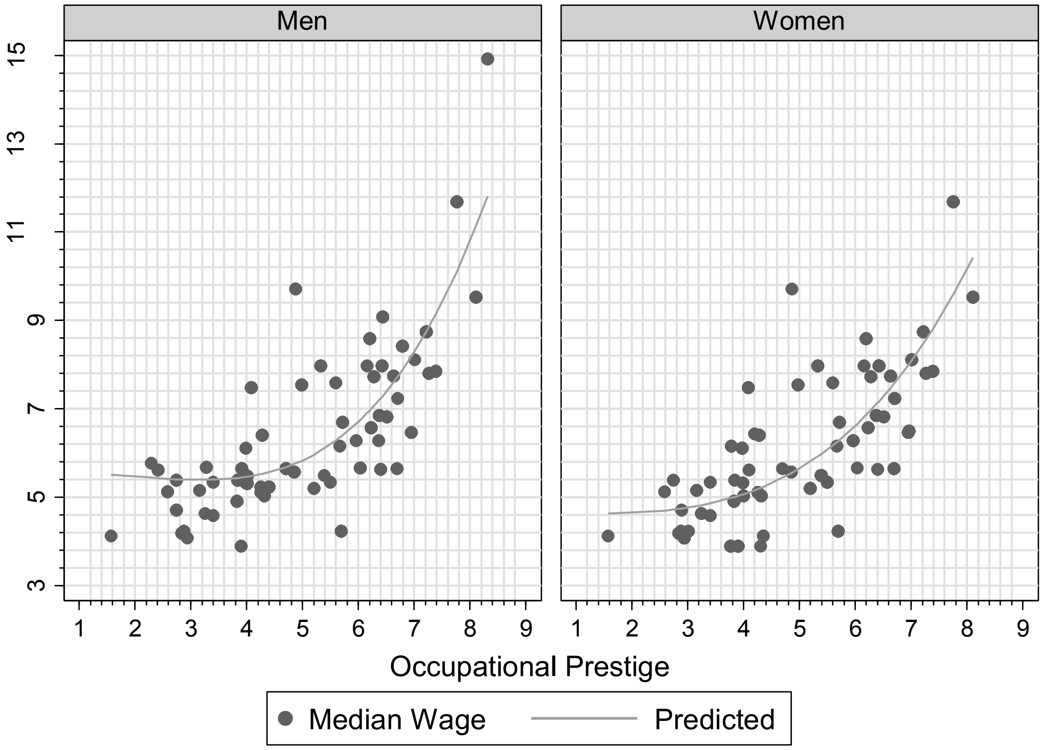


Figure 2: Scatter Plot of Wage and Occupational Prestige by Gender

5. The Effect of Occupational Prestige on Occupational Choice

To assess how gender differences in preferences for occupational prestige and wages affect occupational choice, we estimate a conditional logit model explained in the next subsection. We then discuss the baseline results, followed by an exploration of gender roles as an explanation of why wage and occupational prestige differently affect women's and men's choices of occupation, and potential additional explanations for our results.

5.1 Econometric Model

Since we are interested in the effect of occupation-specific characteristics on the likelihood of an occupation being chosen, we maximize the conditional likelihood with the following conditional probability (Greene 2003):

$$Prob\left(Y_i = j | z_{i1,} z_{i2}, \ldots, z_{iJ}\right) = \frac{e^{\beta' z_{ij}}}{\sum_{j=1}^{J} e^{\beta' z_{ij}}},$$

where j is the chosen occupation, and z_{ij} are the occupation-specific characteristics as well as interaction terms of occupation- and individual-specific characteristics, such as ability and the occupational prestige of an occupation. All models are estimated using robust standard errors. For ease of exposition, we split the sample by gender and present odds ratios. To account for differences in preferences by SES and ability, we include interaction terms of parental income quartiles (1. and 4.), ability quartiles (1. and 4.), and highest parental education with wage and occupational prestige in some of the estimations.

There are two main potential identification issues: reverse causality and confounding variables. Reverse causality in this context could be caused by the share of women in an occupation affecting its occupational prestige, a hypothesis sometimes put forward in sociology. There is, however, no evidence that this might be the case (see England, 1979; Magnusson, 2009). Indeed, according to the survey used in our analysis, mixed occupations (defined as having at least 20% of each gender in an occupation) have the highest occupational prestige. Only three out of the top ten occupations have more extreme gender differences, two of which are overwhelmingly male (*pilots* and *civil engineers*) and one female (*midwives*). Note that since our occupational prestige measures comes from a different survey there is no concern about justifiability bias with individuals giving higher occupational prestige to desired occupations.

Confounding variables are the variables that affect preferences for occupational prestige and wages and occupational choice but are omitted from our empirical model. Two potentially important factors are preferences over risk and work hours. The latter would change the trade-off between wages and occupational prestige since wages are lower for shorter work hours while occupational prestige may not be affected by the number of hours worked. Likewise, the coefficients on wages and occupational prestige could reflect differences in risk aversion if occupations with lower occupational prestige have different risk levels, for example, because prestigious occupations tend to be in the public service. However, we control for these variables by including the standard deviation of wages of an occupation as a measure of risk, and a preference for short/ convenient work hours in a robustness check. The remaining potentially (and likely) confounding variable is the effect of gender roles, which we discuss below in detail.[17]

5.2 Baseline Results and Discussion

The results of our baseline estimation are presented in Table 1. Columns (1) and (3) show the odds ratios when only wage and its standard deviation are included as explanatory variables. Occupations with higher wage are more likely to be chosen. Women and men prefer occupations with lower standard deviations of wages - women more so than men, in line with previous findings that women are more risk averse.

[17] One issue we cannot address in this paper is the role of the marriage market. There is evidence for positive assortative mating by education but not by income (Bruze, Svarer, and Weiss, 2012). Hence, occupational choice might be affected by expectations about a future spouse's income and occupational prestige.

Table 1: Conditional Logit Model of Occupational Choice: Baseline (Odds Ratios shown)

	Women		Men	
	(1)	(2)	(3)	(4)
Wage	1.107***	0.964	1.185***	1.090***
	(0.028)	(0.031)	(0.031)	(0.029)
Occupational prestige		1.240***		1.164***
		(0.031)		(0.034)
Standard deviation of wage	0.752***	0.762***	0.890**	0.898*
	(0.046)	(0.047)	(0.051)	(0.052)
Pseudo R^2	0.004	0.026	0.009	0.022
Log Likelihood	-3,983.81	-3,893.43	-3,697.38	-3,650.28
# of individuals	929	929	867	867
Observations	68,746	68,746	64,158	64,158

Clustered standard errors in parentheses. ^ p<0.15, * p<0.10, ** p<0.05, *** p<0.01. All odds ratios are statistically significantly different between men and women at the 10% percent level or less.

Table 1, rows (2) and (4) show the results with occupational prestige added to the specification. The results show that women place more weight on occupational prestige and less on wages compared to men. These differences are statistically and economically significant. A one unit increase in occupational prestige (about two thirds of a standard deviation, and the equivalent of moving in terms of occupational prestige from a physiotherapist to a police officer) increases women's probability of choosing an occupation 1.24 times and men's 1.16 times. The gender differences in the effects of wages and its standard deviation are not much affected by the inclusion of these two variables though now for women wage becomes not statistically significant.[18] Based on

[18] This non-effect disappears once a more complete specification is used. While this lack of importance of wages for women's occupational expectations in this baseline regression at first might seem surprising, this is in line with previous findings that compared to non-pecuniary factors earnings have only small effects on postsecondary choice of major, especially for women (Zafar, 2013; Wiswall and Zafar, 2011).

the second specification, comparing women's predicted wages with the counterfactual prediction that women have men's preferences for occupational prestige and wages, we find that about half of the predicted 8.4% wage gap can be explained by the gender differences in the effects of wages and occupational prestige on occupational choice. (Note that we assume at this point that there is no gender wage gap within occupations; we discuss this issue in more detail in section 5.4.)

To investigate the robustness of the results presented in Table 1 we conducted various robustness checks for the second specification (results not shown). Using hourly wage instead of annual wage did not affect the results. Excluding occupations chosen by fewer than four individuals or by 125 or more likewise did not affect the results. Lastly, we excluded individual occupations to assess whether the results are driven by specific occupations. Qualitative results did not differ, though in a few cases (when excluding nurses or sales persons) odds ratios of occupational prestige were not statistically different by gender, but the difference in the effect of wage remained.

5.3 Are Gender Differences in Preferences for Occupational Prestige the Result of Gender Roles?

One of the explanations for occupational segregation put forward is the influence of gender role socialization on educational and occupational choices (see, e.g., Eccles, 1994). Occupational choices are influenced by one's socioeconomic background and ability (Turner and Bowen, 1999), and parental income and parental education affect girl's and boy's educational expectations differently (Kleinjans, 2010). Gender roles are more traditional in lower SES families (Dryler, 1998) and for lower ability individuals (Ahrens and O'Brien, 1996; Fassinger, 1990), and parents' approval is an important determinant for children's occupational and college-major choice (Jacobs, Chhin, and Blecker, 2006; Zafar, 2013). This is supported by the high degree of occupational segregation of low-ability individuals in our data: The majority of occupations (79%) in which individuals with low ability expect to work require vocational training or less, and these occupations are highly segregated by gender with 74% of occupations having 75% or more workers of one gender compared to 21% of occupations requiring a master degree. If the importance of occupational prestige and wages for occupational choice is related to gender roles, then we would expect gender differences to be most pronounced for low SES and low ability individuals.

To test this hypothesis, we include interaction terms between ability (measured by a dummy for the lowest quartile and one for the highest quartile) as well as by SES (measured by parental income quartiles and highest parental education) with wage and occupational prestige variables (see Table 2).[19] The results support the hypotheses, showing the greatest gender differences for low ability and low SES individuals, with ability as the most important factor. Women with low ability (or whose parents have low levels of education) choose occupations with lower wages and higher occupational prestige than similar men. The counterfactual predicted wages for either specification, assuming that women had men's preferences for occupational prestige and wages (but their own ability or SES distribution) are similar to the one from our baseline with the standard deviation of wages included, and as expected there is a greater closing of the wage gap for women with lower ability or lower SES. Figure 3 shows the resulting changes in predicted probabilities for the specification including ability interactions, with occupations sorted by occupational prestige. As expected given the gender differences in odds ratios, women's expected occupations change significantly.

Gender role attitudes are transmitted from parents to children. Farre and Vella (2013) have investigated the effects of this transmission on female labor force participation. They find that for daughters, this transmission operates primarily through education, while sons with more traditional views are more likely to marry women with less labor market attachment. To investigate the role of

[19] We do not show the specification including all three measures since cell sizes become rather small for meaningful inference.

parental attitude, we constructed dummies for a low, medium, or high share of women in the mother's and the father's occupation and included those interacted with wage and occupational prestige in the baseline regression including the standard deviation of wages (results not shown). While this asks a lot of our data given the number of interactions with occupational prestige and wage, we find, in line with Farre and Vella's findings, that if there are less than one third of women in the father's occupation then men put less weight on occupational prestige and women put less weight on wages.

Table 2: Effects of Parental SES and Ability on Occupational Expectations

(Odds ratios shown)

	Women		Men	
	(1)	(2)	(3)	(4)
Wage	1.000 ‡	1.039	1.088*** ‡	1.040
	(0.040)	(0.052)	(0.035)	(0.039)
Wage × low ability	**0.549*****		**0.922***	
	(0.047)		(0.043)	
Wage × high ability	1.087*		0.996	
	(0.050)		(0.036)	
Wage × low parental education		0.853*** †		1.016 †
		(0.048)		(0.039)
Wage × high parental education		1.014		0.985
		(0.062)		(0.054)
Wage × low parental income		0.895 ‡		1.047 ‡
		(0.070)		(0.049)
Wage × high parental income		1.043		1.068^
		(0.055)		(0.045)
Occ prestige	1.193***	1.362***	1.226***	1.414***
	(0.041)	(0.072)	(0.047)	(0.082)
Occ prestige × low ability	**1.036**		**0.748*****	
	(0.066)		(0.047)	
Occ prestige × high ability	1.265***		1.378***	
	(0.081)		(0.109)	
Occ prestige × low parental edu.		0.914^ †		0.763*** †
		(0.053)		(0.049)
Occ prestige × high parental edu.		1.186^		1.227*
		(0.140)		(0.144)
Occ prestige × low parental income		0.863**		0.865**
		(0.053)		(0.057)
Occ prestige × high parental income		1.029		1.011
		(0.068)		(0.076)
Standard deviation of wage	0.731*** †	0.746*** †	0.886** †	0.890** †
	(0.049)	(0.049)	(0.052)	(0.052)
Pseudo R^2	0.030	0.022	0.028	0.023
Log Likelihood	-3,880.46	-3,910.21	-3,626.37	-3,647.40
# of individuals	929	929	867	867
Observations	68,746	68,746	64,158	64,158

Clustered standard errors in parentheses. ^ p<0.15, * p<0.10, ** p<0.05, *** p<0.01. Bold (†, ‡) in columns (1)-(10) indicates statistically significantly different odds ratios between men and women at the 1% (5%, 10%) percent level.

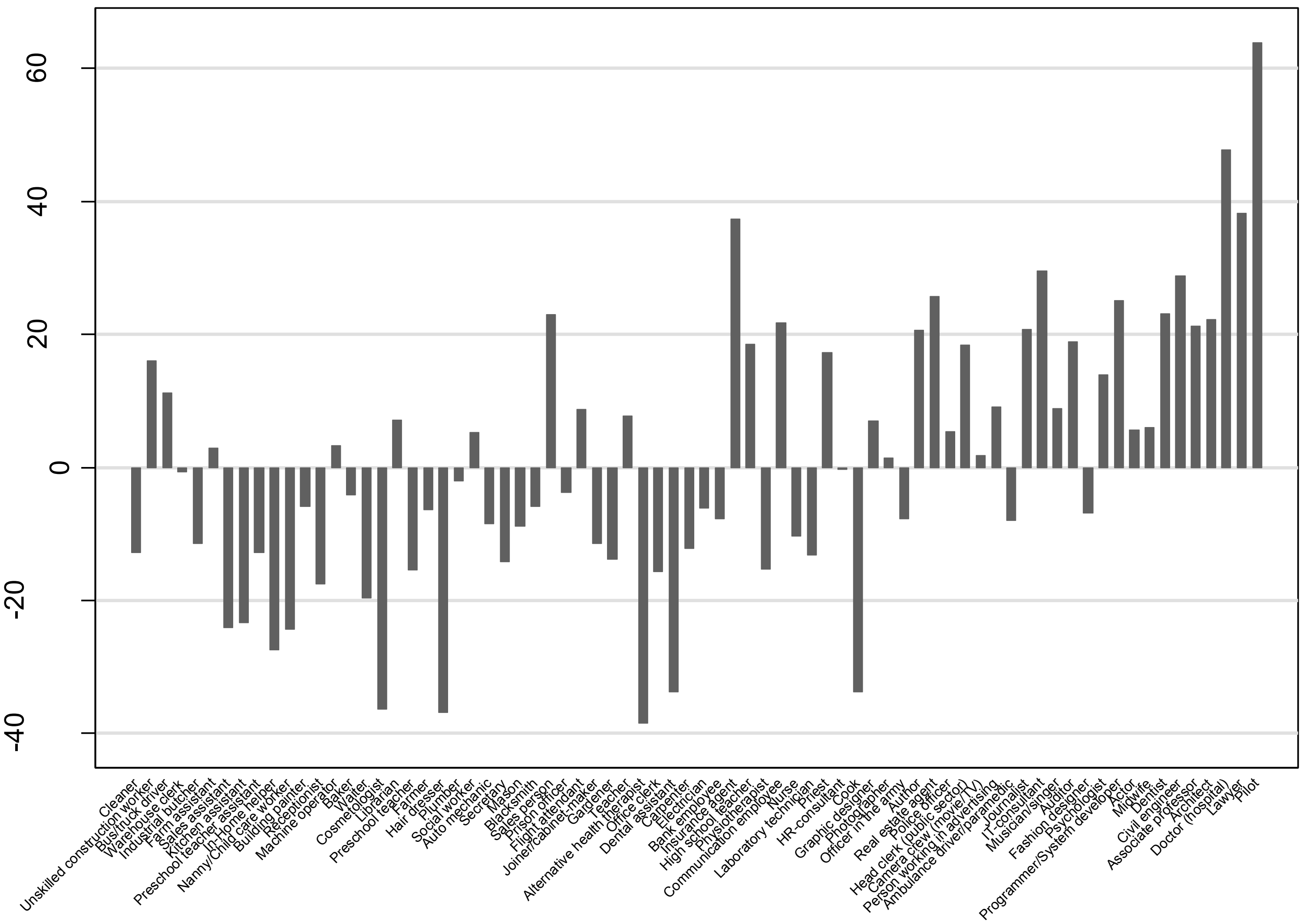


Figure 3: Percentage Change in Predicted Probabilities from Counterfactual

Occupations sorted by Occupational Prestige

5.4 Additional Explanations

Preferences for Shorter and More Flexible Work Hours

To assess whether our results are driven by women preferring work with shorter or more flexible work hours – which may lead to lower expected wages – we reestimated our model using answers to a question in the survey about preferences for work attributes (see the data section for more detail), which included the option of shorter/ convenient work hours. While we found gender differences in the interaction terms of wage risk and wages (women are willing to give up more wage in exchange for lower risk),[20] there was no statistically significant effect for either gender for any of the interactions with short/convenient work hours (results not shown). We conclude from this that there is no evidence that gender differences in preferences for work hours affect our results.

The Role of Choice Set Restrictions through Educational Requirements

So far, we have assumed that all occupations are in individual choice sets. It is possible, however, that certain occupations requiring higher education might be excluded as potential options by those who do not fulfill minimum requirements. To rule out that our findings are the result of not taking this into account, we re-estimated the model without those who do not have a high school degree since many occupations are not available to them because of educational requirements

[20] This could also explain why more women than men in Denmark work in the public sector. While as of 2008, public sector jobs in Denmark do not offer more generous benefits or shorter work hours than jobs in the private sector (Westergaard-Nielsen, 2008) they are still safer. The other facet of public sector employment is that occupations with higher occupational prestige are more likely to be in the public sector because of their higher social contributions.

(results not shown).[21] Doing this reduced the sample size considerably, but the results and predictions from the model including parental SES and ability are qualitatively similar to our earlier results,. Counterfactual predictions (using the specification including ability) show greater average wages for women than for men.

The Gender Wage Gap Within Occupations

So far, we have assumed that women and men in the same occupation expect to receive the same wage. However, this might not be the case, even though a Danish anti-discrimination law makes it illegal to pay different wages for identical work.[22]

In a recent report, the Danish Wage Commission estimates an unexplained gender wage gap of 7.1% (Lønkommissionen, 2010).[23] To investigate whether our results are related to women expecting to earn lower wages, we assumed that women expect to receive 7.1% lower wages than the wages used so far. The results of the estimation are qualitatively similar (not shown). As expected, since women's wages are lower compared to before, the counterfactual prediction (using the specification including ability) shows less of a closing of the wage gap, which is now reduced by one third overall, and more so for women's at the lowest ability quartile, where the gap is reduced by 52%.

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[21] The sample of only those without a high school degree and only occupations not requiring a high school degree was too small for a meaningful analysis.

[22] See https://www.retsinformation.dk/Forms/R0710.aspx?id=121176 (accessed March 25, 2014).

[23] This controls for education, experience, sector, industry, work responsibilities, living alone, number of children, and living in the Copenhagen area.

5.5 Summary

Our estimates show that differences in preferences for occupational prestige and wages can explain about half of the gender wage gap of 8.4% resulting from occupational segregation in our sample. This effect is particularly strong for individuals with low ability or from low-SES backgrounds, which we interpret as supportive evidence for gender roles as the basis for the gender differences in preferences. Gender differences in risk aversion as measured by the standard deviation of wages affect the gender wage gap, but we do not find evidence for gender differences in preferences for shorter or more convenient work hours. Our results are robust to choice set restrictions through the lack of educational attainment and to lower wages expected by women.

6. Conclusions

Despite women's increased educational achievement, women and men often work in different occupations. This occupational segregation can explain up to one half of the raw gender wage gap, but it is not well understood why such segregation persists. In this paper, we investigate an explanation that is based on job attributes, and more precisely, the idea that women place more weight on the occupational prestige of an occupation than men. Women have been found to value an occupation's social contribution more than men, which we proxy with the occupational prestige of an occupation. If occupational prestige gives benefits to holders of occupations, and if these benefits vary by gender, differences in occupational choices can be partly explained by these differences in preferences.

To investigate this hypothesis, we use a Danish data set that includes rich information on individuals' expected occupations, ability, and parental background, and on occupational characteristics. The raw data shows a clear difference in the occupational prestige of expected occupations by gender – at the same wages, women's expected occupations have higher occupational prestige.

We find that women expect to work in occupations with higher occupational prestige and lower median wages than men. This is consistent with the hypothesis that part of the gender wage gap can be explained by the occupational segregation caused by women's stronger preference for occupational prestige – these occupations with higher occupational prestige have, in an equilibrium setting in a competitive labor market, lower wages. We find that gender differences in preferences for occupational prestige and wages are the highest for low ability and low SES individuals, which is in line with the hypothesis that these preferences are affected or maybe even caused by the perception of gender roles. Counterfactual predictions show that a significant part (up to one half) of the gender wage gap can be explained by these preference differences. We conclude from this that an important fraction of the gender wage gap results from different choices that women and men make that are based on differences in preferences for wages and occupational prestige. While we are not able to identify the origin of these gender differences, we find evidence in line with the hypothesis of gender roles as a potential source. If this is indeed the case, then gender differences in preferences for occupational prestige can help us understand the transmission mechanism from gender roles to different occupational choices and, as a result, gender differences in wages.

References

Ahrens, J. A., and K. M. O'Brien. 1996. "Predicting Gender-Role Attitudes in Adolescent Females: Ability, Agency, and Parental Factors." *Psychology of Women Quarterly* 20 (3): 409–417.

Andreoni, J., and L. Vesterlund. 2001. "Which is the Fairer Sex? Gender differences in altruism." *Quarterly Journal of Economics* 116 (1): 293–312.

Anker, R. 1997. "Theories of Occupational Segregation by Sex: An overview." *International Labor Review* 136 (3): 315–339.

Bayard, K., J. Hellerstein, D. Neumark, and K. Troske. 2003. "New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employer-Employee Data." *Journal of Labor Economics* 21 (4): 887–922.

Blau, F. D. 2012. "*Gender, Inequality, and Wages*." Oxford: Oxford University Press.

Blau, F. D., M. A. Ferber, and A. E. Winkler. 2010. "*The Economics of Women, Men, and Work. Upper Saddle River.*" New Jersey: Prentice Hall.

Blau, F. D., and L. M. Kahn. 2007. "The Gender Pay Gap." *The Economists' Voice* 4 (4): article 5.

Blau, F. D., and L. M. Kahn. 2000. "Gender Differences in Pay." *Journal of Economic Perspectives* 14 (4): 75–99.

Bruze, G., M. Svarer, and Y. Weiss. 2012. "The Dynamics of Marriage and Divorce." University of Aarhus Economics Working Paper 2012–06.

Campbell, A. 2003. "A Mind of Her Own: The evolutionary psychology of women." New York: Oxford University Press.

Chartrand, J. M., T. E. Dohm, R. V. Dawis, and L. H. Lofquist. 1987. "Estimating Occupational Prestige." *Journal of Vocational Behavior* 31 (1): 14–25.

Cobb-Clark, D. A., and M. Tan. 2011. "Noncognitive skills, occupational attachment, and relative wages." *Labour Economics* 18 (1): 1–13.

Croson, R., and U. Gneezy. 2009. "Gender Differences in Preferences." *Journal of Economic Literature* 47 (2): 1–27.

Dolton, P. J., G. H. Makepeace, and W. van der Klaauw. 1989. "Occupational Choice and Earnings Determination: The role of sample selection and non-pecuniary factors." *Oxford Economic Papers New Series* 41 (3): 537–595.

Dryler, H. 1998. "Parental Role Models, Gender, and Educational Choice." *The British Journal of Sociology* 49 (3): 375–398.

Eccles, J. S. 1994. "Understanding Women's Educational and Occupational Choices: Applying the Eccles et al. model of achievement-related choices." *Psychology of Women Quarterly* 18 (4): 585–609.

Eliot, L. 2009. "*Pink Brain, Blue Brain: How small differences grow into troublesome gaps – and what we can do about it*." Boston, New York: Mariner Books, Houghton Mifflin Harcourt.

England, P. 1979. "Women and Occupational Prestige: A case of vacuous sex equality." *Signs* 5 (2): 252–265.

Farre, L., and F. Vella. 2013. "The Intergenerational Transmission of Gender Role Attitudes and its Implications for Female Labour Force Participation." *Economica* 80 (318): 219–247.

Fassinger, R. E. 1990. "Causal Models of Career Choice in Two Samples of College Women." *Journal of Vocational Behavior* 36 (2): 225–248.

Fershtman, C., and Y. Weiss. 1993. "Social Status, Culture and Economics Performance." *Economic Journal* 103 (419): 946–959.

Fershtman, C., and Y. Weiss. 1998. "Social Rewards, Externalities, and Stable Preferences." *Journal of Public Economics* 70 (1): 53–73.

Fine, C. 2010. "*Delusions of Gender: How our minds, society, and neurosexism create difference.*" New York, London: W. W. Norton & Company.

Fischhoff, B., A. M. Parker, W. Bruine de Bruin, J. Downs, C. Palmgren, R. Dawes, and C. F. Manski. 2000. "Teen Expectations of Significant Life Events." *Public Opinion Quarterly* 64 (2): 189–205.

Fortin, N. M. 2008. "The Gender Wage Gap among Young Adults in the United States: The importance of money versus people." *Journal of Human Resources* 43 (4): 885–918.

Goldin, C. 2006. "The Quiet Revolution that Transformed Women's Employment, Education, and Family (Richard T. Ely Lecture)." *American Economic Review Papers and Proceedings* 96 (2): 1–21.

Goldin, C., L. F. Katz, and I. Kuziemko. 2006. "The Homecoming of American College Women: The Reversal of the College Gender Gap." *Journal of Economic Perspectives* 20 (4): 133–156.

Greene, W. H. 2003. "*Econometric Analysis*." New Jersey: Prentice Hall/Pearson Education International.

Grove, W. A., A. Hussey, and M. Jetter. 2011. "The Gender Pay Gap Beyond Human Capital: Heterogeneity in Noncognitive Skills and in Labor Market Tastes." *Journal of Human Resources* 46 (4): 827–874.

Hamermesh, D. S. 1999. "Changing Inequality in Markets for Workplace Amenities." *Quarterly Journal of Economics* 114 (4): 1085–1123.

Hellerstein, J., D. Neumark, and M. McInerney. 2008. "Changes in Workplace Segregation in the United States: Evidence from the 1990 and 2000 Decennial Employer-Employee Datasets." In *The Analysis of Firms and Employees: Quantitative and Qualitative Approaches,* S. Bender, J. Lane, K. Shaw, F. Andersson, and T. von Waechter (eds.), 163–195. Chicago: University of Chicago Press.

Jacobs, J. E., C. S. Chhin, and M. M. Bleeker. 2006. "Enduring links: Parents' expectations and their young adult children's gender-typed occupational choices." *Educational Research and Evaluation* 12 (4): 395–407.

Jensen, T. P., and D. Andersen. 2006. "Participants in PISA 2000 – Four Years Later." In *Northern Lights on PISA 2003 – A Reflection from the Nordic Countries*, J. Mejding, and A. Roe (eds.). Denmark: Nordic Council of Ministers.

Kleinjans, K. J. 2010. "Family Background and Gender Differences in Educational Expectations." *Economics Letters* 107 (2): 125–127.

Kleinjans, K. J. 2009. "Do Gender Differences in Preferences for Competition Matter for Occupational Expectations?" *Journal of Economic Psychology* 30 (5): 701–710.

Lambert, P. A. 2008. "The Comparative Political Economy of Parental Leave and Child Care: Evidence from Twenty OECD Countries." *Social Politics* 15 (3): 315–344.

Larsen, M., and H. S. B. Houlberg. 2013. "Lønforskelle Mellem Mænd og Kvinder 2007-2010." Copenhagen, Denmark: SFI-Det Nationale Forskningscenter for Velfærd 13:24.

Le, A. T., P. W. Miller, W. S. Slutske, and N. G. Martin. 2011. "Attitudes towards economic risk and the gender pay gap." *Labour Economics* 18 (4): 555–561.

Lønkommissionen, 2010. "*Lønkommissionens Redegørelse: Løn, Køn, Uddannelse og Fleksibilitet."* Copenhagen, Denmark.

Magnusson, C. 2009. "Gender, Occupational Prestige, and Wages: A Test of Devaluation Theory". *European Sociological Review* 25 (1): 87–101.

Manning, A., and B. Petrongolo. 2008. "The Part-time Penalty for Women in Britain." *Economic Journal* 118 (526): F28–F51.

Marini, M. M., P. L. Fan, E. Finley, and A. M. Beutel. 2006. "Gender and Job Values.2 *Sociology of Education* 69 (1): 49–65.

O'Farrell, B., and S. H. Harlan. 1982. "Craftworkers and Clerks: The Effect of Male Co-Worker Hostility on Women's Satisfaction with Non-Traditional Jobs." *Social Problems* 29 (3): 252–265.

Polachek, S. W. 1981. “Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure.” *The Review of Economics and Statistics* 63 (1): 60–69.

Powell, M. and D. Ansic. 1997. “Gender differences in risk behavior in financial decision-making: An experimental analysis.” *Journal of Economic Psychology* 18 (6): 605–828.

Rosen, S. 1986. “The Theory of Equalizing Differences.” In *Handbook of Labor Economics*, O. Ashenfelter, and R. Layard (eds.), vol. 1, 641–692. Amsterdam: Elsevier Science Publishers.

Rothstein, J., and C. E. Rouse. 2011. “Constrained After College: Student Loans and Early Career Occupational Choices.” *Journal of Public Economics* 95 (1): 149–163.

Shauman, K. A. 2006. “Occupational Sex segregation and the earnings of occupations: What causes the link among college-educated workers?” *Social Science Research* 35 (3): 577–619.

Schoon, I. 2001. “Teenage Job Aspirations and Career Attainment in Adulthood: A 17-year follow-up study of teenagers who aspired to become scientists, health professionals, or engineers.” *International Journal of Behavioral Development* 25 (2): 124–132.

Treiman, D. J. 1977. “*Occupational Prestige in Comparative Perspective*.” New York: Academic Publishers.

Turner, S. E., and W. G. Bowen. 1999. “Choice of Major: The Changing (Unchanging) Gender Gap.” *Industrial and Labor Relations Review* 52 (2): 289–313.

Valian, V. 1998. *Why so slow? The advancement of women.* Cambridge, Massachusetts, London, England: The MIT Press.

Warren, J. R., J. T. Sheridan, and R. M. Hauser. 1998. “Choosing a Measure of Occupational Standing: How Useful Are Composite Measures in Analyses of Gender Equality in Occupational Attainment?” *Sociological Methods & Research* 27 (1): 3–76.

Westergaard-Nielsen, N. 2008. *Low-Wage Work in Denmark*. In *Low-Wage Work in Denmark*, Westergaard-Nielsen (ed.), 16–31. New York: Russell Sage Foundation, Wiswall, M., and B. Zafar. 2011. Determinants of College Major Choice: Identification Using an Information Experiment. Federal Reserve Bank of New York Staff Reports, no. 500.

Zafar, B. 2013. "College Major Choice and the Gender Gap." *Journal of Human Resources* 48 (3): 545–595.

Zhang, Y. 2012. "Money vs. Prestige: Cultural Attitudes and Occupational Choices." Mimeo, University of California, San Diego.

Data appendix

Sample Selection

Table A3 summarizes the sample selection. Our final sample excludes individuals if occupational expectations are missing or expected occupations are not included in the occupational prestige survey. In addition, some respondents gave occupational expectations too vague to be classified (e.g., "*something with people*"). If a respondent answered more than one occupation we use the first one mentioned. Individuals do not expect to work in all 99 occupations in the occupational prestige survey. In total, we are able to match 74 occupations. Dropped and retained men do not differ in terms of ability. Retained women have slightly lower ability than those dropped (see Table A4).

Linking Expected Occupations to Occupation-Specific Variables

We link occupation-specific variables from the Danish registry to the expected occupations that were successfully matched to the occupational prestige survey with the four digit DISCO code, the official Danish version of the International Standard Classification of Occupations (ISCO) by the International Labour Organisation. This is generally straightforward though in 16 cases we are not able to distinguish occupations in the DISCO classification, implying that these occupations are coded with the same occupation-specific characteristics. This applies to 306 individuals. Another side of this issue is that occupations from the occupational prestige survey often share DISCO codes with occupations not in the survey, which are in some cases quite different. This is, for instance, the case with fashion designers, who share a DISCO code with decorators, interior architects, and other types of designers. There are also two occupations (*researcher in a private company* and *politician*) that could not be matched to a DISCO code.

Table A1: Occupation-Specific Characteristics

(sorted by occupational prestige)

Occupation	Occ. Prestige Score	Wage	Standard deviation of wage	# Expecting to Work in Occupation	
				Men	Women
Pilot	8.31	14.9	5.1	8	0
Lawyer	8.11	9.5	4.8	19	27
Doctor (GP)	7.89	11.7	4.2	0	0
Doctor (hospital)	7.76	11.7	4.2	22	35
Researcher in private company*	7.45	.	.	.	.
Architect	7.39	7.9	2.1	13	13
Associate professor	7.27	7.8	2.6	17	10
Civil engineer	7.22	8.7	2.3	109	15
Soccer player	7.15	6.2	3.9	0	0
Dentist	7.01	8.1	2.8	1	11
Midwife	6.96	6.5	1.3	0	17
Actor	6.95	6.5	3.1	6	9
Programmer/System developer	6.79	8.4	2.5	21	0
Psychologist	6.70	7.2	1.7	2	34
Fashion designer	6.69	5.7	2.2	3	14
Auditor	6.63	7.7	4.0	15	28
Politician*	6.55	.	.	.	.
Musician/singer	6.51	6.8	1.8	23	4
IT-consultant	6.43	9.1	2.8	12	0
Journalist	6.42	8.0	2.5	12	22
Ambulance driver/paramedic	6.40	5.6	1.3	4	2
Person working in advertising	6.38	6.9	2.8	14	23
Camera crew (movie/TV)	6.36	6.3	2.5	2	0
Head clerk (public sector)	6.28	7.7	3.0	13	8
Police officer	6.23	6.6	1.0	51	12
Real estate agent	6.20	8.6	4.5	10	18
Author	6.16	8.0	2.5	2	2
Officer in the army	6.03	5.7	1.7	10	1
Photographer	5.96	6.3	2.5	2	10
Graphic designer	5.72	6.7	1.9	12	8
Cook	5.69	4.2	1.3	15	13
HR-consultant	5.67	6.1	1.9	1	2
Priest	5.60	7.6	1.3	2	2
Laboratory technician	5.50	5.3	1.3	2	16
Nurse	5.39	5.5	1.2	1	87
Communication employee	5.33	8.0	2.5	7	14

Occupation	Occ. Prestige Score	Wage	Standard deviation of wage	# Expecting to Work in Occupation	
				Men	Women
Physiotherapist	5.20	5.2	1.2	5	26
High school teacher	4.98	7.5	1.6	12	11
Insurance agent	4.87	9.7	4.7	3	1
Business high school teacher	4.86	7.5	1.6	0	0
Bank employee	4.85	5.6	1.4	21	17
Electrician	4.70	5.6	1.9	49	1
Carpenter	4.40	5.2	1.7	62	0
Dental assistant	4.35	4.1	1.1	0	2
Office clerk	4.32	5.0	1.3	15	34
Alternative health therapist	4.30	3.9	1.4	0	1
Teacher	4.28	6.4	1.1	24	66
Gardener	4.25	5.2	1.7	2	7
Joiner/cabinet-maker	4.25	5.1	1.4	3	0
Flight attendant	4.19	6.4	1.8	0	1
Prison officer	4.10	5.6	0.9	0	2
Sales person	4.08	7.5	2.9	35	11
Nursing aide in a hospital	4.06	4.7	1.1	0	0
Blacksmith	4.01	5.3	1.9	33	0
Mason	4.01	5.5	1.9	16	0
Secretary	4.00	5.0	1.3	0	5
Auto mechanic	3.99	5.3	1.5	30	2
Social worker	3.98	6.1	1.0	2	20
Vocational teacher	3.97	5.2	1.6	0	0
Glazier	3.97	7.5	1.6	0	0
Plumber	3.91	5.6	1.7	8	0
Hair dresser	3.90	3.9	1.4	3	22
Farmer	3.84	5.4	4.0	22	3
Preschool teacher (children aged 3-6)	3.83	4.9	1.2	22	127
Train conductor	3.79	6.7	0.8	0	0
Librarian	3.78	6.1	1.2	0	3
Cosmetologist	3.77	3.9	1.4	0	12
Security guard	3.65	5.2	1.4	0	0
Baker	3.40	5.3	1.7	3	2
Waiter	3.40	4.6	1.8	2	2
Machine operator	3.28	5.7	1.4	5	0
Receptionist	3.25	4.6	1.5	1	4
Building painter	3.16	5.1	1.7	2	8
Medical Orderly	3.13	4.7	1.1	0	0

Occupation	Occ. Prestige Score	Wage	Standard deviation of wage	# Expecting to Work in Occupation	
				Men	Women
Mail carrier	3.07	5.0	1.5	0	0
Nanny/Child care worker	3.01	4.2	1.1	0	2
In-Home helper	2.94	4.1	1.1	1	28
Preschool teacher assistant (children aged 3-6)	2.89	4.7	1.1	0	3
Fisherman	2.88	4.4	5.6	0	0
Kitchen assistant	2.88	4.2	1.3	3	9
Sales assistant	2.84	4.2	1.6	17	36
Industrial butcher	2.74	4.7	1.8	7	2
Farm assistant	2.74	6.0	1.7	0	0
Scaffolder	2.74	5.4	4.0	11	0
Nursing home assistant	2.72	4.7	1.1	0	0
Road worker	2.71	5.2	1.2	0	0
Window cleaner	2.58	5.1	1.5	0	0
Warehouse clerk	2.58	5.0	1.5	6	1
Taxi driver	2.49	5.6	1.4	0	0
Trash collector	2.46	5.5	1.2	0	0
Mover	2.45	5.1	1.5	0	0
Bus/truck driver	2.41	5.6	1.4	9	0
Unskilled construction worker	2.29	5.8	1.6	1	0
Parking attendant	2.22	5.2	1.4	0	0
Cashier	1.87	4.2	1.6	0	0
Cleaner	1.57	4.1	1.3	1	1
Advertising delivery person	1.31	4.8	1.8	0	0
Unemployment benefit recipient	0.68	.	.	0	0
Welfare recipient	0.43	.	.	0	0
Mean	4.55	6.1	2.0	8.76	9.38

Wage is measured as median annual wage and divided by 50,000 to approximate 10,000 U.S dollars. The occupational prestige score is that of 18-29 year olds.* denotes occupations that were dropped since the wage could not be determined. One woman aspiring to be a ‘researcher in private company’, two women aspiring to be ‘politicians’, and four men aspiring to be politicians are dropped due to undeterminable wages.

Table A2: Summary Statistics by Gender: Means

	Men	Women	P-value (t-test)
Attributes of expected occupation			
Occ. prestige (18-29 years)	5.41	5.16	0.000
	(1.52)	(1.47)	
Wage	6.79	6.22	0.000
	(1.85)	(1.78)	
Standard deviation of wage	2.18	1.89	0.000
	(0.96)	(1.05)	
Individual characteristics			
Parental income	5.98	6.01	0.825
	(2.744)	(2.698)	
Parental education			
Low	0.59	0.61	0.274
Medium	0.31	0.30	0.765
High	0.11	0.09	0.175
Reading score	489.86	510.40	0.000
	(99.96)	(93.67)	
Most important job quality			
Shorter/convenient work hours	0.03	0.03	0.593
That it is challenging	0.80	0.79	0.761
Job safety	0.17	0.18	0.576

Standard deviations in parentheses (except for dummy variables). N=867 (men) and N=929 (women) except for the job attribute question where N=860 (men) and N=922 (women) because of nonresponse and “don’t know” answers. Wage is the median annual wage divided by 50,000 to approximate 10,000 U.S. dollars.

Table A3: Sample Selection

Sample Restriction	Individuals dropped			Occupations dropped	Number of observations
	Men	Women	Total		
Danish PISA Longitudinal Data *					3,073
Reading score missing	1	1	2		3,071
Occupational expectations					
No answer recorded	52	37	89		2,982
Respondent answered “don’t know”	141	122	263		2,719
Respondent answered “nothing”	20	15	35		2,684
Answer too vague	69	106	175		2,509
Occupation not in occ. prestige survey	347	348	695		1,814
Occupation has no wage data	4	3	7		1,807
Register data					
No parental income data	1	0	1		1,806
No parental education data	2	8	10		1,796
Number of individuals					1,796
Reshape of data: 1,796 · 99					*177,804*
Occupations in which no one expects to work				25 · 1,796 = 44,900	132,904
Estimation sample					132,904

* This includes individuals who were tested in PISA and answered the follow-up survey.

Table A4: Comparison of Sample and Dropped Observations

		Sample		Dropped		P-value
		Mean	N	Mean	N	(t-test)
Men	Parental income	5.98	867	6.22	636	0.128
		(2.74)		(3.18)		
	Parental education					
	Low	0.59	867	0.56	629	0.198
	Medium	0.31	867	0.32	629	0.6
	High	0.11	867	0.13	629	0.22
	Reading score	489.86	867	496.62	636	0.188
		(99.96)		(96.89)		
Women	Parental income	6.01	929	6.00	639	0.917
		(2.70)		(3.09)		
	Parental education					
	Low	0.61	929	0.60	620	0.683
	Medium	0.30	929	0.30	620	0.828
	High	0.09	929	0.10	620	0.309
	Reading score	510.40	929	523.35	639	0.006
		(93.67)		(88.44)		

Standard deviations in parentheses (except for dummy variables).

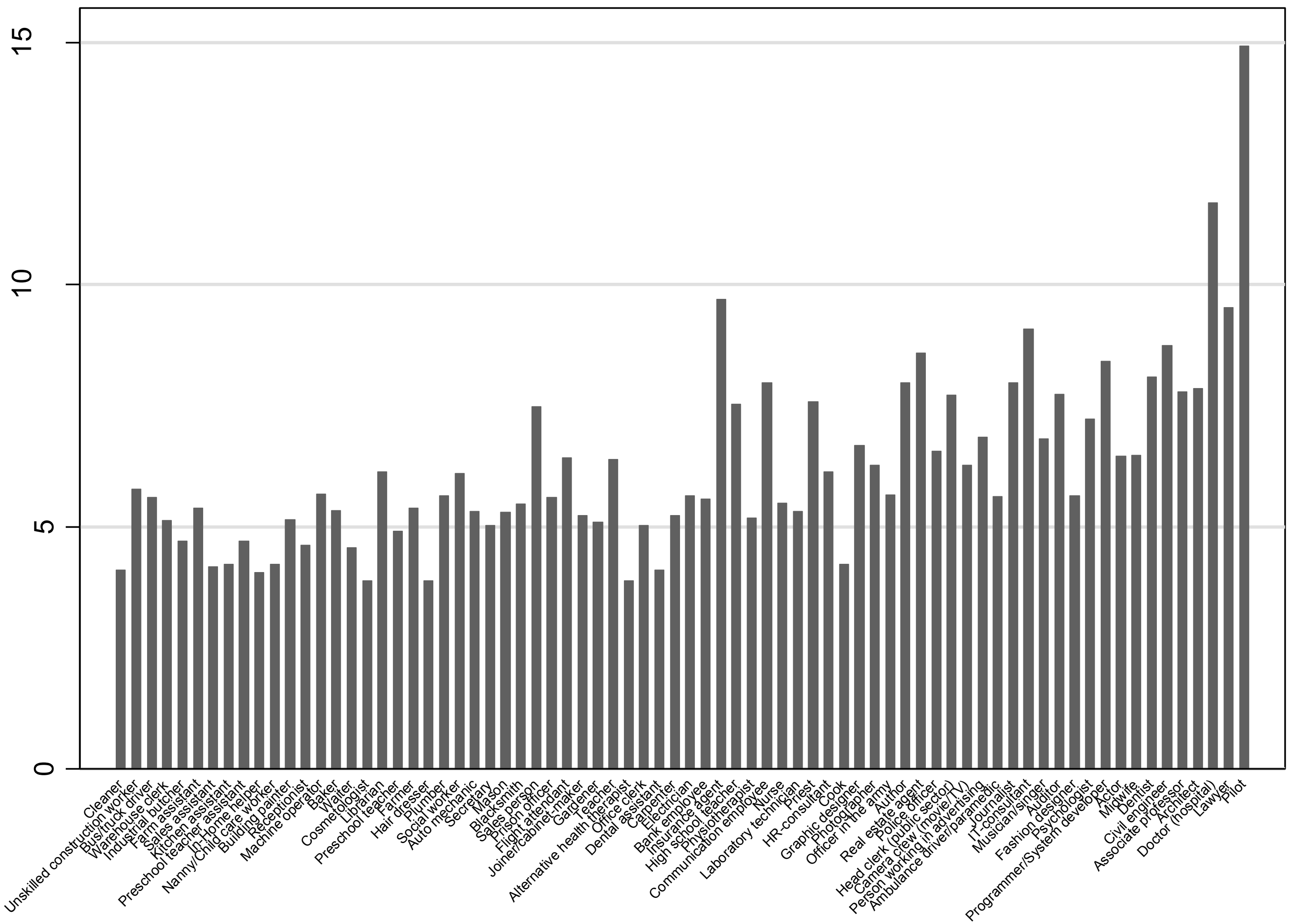

Figure A1: Distribution of Wage – Occupations Sorted by Prestige