When the Kids Are Not Alright

Essays on Childhood Disadvantage and Its Consequences

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Abstract

This thesis consists of three self-contained essays on childhood disadvantage and its consequences in Sweden.

A Longitudinal Look at Child Poverty Using Both Monetary and Non-monetary Approaches. In this paper, we broaden the analysis of child poverty by using both monetary and non-monetary measures of poverty and by comparing these over time. We use a composite of questionnaire answers from children regarding possession of socially perceived necessities and participation in social activities to develop two non-monetary child-centric concepts of disadvantage: material deprivation and social exclusion. The empirical analysis is based on two cross-sections and a panel of children in the Swedish Level-of-Living Survey matched with parental survey data and administrative income records. Consistent with previous findings, we find that relative income poverty among children increases significantly between the year 2000 and 2010. The fraction of children that is disadvantaged in two dimensions, monetary and non-monetary, is relatively small (0.9–7.0 percent) but increases significantly during the period of study. The modest size of the overlap suggests that our measures capture different dimensions of disadvantage, thereby pointing to the importance of alternative poverty indicators. We also find that income status in childhood is the best predictor of socio-economic outcomes in young adulthood.

The Aspirations-attainment Paradox of Immigrant Children: A Social Networks Approach. Using two independent and nationally representative samples of Swedish children, I compare the university aspirations and expectations between children of immigrants and children of natives. In line with existing findings, I find that children with foreign-born parents have significantly higher aspirations and expectations than their native-majority peers with and without conditioning on school performance, academic potential and friendship networks. I do not find any evidence of a significant immigrant-non-immigrant aspirations-expectations gap; immigrant children's aspirations and expectations are not less aligned than those of their native-majority peers. This result suggests that immigrant-native disparities in school outcomes are not driven by an aspirations-expectations gap. Finally, the results reveal significant gender differences. Native-majority girls with academic potential are, for example, more likely to express an aspirations-expectations gap. Moreover, having only female friends makes one less likely to belong to the aforementioned category.

The Key Player in Disruptive Behavior: Whom Should We Target to Improve the Classroom Learning Environment? In this paper, I address the question: Who is the individual that exerts the greatest negative influence on the classroom learning environment? To answer this question, I invoke the key player model from network economics and use self-reported friendship data in order to solve the methodological problems associated with identifying and estimating peer effects. I overcome the issue of endogenous group formation by using the control function approach where I simultaneously estimate network formation and outcomes. The results show that the typical key player scores well on language and cognitive ability tests and is not more likely to be a boy than a girl. I also find evidence that removing the key player has a significantly larger effect on aggregate disruptiveness in a network than removing the most disruptive individual, implying that policy aimed at the most active individual could be inadequate.

Keywords: *childhood disadvantage, social networks, education, disruptiveness, income poverty, immigrant children, aspirations, Sweden.*

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To my family

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Acknowledgements

Biednemu wiatr w oczy wieje.

When I was a child my mother used to tell me that life is unfair. The Polish proverb cited above can be loosely translated as “The wind blows in the eyes of the poor”, reminding us that those born unlucky are more likely to be struck by bad luck. Using the tools of economics and statistics I set out to test my mother’s conviction when I started the Ph.D. program in economics in August 2011.

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I dedicate this thesis to my beloved family: Joanna, Wojtek, Titus and Maksim who make me one of the lucky ones.

Stockholm, November 2017

* * *

Preface

This thesis consists of three self-contained essays on childhood disadvantage and its consequences in Sweden. All three essays make use of survey data: either the Swedish Level-of-Living Survey (LNU), the Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU, Kalter et al. (2016a,b)) or both. In *chapter 1*, which is joint work with Markus Jäntti, we also link the LNU survey data to registers to obtain reliable measures of parental income. The aim is to arrive at more comprehensive measures of childhood living standards.

The other two essays are based on the CILS4EU dataset which contains an oversampling of children with an immigrant background. Children with foreign-born parents have, on average, lower grades and are more likely to have incomplete grades or dropout. Both essays are also concerned with friendship networks and their role in the formation of individual preferences, beliefs or behavioral decisions. *Chapter 2* looks at immigrant-native disparities in educational aspirations, educational expectations and the gap between the two. I investigate whether high-achieving immigrant children are more likely to express a gap in aspirations and expectations, a potential mechanism behind the immigrant-native gap in school outcomes. In the analysis, I specifically study the influence of the characteristics of best friends. *Chapter 3* is based on detailed friendship network data and self-reported disruptive behavior of students in classrooms. I use simulation to identify the key players of disruptive behavior in order to point to potential policy interventions. Below follows a short summary of each essay.

A Longitudinal Look at Child Poverty Using Both Monetary and Non-monetary Approaches. In this paper, we broaden the analysis of child poverty by using both monetary and non-monetary measures of poverty and by comparing these over time. We use a composite of questionnaire answers from children regarding possession of socially perceived necessities and participation in social activities to develop two non-monetary child-centric concepts of disadvantage: *material deprivation* and *social exclusion*. The empirical analysis is based on two cross-sections and a panel of children in the Swedish Level-of-Living Survey matched with parental survey data and administrative income records. Consistent with previous findings, we find that relative income poverty among children increases significantly between the year 2000 and 2010. The fraction of children that is disadvantaged in two dimensions, monetary and non-monetary, is relatively small (0.9–7.0 percent) but increases significantly during the period of study. The modest size of the overlap suggests that our measures capture different dimensions of disadvantage, thereby pointing to the importance of alternative poverty indicators. We also find that income status in childhood is the best predictor of socio-economic outcomes in young adulthood.

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Sammanfattning

Denna avhandling består av tre fristående uppsatser som behandlar skillnader i barns uppväxtvillkor i Sverige och vilka konsekvenser de har på kort och lång sikt. Nedan följer en kort sammanfattning av varje uppsats.

Kapitel 1: I denna studie genomför vi en bred analys av barnfattigdom genom att studera både monetära och icke-monetära barnfattigdomsmått över tid. Vi använder barns enkätsvar gällande materiella resurser och social delaktighet för att konstruera två barn-fokuserade mått på fattigdom: materiell fattigdom och social exkludering. Analysen bygger på dels tvärsnittsdata, dels en panel av individer i Levnadsnivåundersökningen (LNU) sammanlänkad med föräldrarenkäter och registerdata för inkomster. I likhet med tidigare forskning finner vi att den relativa inkomstfattigdomen ökar signifikant under perioden 2000–2010. Andelen barn som är fattiga i mer än en dimension är förhållandevis liten (0.9–7.0 procent) men ökar signifikant under den studerade perioden. Att överlappningen är relativt liten innebär att måtten fångar olika dimensioner av barnfattigdom vilket pekar på ett behov av alternativa mått. Av våra mått är det inkomststatus i barndomen som bäst predicerar socioekonomiska utfall senare i livet.

Kapitel 2: Jag använder två oberoende och representativa urval av barn i Sverige för att jämföra skillnader i utbildningsaspirationer och utbildningsförväntningar mellan barn till Sverigefödda och utlandsfödda föräldrar. Resultaten ger stöd för att barn med utlandsfödda föräldrar har högre aspirationer och högre förväntningar om utbildning än barn till majoritetsbefolkningen både med och utan kontroller för elevernas skolresultat, akademisk potential och vänskapsnätverk. Jag finner däremot ingen signifikant skillnad i gapet mellan aspirationer och förväntningar mellan de två grupperna. Resultaten talar för att skillnader i aspirationer och förväntningar inte är en viktig förklaring till att barn till ut-

landsfödda har relativt låga skolresultat. Jag hittar dock signifikanta könsskillnader. Flickor med Sverigefödda föräldrar som visar tecken på akademisk potential är till exempel överrepresenterade bland elever som uttrycker aspirationer om högre utbildning som inte motsvaras av samma förväntningar. Därtill är sannolikheten att tillhöra tidigare nämnd kategori lägre om samtliga vänner är flickor.

Kapitel 3: Med hjälp av en strategi som går ut på att identifiera inflytelserika individer i kamratnätverk, så kallad key player-strategin, undersöker jag vem som har störst negativ påverkan på undervisningsmiljön i ett klassrum. Jag använder nätverksdata för att identifiera och mäta kamrateffekter. Jag kommer runt endogenitetsproblemet kring vänskapsformation genom att simultant estimera två modeller: vänskapsformation och kamrateffekter. Resultaten visar att en typisk key player i genomsnitt presterar högre än sina kamrater på både språk- och kognitiva tester. Key playern är inte mer sannolikt en pojke än en flicka. Det visar sig även att key player-strategin har en signifikant större inverkan på stökigheten i ett klassrum än alternativa strategier (t.ex. att rikta in sig mot den stökigaste eleven). Resultaten pekar därför på att strategier som fokuserar på den stökigaste eleven kan vara otillräckliga.

Chapter 1

A Longitudinal Look at Child Poverty Using Both Monetary and Non-monetary Approaches*

1 Introduction

Children are typically considered to be a vulnerable group in society with higher relative risks of poverty as compared to the overall population. Importantly, exposure to disadvantage in the domains of social life during childhood may have significant long-term consequences in terms of both social and economic outcomes (Heckman, 2006). The commodification of childhood necessitates more comprehensive measures of the living standard of children. Moreover, well-informed policy formation calls for more attention to be devoted to children's own reports of level of living.

This paper broadens the set of measures for assessing child poverty by introducing measures based on children's self-reported level of living. We investigate the general living standard of children in Sweden using

*This chapter represents joint work with Markus Jäntti. We thank Eskil Wadensjö, Matthew Lindquist, Gabriella Sjögren Lindquist, Anders Björklund, Tuomas Pekkarinen, Anne Boschini, Niklas Kaunitz and Dany Kessel for helpful comments. We also thank seminar participants at The Swedish Institute for Social Research (SOFI) for valuable comments and suggestions.

an income-based measure of poverty and compare it with non-monetary concepts of poverty derived from children's self-reported living conditions. Finally, we test the predictive power of these measures for later educational and labor market outcomes. To the best of our knowledge, this is the first study that both develops indices of self-assessed level of living among children and tests their predictive power for later educational and labor market outcomes against more conventional income-based measures of child poverty. Furthermore, we elaborate on how different measures of poverty affect the analysis of economic status and welfare.

Child poverty is a complex and context-specific phenomenon. According to a recent report from the OECD (2015) entitled *In It Together: Why Less Inequality Benefits All*, Sweden experienced the largest growth in income inequality among all OECD countries during the 1980's and 2010's, albeit from a low base.

Recent decades of increased refugee immigration and rising income inequality have given a new impetus to social issues such as ethnic integration, life chances and social cohesion in Western European societies. Being one of the highest per capita recipients of refugees in Europe, questions concerning redistribution and welfare are central in the public debate in Sweden. Although there is already a large body of evidence on child poverty and its consequences in the US, the generalizability of the results beyond the US context is questionable. Understanding the evolution of child poverty in Sweden is necessary in its own right, and all the more important during periods of demographical changes and rising inequality.

We use a panel of survey data in the Swedish Level-of-Living Survey (LNU, n=924) collected in 2000 when the respondents were in the ages 10-18 and ten years later, in early adulthood.[1] The LNU is a longitudinal cohort survey conducted in Sweden since 1968. Since the

[1]The cross-section data sets consist of 1,288 and 910 individuals, respectively. Due to non-response and attrition, the final panel analysis sample consists of 801 individuals.

data set we use is a panel, we can also compare which measure of child poverty – monetary or non-monetary – best predicts socioeconomic outcomes later in life. We address the following questions: (i) how well do standard income-based measurements of child poverty coincide with children's self-reported standard of living? and (ii) how well do monetary and non-monetary measures predict socioeconomic outcomes in young adulthood?

The analysis is structured as follows. First, we use information on children's self-reported conditions to investigate which children were poor in the year 2000 and 2010, respectively. We use a composite of questionnaire answers regarding possession of items and participation in social activities to create the indices *material deprivation* and *social exclusion*. The indices are constructed using factor analysis and alternative thresholds of poverty status are considered. We next explore the persistence of poverty during the period 2000–2010, using both the income-based measure and the material deprivation and social exclusion indices. We also give an overview of child poverty trends in selected European countries. Finally, we compare the income-based measure to our indices of self-reported poverty and explore to what extent these overlap.

Welfare norms and perceptions of what poverty means can change over time. Our data allows us to study welfare dimensions longitudinally. In a final step, we use the panel to see whether the children who were poor according to each of these measures in 2000 were poor also as young adults in 2010. We ask the following question: Who moves on to study at the university and who is employed? We compare which measure of child poverty – monetary or non-monetary – that best predicts socioeconomic outcomes later in life.

Our findings suggest a significant increase in child poverty estimated using monetary measures: from 6.6 percent in 2000 to 14.8 percent in 2010. Although the fraction of individuals that are poor in two dimensions is relatively small (0.9–7.0 percent), it grows significantly during the period of study. The modest size of the overlap suggests that the measures are complementary rather than competing, i.e. they capture different individuals and different dimensions of scarcity. We also find that the income status in childhood strongly predicts adult socioeconomic outcomes. Being classified as income poor in 2000 makes an individual significantly more likely to be labeled as income poor as an adult and less likely to study at the university. Thus, experiences of economic deprivation in childhood seem to be related to adverse economic outcomes in adulthood. Finally, our findings suggest that the monetary measure of child poverty is the most powerful predictor of socioeconomic outcomes later in life.

The paper proceeds in the following way. Section 2 gives a literature review. Section 3 introduces the data and the poverty measures we use. Our results are presented in sections 4–6. In section 7, we discuss the policy implications of our findings and conclude the paper.

2 Conceptual framework

How to measure an individual's opportunities to live a full life and participate normally in society remains an open question. Previous literature on child poverty and its dynamics is extensive (Jäntti and Danziger, 1994; Duncan et al., 1993; Oxley et al., 2000). The aforementioned studies and their various measures of poverty bear witness to the lack of a consensus on a universal definition of poverty.[2] Thus, a number of conceptual and practical issues need to be addressed when studying a complex and multifaceted phenomenon such as poverty (Jäntti and Danziger, 2000). These are essentially a matter of choices with regard to the resource measure (income or consumption?), the poverty cut-off (absolute or relative?) and the equivalence scale (how to account for economies of scale within a family).

The first issue concerns the space of poverty measurement. The

[2] See also Lindquist and Sjögren Lindquist (2012), Mood and Jonsson (2013), Mood and Jonsson (2016b), Galloway et al. (2009) and Hansen and Wahlberg (2009) for the Swedish case.

utilitarian approach to measuring poverty, which is very much the convention within the field of economics, is based on income and individual preferences. Thus, a common feature in the literature on child poverty is to use some type of monetary measure, such as administrative data on household income and survey-based reports on income or consumption expenditure.[3] Although income and consumption data has its apparent advantages, for instance being relatively easy to interpret and measure over time, other measures of level of living and well-being that could supplement income poverty are increasingly being demanded by scholars and public policy makers alike (see, for example, Chen and Corak (2008) and Mood and Jonsson (2016b)).[4] Furthermore, there is a number of concerns with using income-based measures, for example, as a measure it is volatile – it can change significantly from year to year, it assumes an equal distribution of resources within a household and the choice of poverty threshold can appear to be rather arbitrary (Bradshaw and Finch, 2003).

Household income and consumption are only telling part of the story of children's level of living. Consumption such as clothing and participation in social activities can play an important social role in children's lives. These are welfare dimensions that can, in essence, only be captured by directly asking individuals about their level of living and well-being. In spite of stretched household finances, parents may still give priority to their children's conspicuous consumption over basic goods. Owning the "right" cellphone could, for instance, be valued more than other personal and social needs within the family. Low income can in some cases lead to parental poverty but not child poverty if parents prioritize certain aspects of their children's material living standard. Thus, children's own reports of their standard of living are becoming increasingly important for assessing both household and child poverty.

This paper relates to both the income and subjective poverty lit-

[3]In general, welfare statistics are country specific and higher-income countries typically use relative measures.

[4]See a discussion of the Multidimensional Poverty Index (MPI) in Aaberge and Brandolini (2015).

erature by using a combination of income-based and self-reported deprivation measures to analyze the incidence of child poverty. In some respects, the self-assessed level of living measure falls somewhere in between the income-based and the subjective measures of poverty. While it is based on individual reports, it concerns both material and psychological aspects of well-being and, as such, it covers a broader range of life circumstances.

There is also a strand of the poverty literature that instead of income data uses survey respondents' self-assessments of economic welfare, for example if they "feel poor". Household poverty can be measured using individuals' qualitative perceptions of income or consumption adequacy derived from questions such as "the economic ladder question" (ELQ), "satisfaction with life" (SWL) or the minimum income question (MIQ).[5] An alternative non-monetary way of measuring poverty is to use individuals' self-assessments of economic welfare or own perception of well-being on social welfare concepts (Allardt, 1976; Nussbaum and Sen, 1993; Sen, 1985; Townsend, 1985). This approach moves beyond individual preferences and economic resources. In the seminal work of Allardt (1976), the concept of level of living is defined as "... material and impersonal resources with which individuals can master and command their living conditions"(p. 228). Our study uses data from the Swedish Level-of-Living Survey (LNU) which is a longitudinal cohort survey specifically designed for measuring broader dimensions of individual wellbeing such as material resources, participation and consumption.[6]

[5]The study of Van den Bosch et al. (1993) uses the MIQ concept and exploits comparative socioeconomic surveys in seven European countries to define so-called subjective poverty lines indicated by survey questions such as: "What is the minimum amount of income you need to make ends meet?". A somewhat different but related approach is presented in Pradhan and Ravallion (2000) which measures poverty using qualitative perceptions of consumption adequacy. A related topic is happiness and life satisfaction. The influential work of Cantril (1965) and Van Praag (1968) captures non-income dimensions of welfare.

[6]Mood and Jonsson (2013) use the LNU child survey in order to study trends in child poverty in Sweden. They do, however, not make use of the child panel (2000-2010). See Veenhoven (2004) for a discussion on substance and assessment of social indicators.

The second conceptual issue is related to the choice of poverty cutoff, i.e. should welfare be assessed using absolute or relative measures? An individual is classified as poor according to the absolute measure if his or her resources fall short of the poverty line which is *fixed* at the estimated cost of a basket of consumption goods (also called minimum income standard) (Foster, 1998). The relative threshold is set in relation to the distribution of incomes or resources. A common poverty threshold is 50 or 60 percent of the median income. We address this issue by using both a fixed and a moving threshold.

We address the third and final issue regarding family structure and the division of resources within the household using a conventional equivalence scale (see section 3.2 for more details). Equivalence scales account for variations in family configurations and differences in family size. A related conceptual issue concerns the intra-household division of resources. An advantage of the child survey is that the questions are asked of the children themselves rather than their parents. Hence, we can identify potential intra-household inequalities and thus gain a broader picture of how children fare in various family constellations and economic conditions. Unlike adults, children do typically not have control over money in the household, which is another argument for studying their self-reported relative deprivation.

A related literature can be found within sociology, where a handful of studies have investigated the overlap between income-based poverty and indicators of deprivation (Gross-Manos, 2015; Bradshaw and Finch, 2003; Mood and Jonsson, 2013).[7] Table 1 gives an overview of the related literature and common child poverty measures.

[7] For studies using Swedish data, see for example Mood and Jonsson (2013) which compares child reported and parent reported deprivation over time. See also Mood and Jonsson (2016a) which looks at the impact of economic hardship for social outcomes such as close social relations and political participation.

Table 1: Literature review

Study	**Poverty measure**		
	Absolute income	*Relative income*	*Material deprivation or social exclusion*
Duncan et al. (1993)		✓	
Jäntti and Danziger (1994)		✓	
Oxley et al. (2000)		✓	
Bradshaw and Finch (2003)		✓	✓
Saunders et al. (2008)		✓	✓
Chen and Corak (2008)	✓	✓	
Jonsson and Östberg (2010)			✓
Mood and Jonsson (2013)	✓	✓	✓
Main and Bradshaw (2012)			✓
Mood and Jonsson (2016b)	✓	✓	✓
Gross-Manos (2015)			✓

Our study is most closely related to Gross-Manos (2015) and Main and Bradshaw (2012). Both of these studies develop child-centric indicators, but in contrast to the latter, Gross-Manos (2015) also investigates the overlap between them. They find a 4.7 percent overlap between the material deprivation and the social exclusion measure (the sample size was 1081, aged twelve, conducted during 2011–2012).[8] Two other studies worth mentioning are Bradshaw and Finch (2003) and Saunders et al. (2008) which also explore the overlap but in contrast to Gross-Manos (2015) and this paper, they focus on poverty among adults. Bradshaw and Finch (2003) explore the overlap between three measures of poverty, namely lacking socially perceived necessities; being subjectively poor and having a relatively low income. They find an overlap of 30–40 percent. Saunders et al. (2008) investigate the overlap between income poverty, material deprivation and social exclusion and find that the overlaps of income poverty and the two other indicators are in the same range.[9] We contribute to this body of literature by exploring the overlap between the monetary and non-monetary measures *over time*. We also test their predictive power which, to the best of our knowledge, has not yet been done.

[8] In this paper, we develop a child-centric material deprivation measure similar to that of Main and Bradshaw (2012). Their study is based on data from two surveys conducted by the Children's Society (n=2000, children aged 8–16). They also have information on income data provided by parents.

[9] See also Saunders and Bradbury (2006) for a discussion on the incidence and trends in child poverty and related policy questions (how to measure hardship etc.). This paper also relates to that of Kingdon and Knight (2006) as it uses subjective well-being as the criterion for poverty and compare subjective with income-based measures of poverty by testing whether these are competing or complementary. Children's self-stated level of living is addressed in, for example, Mood and Jonsson (2016b) which presents four indicators of individual level of living: material resources (deprivation), cash margin, participation and consumption. See also Ridge (2011) and Jonsson and Östberg (2010). An example of a cross-country study within this field is Sarriera et al. (2015).

3 Data and measures

The Swedish Level-of-Living Survey (LNU) is a longitudinal cohort survey that has been carried out approximately every tenth year since 1968.[10] It consists of a representative sample of the Swedish population (ages 19–65 in 2000 and 19–75 in 2010). The survey is conducted by Statistics Sweden (SCB) and respondents are re-interviewed in subsequent waves if they remain in the age span, have not died or moved abroad. The respondents are interviewed either in person in their homes or by telephone.

In 2000, the LNU also included a child interview module. The child respondents, aged 10–18 and living at home, filled out a questionnaire by listening to recorded questions with a tape recorder using headphones. The child interviews took place in their homes while the parent was being interviewed. They lasted approximately 30 minutes and covered a broad range of areas, such as material living conditions and financial resources, leisure time activities, health, neighborhood characteristics and education. The respondents answered questions like: "Do you have a mobile phone?" and "Do you feel safe in your neighborhood?" See all the relevant questionnaire items in Appendix B.

The total number of respondents in the LNU 2000 child survey is 1,304. In 2010, the survey was supplemented with a separate child survey of the children of foreign-born individuals in the LNU (called the Swedish Level-of-Living Survey 2010 – Immigrants and their children, LNU-UFB). The questionnaires were identical to the LNU child forms. The number of respondents in the LNU-UFB child sample is 435.

The latest wave of the LNU survey was carried out during 2010–2012 and included interviews with a total of 6,259 individuals. Both LNU 2000 and 2010 include postal questionnaire answers from the respondents' partners. The partner questionnaires are short versions of the respondents' interviews.

[10] See, for example, Mood and Jonsson (2013), Jonsson and Östberg (2009) or Jonsson and Östberg (2004). The last one offers detailed information on the Child-LNU survey.

We utilize both the cross-sectional and panel element of the LNU survey. We use the child survey from 2000 and a matched follow-up of these individuals in the LNU 2010 survey so our analysis sample consists of both a pooled cross-section of children, the LNU child surveys of 2000 and 2010, and a panel of respondents from the 2000 and 2010 waves of LNU. Each respondent is linked to a parent included in LNU 2000; thus, we have data on household disposable income, parents' employment biography in 2000 and individual education history. All in all, we are able to match 924 individuals with the LNU 2000 child survey. In 2010, these individuals were aged 20–29.

The response rate of the main sample was approximately 77 percent in 2000 and 72 percent in 2010. Not all children in the sampled households took part in the survey, implying a potential selection bias. Non-response among children was less than 30 percent.[11] As demonstrated in figure C.1 in Appendix C, a substantial part of the sample consists of siblings. Large families could potentially cause the number of poor persons to be overestimated compared to the overall population. We address this issue by using sampling weights for children provided by Statistics Sweden.

We use administrative data from LISA (Longitudinal integration database for health insurance and labor market studies, SCB (2016)) to obtain reliable income measures and additional information on the parents' background. LISA was constructed by Statistics Sweden, the Social Insurance Agency and the Swedish Agency for Innovative Systems and consists of annual registers since 1990. It includes all individuals aged 16 and above registered as living in Sweden as of December 31 each year.

3.1 Descriptive statistics

Descriptive statistics for the analysis samples are provided in table 2. The cross-section samples of the years 2000 and 2010 consist of 1,304

[11]More information about the calibration of sampling distributions and non-response in the LNU survey can be found in SCB (2012).

and 918 individuals, respectively. The average age is approximately 14 and half the sample is female in both cross-sections.

Table 3 shows that overall, children in Sweden have a high material living standard. A little more than half of the first wave sample reports having an own TV (see table 3). The proportion of children having an own TV in the second wave sample is close to 60 percent. One third of the 2010 wave reported a lack of an own computer and more than 4 percent of the children lacked a mobile phone.

The social activities are presented in table 4. The proportion of children reporting that they use the Internet every day is about 55 percent in 2010 as compared to 11 percent in 2000. The social activities involving spending time with friends seem to be relatively stable from 2000 to 2010 (see questionnaire item 8 in Appendix B).

Table 2: Summary statistics, cross-sections and the panel

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A: LNU 2000					
Age	13.578	2.532	10	18	1288
Girl	0.512	0.5	0	1	1288
Immigrant parents	0.02	0.141	0	1	1288
Number of children in hh	2.24	1.165	1	8	1288
Lone parent	0.175	0.38	0	1	1288
Intact family	0.825	0.38	0	1	1288
Non-manual/Employers	0.404	0.491	0	1	1288
Panel B: LNU 2010					
Age	14.181	2.602	10	18	910
Girl	0.5	0.5	0	1	910
Immigrant parents	0.047	0.212	0	1	910
Number of children in hh	2.027	1.151	0	8	910
Lone parent	0.199	0.399	0	1	910
Intact family	0.819	0.385	0	1	910
Non-manual/Employers	0.73	0.444	0	1	883
Panel C: LNU panel 2000–2010					
Age (wave 1)	13.433	2.534	10	18	803
Age (wave 2)	23.671	2.598	20	29	803
Girl	0.521	0.5	0	1	803
Immigrant parents	0.014	0.116	0	1	803
Number of children in hh	2.267	1.141	1	8	803
Lone parent	0.133	0.34	0	1	803
Intact family	0.867	0.34	0	1	803
Non-manual/Employers	0.408	0.492	0	1	803

Table 3: Do you have any of the following..., as a percentage of the sample (n=1304 in 2000 and n=918 in 2010)

	2000		2010	
Necessity	Do not have	Have	Do not have	Have
Room	10.81	89.19	8.71	91.29
Pet	56.29	43.71	50.44	49.56
TV	48.39	51.61	41.18	58.82
Mobile phone	58.05	41.95	4.03	95.97
Computer	74.39	25.61	33.01	66.99
Have not (things)	98.08	1.92	99.46	0.54

Table 4: How many days a normal week do you..., as a percentage of the sample (n=1304 in 2000 and$n$=918 in 2010)

Activity	Every day	Several times a week	Once a week	Seldom	Never	Missing values
2000						
Read	17.87	26.07	17.18	27.45	11.20	0.23
News	18.63	36.43	16.64	18.40	9.66	0.23
Play	15.87	34.28	18.33	21.55	9.89	0.08
Internet	11.20	27.76	17.48	21.63	21.78	0.15
Friends home	5.75	45.55	23.93	22.09	2.38	0.31
Home friends	6.13	54.68	21.63	15.80	1.69	0.08
Sport	5.52	44.56	15.57	8.21	25.84	0.31
Other activities	0.92	6.06	15.11	14.95	62.12	0.84
Meet friends	34.28	36.58	12.42	12.35	3.91	0.46
Leisure	10.12	38.11	26.69	21.63	3.07	0.38
2010						
Read	13.18	25.60	14.81	32.57	13.51	0.33
News	14.38	33.01	21.02	21.35	9.69	0.54
Play	29.74	30.50	11.33	18.19	9.91	0.33
Internet	55.56	30.50	4.79	5.56	3.27	0.33
Friends home	2.72	40.31	28.00	25.05	3.59	0.33
Home friends	2.18	47.06	28.00	20.92	1.63	0.22
Sport	6.10	45.86	13.51	8.39	26.03	0.11
Other activities	1.09	7.19	14.16	11.98	64.81	0.76
Meet friends	34.53	38.67	12.75	11.33	2.29	0.44
Leisure	6.86	38.34	26.80	23.64	3.27	1.09

3.2 Monetary poverty measures

A common income-based measure of poverty is the needs-adjusted income per family member based on disposable income. We use the equivalence scale as defined by Statistics Sweden for comparability of the incomes in Hushållens ekonomi (HEK), an annual survey of a representative sample of Swedish households (about 10,000 to 19,000 households). The HEK equivalence scale is presented in table C7 in Appendix C. The unit of analysis is the individual but income is calculated based on the family.

We follow the RTB (The total population register) family definition where the family consists of all individuals with family ties that are registered at the same address.[12] Unfortunately, the RTB family does not always correspond to the actual household. For example, it excludes individuals with children who are not living together (partners who are not cohabiting). In these instances, we probably understate the family resources and thus overstate the number of poor children. In addition, in case there is a trend in civil status, for instance if single parenthood is more common in 2010 than in 2000, the bias will also have a trend. Different definitions may produce different results and the levels should therefore be interpreted with caution.

We assume that the resources are shared equally among all family members.[13] Family disposable income is defined as the sum of the household's total pretax incomes, sickness and unemployment benefits, net income from capital plus all government transfers (positive and negative) less taxes.[14] The needs-adjusted income per family member is calculated by adding all incomes of the family members and dividing them by the number of adults and the weighted number of children in the household in ages 0-17. Children are assumed to require less than

[12] An interesting future extension is to consider both the HEK and the RTB family definition.

[13] Although there is evidence of parents' cushioning their children. This topic is discussed in, for example, Mood and Jonsson (2016b).

[14] Lindquist and Sjögren Lindquist (2012) provide an overview of Swedish family-oriented transfers.

their parents (see table C7 in Appendix C). We make use of the administrative variables in both waves and the income data covers the year before each wave of the survey, namely 1999, 2009 and 2010. Since some of the respondents in the LNU 2010 survey were interviewed one year later in 2011, we match these with the registers from 2010 instead of 2009.

As a starting point, we use the median value in SEK of equalized disposable yearly income in 2014 prices of all households ages 20 and older (see alternative cutoffs in the sensitivity analysis presented in Appendix A). The median equivalized disposable family income was SEK 156,700 in 1999, SEK 209,000 in 2009 and SEK 211,900 in 2010 (2014 year's prices). We use nominal incomes adjusted for inflation using Statistics Sweden's CPI calculator (SCB, 2015). It is worth noting that all public statistics of Statistics Sweden on disposable incomes are taken from the Household Finances Survey (HEK, previously called Swedish Household Income Survey (HINK)). Family disposable income is calculated using survey respondents' answers about the household composition and incomes are taken from registers. Hence, the HEK family definition captures more family members than the RTB.

We use a relative poverty line defined as 50 percent of the median equivalent disposable income. For comparability of incomes over time (year 1999 and 2009/2010), we also present the results based on real incomes corrected for inflation using the index year 1999. Individual children are classified as disposable income poor (henceforth referred as income poor), if their equivalized disposable income falls below this threshold. We use both a fixed and a moving threshold. The *absolute* or *fixed* poverty line in 2010 corresponds to 50 percent of the median disposable income in 1999 adjusted for inflation.

We choose a relative poverty measure as the focus in this paper is children's welfare. The relative poverty measure is affected by the income distribution and changes in economic conditions which is also why it is our preferred measure of poverty. The threshold is set based on the income distribution of the overall population; thus, we define the poverty status of the children in relation to all households in Sweden and not only those comprised of children. We consider alternative income distributions in the sensitivity analysis in Appendix A.

We remove all cases with missing data on the questions underlying the non-monetary indices of poverty. With regard to sampling weights, we use the weights provided in the technical report by Statistics Sweden of both waves of LNU (SCB, 2012).

3.3 Non-monetary measures of poverty

In order to define deprivation among children based on the 2000 and 2010 LNU child interview modules, we do, in principle, have several different alternatives available. We are, however, constrained in a few different ways that affect our choices. As we wish to study changes across time, it appears prudent (although not strictly necessary) to use questions asked in both 2000 and 2010. Thus, we restrict our interest to questions asked in both periods. Some questions were asked only of older children; as we wish to examine all children, we focus on those of all children. While LNU examines several different domains – many deal with health and general wellbeing – we choose to focus on two domains in particular, namely the material and social interactions, each comprising 5 and 6 indicators, respectively.

The next issue to address is how to summarize the information. One pragmatic option would be to define a simple deprivation index in each domain by simply counting the number of items or activities. The more complex approach, followed by Gross-Manos (2015), is to use exploratory factor analysis to find the latent variable(s) onto which the indicators load, assessing the appropriate number of factors based on statistical criteria. We opted for an in-between solution and simply estimated (using confirmatory factor analysis) one factor per domain in each of the LNU waves, and generated the fitted factor scores for every observation.

One reason why we did not pursue exploratory factor analysis is that a proper factor analysis in each wave should probably use more information than we currently do, as we restrict ourselves for purposes of over-time comparisons to questions available in both waves. Finally, to generate deprivation indices similar to the binary income poverty indicators we use, we need to define a way of separating the deprived from the non-deprived. Here, we use two different approaches, one defining the socially excluded or materially deprived as those whose latent score is less than half the median score, the other treating a child as deprived if he or she is in the lowest fifth in the distribution of the score. The results from the former approach is presented in Appendix A.[15]

The underlying questionnaire items for the *material deprivation* and *social exclusion* indices are found in Appendix B. The material deprivation index is constructed using questions regarding children's material living conditions: if they have their own room, a pet, own TV, own mobile phone, own computer, or none of these. Having an own room is likely more common in rural areas than in larger cities, where housing is more expensive and compact.[16] The importance of having an own room can also vary with respect to the age of the child. Young children may want to share rooms with siblings while older children may prefer having a room of their own. For this reason, we control for age in all regressions. There could also be a gender dimension: same-sex siblings could be more likely to want to share rooms than others.

The social exclusion index is derived from respondents' answers to the question: "How many days during a normal week do you: read books; follow the news on TV; radio or the newspaper; use the Internet; play computer or TV games; have friends at home; visit friends in their home; spend time with friends in some other place (e.g. outside); participate in some organized sports activity". The respondents have been given the options Every day, Several times a week, Once a week, Seldom, and

[15]We follow the setup of the Multidimensional Poverty Index (MPI) by first choosing dimensions of welfare and then indicators within each dimension. See, for example, Aaberge and Brandolini (2015) for a discussion.

[16]An interesting extension in future work would be to account for geographic differences.

Never and these are coded from 1 (Never) to 5 (Every day).[17] Table 2 in section 3.1 shows summary statistics for the underlying variables. Each panel, A and B, includes a dimension and several domain-specific indicators (underlying variables).

We only consider observations with non-missing values on all the underlying questionnaire items. The indicator variables *read*, *news*, *other activities* and *leisure* are excluded. Thus, we are left with the following variables underlying the social exclusion index: *play*, *internet*, *friends home*, *home friends*, *meet friends* and *sport*. We estimate factor loadings and the implied ("fitted") factor scores in both domains for the respective years. Suppose that we observe a $p \times 1$ vector $\boldsymbol{x}$ of outcomes that we believe to be linearly related to $q \times 1$ latent factors $\boldsymbol{f}$. The factor model relates $\boldsymbol{x}$ and $\boldsymbol{f}$ by a $p \times q$ matrix of factor loadings Γ and an error term:

$$\boldsymbol{x}' = \boldsymbol{f}\Gamma' + \boldsymbol{e}. \tag{1}$$

Denoting the correlation matrix of $\boldsymbol{x}$ by Σ, the estimation is based on

$$\Sigma = \Gamma\Omega\Gamma' + \Psi, \tag{2}$$

also called the *discrepancy function*. The first term $\Gamma\Omega\Gamma'$ represents the common factors. The factor loadings Γ are estimated using maximum likelihood assuming normal $\boldsymbol{e}$, but the same set of estimates can be shown to emerge also without assuming multivariate normality.[18] Table 5 reports the factor loadings of the underlying indicator variables.

With regard to the material deprivation index, the factor loadings for the indicator variables room, pet and computer increase from the year 2000 to 2010. The factor loadings for TV and mobile decrease during the period of study. The results in table 5 show that the factor loadings of the indicator variables underlying the latent variable social exclusion are relatively stable for all variables except play and internet. Social

[17] We follow the previous literature (e.g. Gross-Manos (2015)) when choosing relevant variables.

[18] We use the factor function in Stata which fits a common factor model by maximum likelihood.

Table 5: Factor loadings of the indicator variables underlying the latent variable *material deprivation* and *social exclusion* in 2000 and 2010, respectively

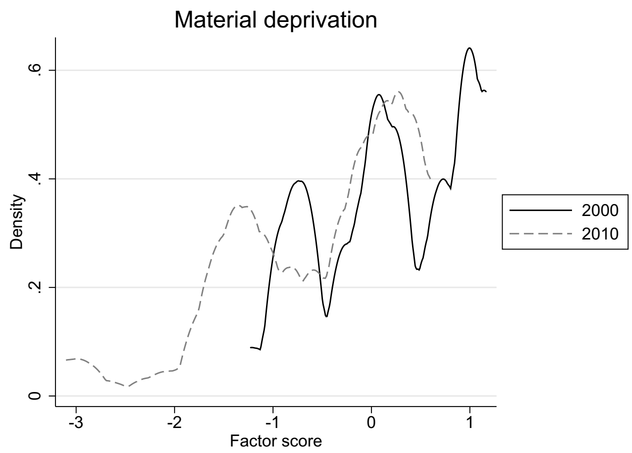
	Factor loadings	
	2000	2010
Panel A: Material deprivation		
Room	0.2517	0.5978
Pet	0.0444	0.1988
TV	0.6040	0.3959
Mobile	0.5069	0.3784
Computer	0.2986	0.4020
Panel B: Social exclusion		
Play	0.1907	0.0800
Internet	0.1289	0.0744
Friends home	0.5978	0.6968
Home friends	0.8495	0.8827
Meet friends	0.2767	0.2159
Sport	0.1524	0.1326

activities such as having friends at home or spending time at friends' homes seem to matter the most.

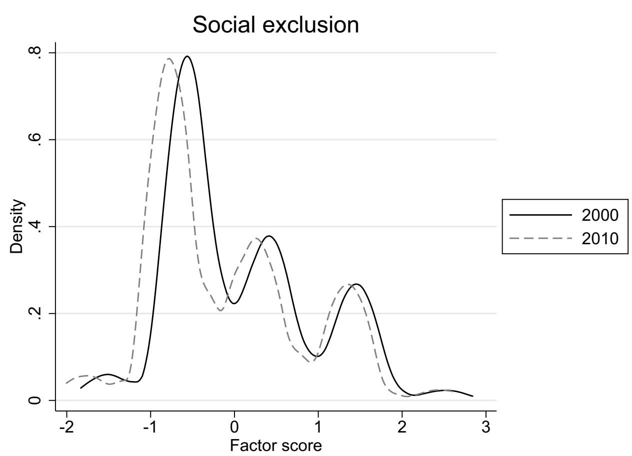
Figure 1 shows the distributions of the material deprivation and social exclusion indices in 2000 and 2010, respectively. Both indices have multi-modal distributions (several large peaks). We discuss the implications of this result in section 4.1.

Figure 1: Distributions of the *material deprivation* and *social exclusion* indices in 2000 and 2010, respectively

(a)



(b)



3.4 Validity and reliability

Following previous literature (Main and Bradshaw, 2012; Gross-Manos, 2015; Bradshaw and Finch, 2003), we assess the validity of our constructed measures by investigating the correlation between the measures and indicators of socioeconomic status and well-being, as suggested in the related literature on child-centric poverty indicators. In contrast to Gross-Manos (2015), who uses the mean income of the locality of the child's school, we utilize individual incomes from registers which reduces the potential measurement error.

Table 6 indicates the correlations between our indicators and the variables household equivalized income, self-reported psychological health and neighborhood quality (proxied by feeling safe). Based on these associations, we find that our measures are valid.

With regard to reliability, Gross-Manos (2015) develops and tests two measures and use focus groups to identify relevant necessary items. If the lack of an item was owing to choice by more than 20 percent of the sample, it was removed from the list. We use the existing questionnaire items in LNU 2010 and base our indicators on items similar to those used by Gross-Manos (2015) to attain reliable child poverty measures.

Table 6: Correlations of indicators with proxies for socio-economic status

	Material deprivation		Social exclusion	
	2000	2010	2000	2010
Income	-0.000393^{***}	-0.0000362	0.000153	0.0000848
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1288	910	1288	910
Sad or down	0.0415	-0.0253	-0.107^{***}	-0.139^{***}
	(0.036)	(0.041)	(0.031)	(0.038)
Observations	1284	909	1284	909
Feel safe	-0.157^{***}	-0.0813	0.0359	0.0107
	(0.043)	(0.076)	(0.038)	(0.072)
Observations	1288	910	1288	910

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from OLS regressions. Material deprivation and social exclusion is defined as belonging to the lowest quintile of the respective index. Income is defined as equivalized disposable family income. The variable *Sad or down* is created using the questionnaire item “I often feel sad or down”. The variable *Feel safe* is a dummy variable drawn from the question: “Do you feel safe in your neighborhood?”.

4 Incidence and persistence of poverty

In this section, we report the incidence and persistence of poverty during the period 2000–2010. First, we give an overview of previous findings on the incidence and dynamics of poverty in Sweden and in selected Western European countries. We then turn to our data in order to deepen the analysis of poverty in our two survey years. The two cross-sections 2000 and 2010 consist of different samples; hence, the analyses only give one-shot poverty snapshots. In the following step, we explore to what extent material deprivation and social exclusion measures overlap with the income-based measure. The results are discussed in section 5. In section 6, we introduce the time dimension by utilizing the panel element in the LNU, which consists of respondents who were children during the first wave and young adults at the time of the subsequent wave in 2010.

4.1 Child poverty trends 2000–2010

The economic recession of the 1990's left its mark on the poverty rates in many European countries and Sweden was no exception. In less than a decade the proportion of poor children according to an absolute poverty line increased from 8 to 19 percent (Mood and Jonsson, 2016b). Figures 2 and 3 show the trends in child poverty in selected north European countries during the period of study.

Figures 2 and 3 demonstrate a rising trend in the number of poor households in Europe. The economic downturn during of the 2000's with rising unemployment rates reduced the market incomes for many households. In Sweden, a country known for its extensive welfare state, the child poverty rate surged from approximately 3 percent to more than 9 percent during 2000–2010, as reported in figure 3, where poverty status is defined as having a yearly disposable income below 1/2 of the median of the overall population (OECD, 2017). Although all Nordic countries were faced with rising child poverty rates, the Swedish child poverty level stands out as strikingly high. As indicated in figure 3, Norway, Finland and Sweden start out at similar levels of income-based child poverty in

Figure 2: Trends in poverty, all and children (Source: OECD IDD)

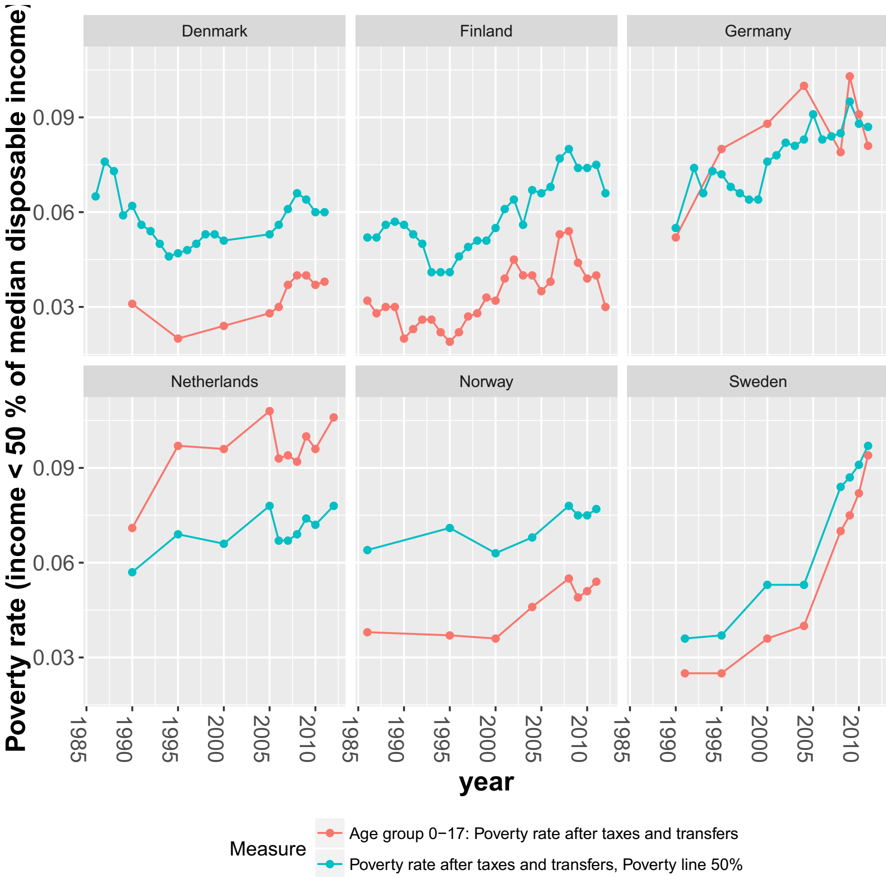
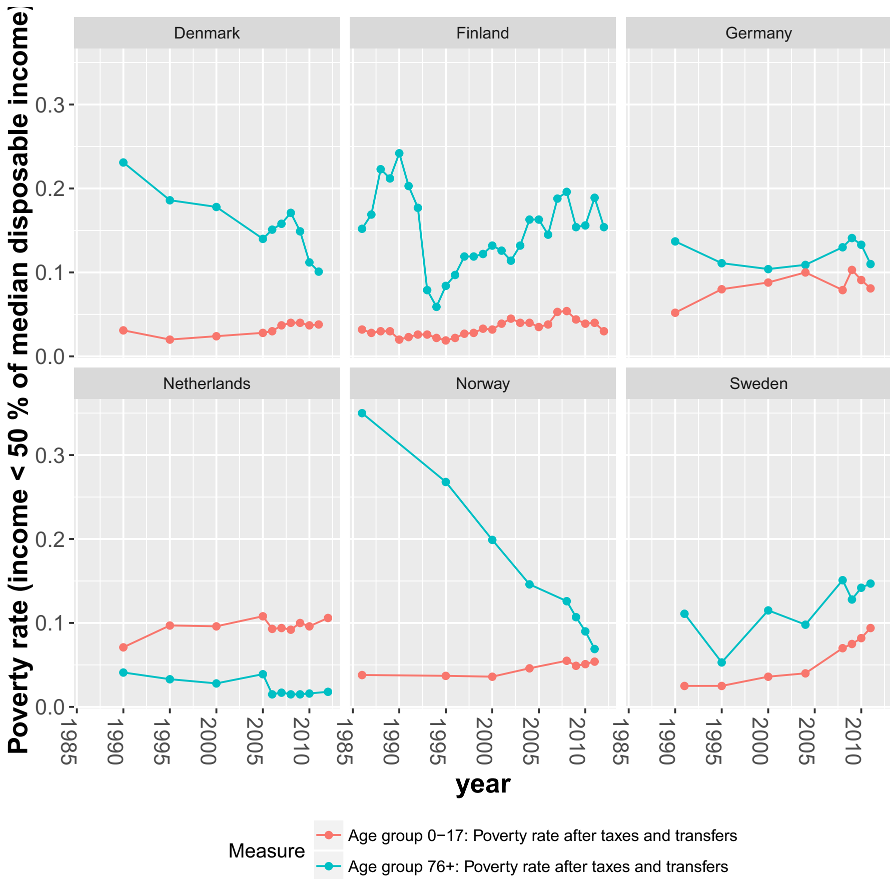


Figure 3: Trends in poverty, children and the elderly (Source: OECD IDD)



2000 but, by the end of the period, the Swedish child poverty rate is estimated to more than 9 percent (as compared to 3 percent in Finland and approximately 6 percent in Norway).[19]

Overall, the trends in child poverty across our selected countries are similar to those of the overall poverty rate and among the elderly (76+). The age group 76+, a subgroup particularly vulnerable to changes in economic conditions, seem to have suffered the most during the period of study: 15 percent of the elderly were labeled as income poor in 2010.

In 2007, the Swedish government introduced a workforce reform and a number of transfer cuts were made along with this reform (benefits of various kinds). The rolling tax reduction, the so-called "Jobbskatteavdraget", lowered the tax burden for wage earners. The reform was aimed at increasing labor supply at the extensive margin by reducing the tax on employment. In addition, during the first part of the 2000's, real wages grew rapidly but the real value of transfers did not (Gustafsson and Österberg, 2016).

Sweden experienced a rapid growth in inequality in the 2000's (OECD, 2015). While the overall poverty rate returned to its pre-recession levels in 2005/2006, disposable income inequality continued to grow. Much of the rising inequality can be explained by flows into and out of the labor market. In the years following the workforce reform, the proportion of poor children with non-employed parents suddenly increased. A potential explanation for this development is that the anticipated positive labor supply response to the work incentives was not sufficient to compensate for the cuts in transfers. The economic crisis was, however, relatively short-lived in Sweden and it has been argued that the economic downturn in 2008–2009 had a limited impact on the number of poor children in Sweden as compared to other European countries (Mood and Jonsson, 2016b). Similarly to the aftermaths of the economic downturn in the early 1990's, the gap in market incomes seemed to be the driver of the growing income inequality of the 2000's.

[19] Naturally, all the data sets suffer from similar measurement error issues as the Swedish data and therefore the numbers should be interpreted with caution.

Children growing up in households in the lowest quintile of the disposable income distribution are especially vulnerable to changes in taxes and transfers since these families are more likely to rely on social benefits. The households' labor market status is a key predictor of the poverty status of the children within the household. Single parent households and immigrants, two categories that are often found at the lower end of the income distribution, are to a large extent exposed to poverty risk through changes in social transfers and benefits. Prior to, as well as during the period of study, Sweden experienced an increased inflow of refugees.

Mood and Jonsson (2016b) go further back in time than we do by demonstrating the trends in different child poverty measures from the 1980's and onwards.[20] Their results reveal striking changes in relative poverty but not in absolute poverty. While the absolute poverty rate has decreased since the 1990's and remained fairly stable after 2006, relative poverty has increased significantly. Their child-centric measures of poverty include economic and material deprivation. Despite rising income inequality and relative income poverty, they do not find any rising trend in any of these measures during this period.

Moving on to our data, table 7 reports the proportions of poor children in 2000 and 2010, respectively. The proportion of income poor children is 6.6 percent in the year 2000 and 14.8 percent in the year 2010, a substantial and statistically significant increase in income-based child poverty of 8.2 percentage points.[21]

A related study, Mood and Jonsson (2014), finds that the proportion of poor children aged 0–19 is approximately 4 percent in the year 2000. Their results are based on HEK (using the same relative poverty line) and show a positive trend in child poverty with a rate of 9 percent in 2010, implying a more than doubling of the proportion of poor children. These results are consistent with the OECD estimates (OECD, 2017)

[20] Domeij and Floden (2010) document a rising inequality in disposable income and earnings net taxes and transfers in the early 1990's.

[21] We test the equality of the means using a two-sided Wald test (α=0.05) which takes into account the sampling weights. The Wald test is a t-test for survey data.

Table 7: Child poverty according to monetary and non-monetary measures in 2000 (n=1288) and 2010 (n=910), means and s.e., lowest quintile in score

	Income	Material	Social	Overlap		
				I and M	I and S	M and S
2000	0.066	0.299	0.201	0.028	0.009	0.051
	(0.008)	(0.013)	(0.012)	(0.005)	(0.003)	(0.006)
2010	0.148	0.255	0.200	0.070	0.027	0.042
	(0.014)	(0.016)	(0.014)	(0.011)	(0.007)	(0.008)
Difference	0.082	-0.044	-0.000	0.042	0.018	-0.008

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as belonging to the lowest quintile of the respective index.

demonstrating an increase from almost 4 percent to more than 9 percent as indicated in figure 3. Overall, the trends in child poverty are similar across the different data sources. We find somewhat higher levels of child poverty than Mood and Jonsson (2014) which is related to differences in data and measures but our estimates lie within or close to the margin of error.[22]

We define material deprivation and social exclusion as belonging to the bottom quintile in our sample; thus, the proportion of children labeled as poor according to these measures is set at 20 percent. In the sensitivity analysis in Appendix A, we also use the definition 1/2 of median of the index score distribution. We choose this particular threshold because we are interested in the overlap of these measures with the income-based measure. The overlaps of these measures are discussed in section 5.

Tables 8 and 9 show the results divided by age and gender. Poverty rates refer to the number of children below the poverty line, expressed as a percentage of all children in our sample.

At first glance, the differences in the means of material deprivation of

[22]The research report of Mood and Jonsson (2014) does not report confidence intervals.

Table 8: Child poverty according to monetary and non-monetary measures in 2000, means and s.e., lowest quintile in score, n=1288

	Income	Material	Social	Overlap		
				I and M	I and S	M and S
All	0.066	0.299	0.201	0.028	0.009	0.051
	(0.008)	(0.013)	(0.012)	(0.005)	(0.003)	(0.006)
All in ages 10-14	0.071	0.425	0.222	0.042	0.010	0.082
	(0.011)	(0.018)	(0.015)	(0.008)	(0.004)	(0.010)
All in ages 15-18	0.058	0.104	0.167	0.007	0.008	0.002
	(0.013)	(0.014)	(0.018)	(0.004)	(0.005)	(0.002)
Girls	0.074	0.329	0.144	0.031	0.008	0.050
	(0.012)	(0.019)	(0.015)	(0.007)	(0.004)	(0.009)
Girls in ages 10-14	0.079	0.478	0.170	0.048	0.009	0.082
	(0.015)	(0.026)	(0.020)	(0.011)	(0.005)	(0.014)
Girls in ages 15-18	0.068	0.118	0.108	0.007	0.008	0.003
	(0.020)	(0.020)	(0.021)	(0.005)	(0.008)	(0.003)
Boys	0.057	0.267	0.260	0.025	0.010	0.051
	(0.011)	(0.019)	(0.018)	(0.008)	(0.004)	(0.009)
Boys in ages 10-14	0.063	0.372	0.273	0.035	0.010	0.081
	(0.015)	(0.026)	(0.024)	(0.011)	(0.005)	(0.014)
Boys in ages 15-18	0.046	0.087	0.238	0.007	0.009	0.000
	(0.015)	(0.019)	(0.029)	(0.007)	(0.006)	(0.000)

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as belonging to the lowest quintile of the respective index.

the two cross-sections may seem worrying as they should be close to 0.20 by definition. The proportion of materially deprived children in the year 2000 is 29.9 percent (>20) because the underlying distribution is quite lumpy. The distribution of the material score index as presented earlier is multi-modal with several large peaks. In part, this is also due to a small sample size and sampling weights (we have adjusted the estimates using sampling weights provided by Statistics Sweden).

Tables 8 and 9 show that age seems to be negatively related to material deprivation. Consistent with previous findings, our results suggest a significant increase in child poverty estimated using monetary measures: from 6.6 percent in 2000 to 14.8 percent in 2010.

A closer inspection of the results divided by gender in tables 8 and 9 reveals that the proportion of girls that are income poor is higher than

Table 9: Child poverty according to monetary and non-monetary measures in 2010, means and s.e., lowest quintile in score, n=910

	Income	Material	Social	Overlap		
				I and M	I and S	M and S
All	0.148	0.255	0.200	0.070	0.027	0.042
	(0.014)	(0.016)	(0.014)	(0.011)	(0.007)	(0.008)
All in ages 10-14	0.149	0.342	0.239	0.079	0.027	0.065
	(0.020)	(0.024)	(0.021)	(0.016)	(0.009)	(0.012)
All in ages 15-18	0.145	0.163	0.159	0.061	0.028	0.018
	(0.021)	(0.021)	(0.019)	(0.015)	(0.011)	(0.008)
Girls	0.155	0.271	0.153	0.073	0.015	0.033
	(0.020)	(0.023)	(0.019)	(0.015)	(0.007)	(0.010)
Girls in ages 10-14	0.153	0.342	0.209	0.074	0.013	0.046
	(0.028)	(0.034)	(0.030)	(0.020)	(0.009)	(0.016)
Girls in ages 15-18	0.156	0.196	0.093	0.071	0.017	0.019
	(0.030)	(0.030)	(0.021)	(0.022)	(0.012)	(0.011)
Boys	0.140	0.238	0.248	0.068	0.040	0.053
	(0.021)	(0.023)	(0.022)	(0.016)	(0.011)	(0.011)
Boys in ages 10-14	0.145	0.342	0.270	0.085	0.041	0.086
	(0.029)	(0.034)	(0.030)	(0.025)	(0.015)	(0.019)
Boys in ages 15-18	0.135	0.130	0.225	0.050	0.039	0.018
	(0.030)	(0.028)	(0.031)	(0.021)	(0.017)	(0.011)

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as belonging to the lowest quintile of the respective index.

that of boys. This seems to be the case in both cross-sections. Moreover, the proportion of socially excluded boys is higher than that of girls (both in 2000 and 2010). We will inspect these differences more closely in section 4.2, when we estimate the relative risks and can control for age. Table 10 below shows the corresponding estimates for the panel sample. The age and gender differences are still there but much less pronounced.

As a final part of the "snapshot" analysis, we also calculate the proportion of poor according to a *fixed* poverty level which can also be interpreted as an absolute poverty measure. We set the poverty line in 2010 to 50 percent of the median disposable income in 1999 corrected for inflation. The proportion of absolute income poor children is 4.4 percent (s.e.=0.0081), which is in line with the aforementioned studies.

All in all, we find a significant rising trend in relative child poverty

Table 10: Child poverty according to monetary and non-monetary measures in 2000, panel, means and s.e., lowest quintile in score, n=803

	Income	Material	Social	Overlap		
				I and M	I and S	M and S
All	0.064	0.205	0.200	0.028	0.011	0.032
	(0.010)	(0.015)	(0.014)	(0.006)	(0.004)	(0.006)
All in ages 10-14	0.069	0.278	0.225	0.040	0.013	0.050
	(0.012)	(0.021)	(0.019)	(0.009)	(0.005)	(0.009)
All in ages 15-18	0.055	0.077	0.157	0.008	0.006	0.000
	(0.016)	(0.016)	(0.022)	(0.006)	(0.006)	(0.000)
Girls	0.067	0.184	0.150	0.023	0.008	0.026
	(0.014)	(0.019)	(0.018)	(0.007)	(0.005)	(0.008)
Girls in ages 10-14	0.064	0.263	0.196	0.034	0.006	0.041
	(0.017)	(0.028)	(0.025)	(0.011)	(0.004)	(0.012)
Girls in ages 15-18	0.072	0.050	0.072	0.005	0.011	0.000
	(0.026)	(0.017)	(0.024)	(0.005)	(0.011)	(0.000)
Boys	0.060	0.228	0.254	0.034	0.013	0.039
	(0.014)	(0.022)	(0.023)	(0.011)	(0.006)	(0.010)
Boys in ages 10-14	0.074	0.294	0.255	0.046	0.021	0.060
	(0.019)	(0.030)	(0.028)	(0.015)	(0.009)	(0.015)
Boys in ages 15-18	0.035	0.107	0.252	0.013	0.000	0.000
	(0.018)	(0.027)	(0.038)	(0.012)	(0.000)	(0.000)

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as belonging to the lowest quintile of the respective index.

which is consistent with previous findings. The results also suggest interesting age and gender differences which we examine more closely using relative risk estimations in the following section.

4.2 Relative poverty risks

In this section, we investigate the relative poverty risks of different household-level characteristics using binary logistic regression where the dependent variable is a dummy indicating either childhood material deprivation or social exclusion. The mathematical expression of the logit model is:

$$P(y_i = 1|x_i) = \frac{\exp(x_i\beta)}{1 + \exp(x_i\beta)} \tag{3}$$

We assume that the error terms are independent and follow a logistic distribution. Since the model is estimated by logistic regression, we estimate the following latent linear response model:

$$\begin{aligned} Indicator_i^* = \alpha + \beta SingleParent_i + \sigma NrChildren_i \\ + \lambda Immigrant_i + \mathbf{x_i}'\gamma + \epsilon_i, \end{aligned} \tag{4}$$

where we only observe $Indicator_i = I(y_i^* > 0)$ for the latent variable $Indicator_i^*$ above.

Material deprivation and social exclusion, our two non-monetary indicators, are defined as belonging to the lowest quintile of the respective index distribution. The unit of analysis is the child i, α is a constant, $SingleParent_i$ indicates whether the child lives in a single parent household, $NrChildren_i$ represents the number of children in the household and $Immigrant_i$ indicates whether the child has two parents born abroad. $\mathbf{x_i}'$ represents a vector of control variables including age, gender and socioeconomic background. We use the Swedish standard socio-economic classification (SEI, Statistics Sweden) to create a dummy indicating whether a child has at least one parent whose occupation belongs to the non-manual employee or employer category of SEI. Potential key risk factors of poverty identified in previous literature include living in a single parent family, the number of children in the household and having foreign-born parents (Chen and Corak, 2008; Lindquist and Sjögren Lindquist, 2012).

We use 50 percent of the median disposable equivalent income of all households ages 20 and older in Sweden in the year prior to the survey. We do the same for the income poor outcome for the years 2000 and 2010, respectively and the results are shown in table 11. The estimates represent the relative risks of poverty (odds ratios) and standard errors are reported in parentheses.

Table 11: Relative risks of child poverty, monetary and non-monetary measures in 2000 and 2010, respectively

	Income poor		Material deprivation		Social exclusion	
	2000	2010	2000	2010	2000	2010
Age	0.960	1.066	0.668***	0.807***	0.964	0.899***
	(0.049)	(0.063)	(0.023)	(0.030)	(0.027)	(0.032)
Girl	1.171	1.088	1.477***	1.481**	0.481***	0.536***
	(0.339)	(0.270)	(0.217)	(0.265)	(0.077)	(0.102)
Number of children in hh	1.757***	1.558**	1.597***	1.478***	1.004	0.893
	(0.259)	(0.309)	(0.129)	(0.141)	(0.071)	(0.107)
Single parent	4.751***	3.714***	0.996	1.052	0.793	0.902
	(1.838)	(1.704)	(0.230)	(0.301)	(0.202)	(0.256)
Immigrant parents	0.669	5.787**	0.856	3.149***	0.784	0.640
	(0.773)	(4.129)	(0.577)	(1.207)	(0.423)	(0.314)
Non-manual/Employers	0.507*	0.321***	0.961	0.665*	0.977	0.961
	(0.188)	(0.123)	(0.153)	(0.150)	(0.149)	(0.207)
Observations	1288	883	1288	883	1288	883
Pseudo R^2	0.112	0.160	0.186	0.122	0.024	0.029

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from logistic regressions with robust standard errors clustered at the family level. Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as belonging to the lowest quintile of the respective index.

The pseudo R^2 of the specifications for income poverty and material deprivation in table 11 ranges from 0.11 to 0.19, indicating a fairly good model fit. In contrast to the other models, the pseudo R^2 is only about 0.02 for the model predicting social exclusion.

We find a negative association of child poverty status and age. However, the relationship is not significant in the specifications where the dependent variable is the income poverty indicator. There seem to exist significant gender differences in poverty status; material deprivation is more likely among girls than among boys. Only gender and age come out as significant explanatory variables in the specification for social exclusion; being a girl makes one significantly less likely to be labeled as socially excluded (OR=0.481 in 2000 and OR=0.536 in 2010).

When studying child poverty, an important sub-group is single-parent households. Children who grow up with single parents are typically at a higher risk of poverty (see, for example, Gornick and Jäntti (2011)). Unfortunately, the analysis sample is too small to conduct a separate analysis on this subgroup. Hence, we address this issue by including a dummy for single-parent households in the regressions. The results in table 11 demonstrate that the odds of being income poor are significantly higher for children growing up in single-parent families; they are almost four to five times as high with respect to income poverty. Furthermore, parents' occupational status also seems to matter. Having at least one parent with a non-manual occupation makes one significantly less likely to be labeled as income poor.

One potential measurement issue refers to the resources of lone parents. There could be income transfers between parents that cannot be observed in the data. The issue can, however, be explored further using survey answers to a question regarding time spent with the other parent (who is not registered at the same address). Bearing this in mind, our findings suggest that living in a single-parent household makes one between 4 and 5 times more likely to be income poor during the period of study compared to living with two parents. We do not, however, find such a relationship in the specifications where the dependent variable is our material deprivation or social exclusion indicator.

As mentioned above, there seem to exist significant gender differences in poverty status. The results presented in table 11 suggest that boys and girls experience different forms of childhood scarcity. For example, material deprivation is more likely among girls than boys. Only gender comes out as a significant explanatory variable in the specification for social exclusion; being a girl makes one significantly less likely to be labeled as socially excluded.

Immigrant children are overrepresented among poor children (Gustafsson and Österberg, 2016; Lindquist and Sjögren Lindquist, 2012; Galloway et al., 2009). However, the likelihood of being classified as poor among immigrant children declines with the years since migration. Table 11 shows that having immigrant parents makes an individual significantly more likely to be labeled as income poor and materially deprived in 2010. The odds of being materially deprived are more than three times as high for children with immigrant parents as compared to children with at least one native-born parent. In 2010, the odds ratio of being income poor between children with foreign-born parents and children with native-born parents is 5.79 ($p<0.05$).

In sum, the relative risk factors of child poverty seem to be stable from the year 2000 to 2010. In line with previous findings of, for example Gornick and Jäntti (2011), we find that children at-risk are those living with single parents and in larger families (consisting of a larger number of siblings). Taken together, these results point to the importance of following vulnerable subgroups such as single-parent households and immigrants closely over time and even more so during periods of increasing inequality.

The data that we use consist of a small number of immigrant families and due to both statistical and ethical considerations, a separate analysis of this group is not possible. The Swedish Level-of-Living Survey 2010 – Immigrants and their children (LNU-UFB), conducted in parallel with the LNU 2010, was designed for the purpose of studying this group more closely and allows for deeper analysis of the economic and social well-being of foreign-born individuals and their children. Such analyses are outside the scope of this paper, but it is undoubtedly an interesting and important avenue of future research. Finally, the results suggest that social exclusion seems to be more common among boys than among girls. Such gender differences could have long-lasting individual consequences which suggest that they should be studied further, preferably over longer periods of time.

5 Overlap of poverty measures

In this section, we investigate to what extent our child poverty measures overlap in 2000 and 2010, respectively.[23] Table 8 shows child poverty according to income, material deprivation and social exclusion and the overlap between these three in the year 2000. The corresponding results for 2010 are shown in table 9. Overall, the fraction of children that is disadvantaged in two dimensions, monetary and non-monetary, is relatively low in the year 2000: only 2.8 percent of the sample are classified as both income poor and materially deprived. The overlap between the former and the social exclusion indicator is even smaller (<1 percent). The largest overlap is observed between our two non-monetary indices: 5.1 percent of the children in the sample are both materially deprived and socially excluded.[24] The overlap is larger in year 2010 than 2000 for income and material deprivation (7.0 percent versus 2.8 percent) and income and social exclusion (2.7 percent versus 0.9 percent). The fraction of children that are both materially deprived and socially excluded decreases during the period of study from 5.1 percent to 4.2 percent.

Going back to table 7, the overlap between the income measure and the non-monetary measures increases significantly from the year 2000 to

[23] See, for example, Bourguignon and Chakravarty (2003) on correlations between different dimensions of poverty.

[24] Although not in relative terms as, for example, the overlap between income poverty and material deprivation is larger than the overlap between material deprivation and social exclusion: 0.028/(0.066*0.299)>0.051/(0.299*0.201). The largest overlap in both cross-sections is between income poverty and material deprivation and it displays a rising trend.

2010. While the overlap in income poverty and material deprivation increases by 4.2 percentage points, the overlap between income and social exclusion increases by 1.8 percentage points.

A potential issue with non-monetary indicators is that they are sensitive to technological and cultural consumption trends which could render them less consistent over time, compared to standard monetary measures. If this is the case, non-monetary measures could be measuring consumption trends rather than changes in poverty levels. Interestingly, the factor loadings for the variables TV, mobile and computer shown in Panel A in table 5 decrease during the period of study. In contrast to these variables, the factor loadings for owning a computer go in the other direction and increase. The observed increase in the overlap between the income poverty and material deprivation measures could mainly be driven by the computer question if material deprivation is better captured in 2010 than in 2000.

According to the results in table 7, the overlap between the two non-monetary measures decreases, but this change is insignificant. The results show that the children who were income poor in 2010 were also poor in other dimensions to a larger extent than those who were labeled as income poor in 2000. A larger proportion of children are classified as poor in two dimensions in 2010 than in 2000.

The small overlap between the measures could be explained by a number of factors, some of which have previously been discussed by Bradshaw and Finch (2003). First, a household can transition between different poverty statuses. For example, a household previously labeled as poor according to both the income poverty *and* the material deprivation measure in a certain year can move into the non-poor category with respect to the income measure the following year as income is more volatile. However, the household may still not have acquired the necessities needed to move to the non-poor state with respect to possession of goods and thereby still be labeled as materially deprived. The same applies to movements in the opposite direction. Such transitions can in part be explained by income transfers across generations with, for example, grandparents chipping in when times are especially hard.

The results in table 7 seem to suggest that parents are not able to cushion their children to the same extent as before. Stagnating incomes at the lower end of the distribution, along with changing consumption norms, could be an explanation behind this development. If it is harder for these families “to keep up with the Joneses” due to, for example, increasing consumption costs, their children could suffer in the long run. Social exclusion in childhood may have detrimental effects on non-cognitive skills and lacking socially perceived necessities or not being able to take part in social activities that are considered normal may have long-term consequences for their social outcomes. We investigate some potential long-term effects in section 6.

To summarize, the overlap between the income measure and the non-monetary measures increases significantly from the year 2000 to 2010 and this rise was mainly driven by an increase in the proportion of income poor. Part of this result could also be related to the multimodal character of the material deprivation score distribution. The 2010-sample is to a larger extent than the 2000-sample also poor in other dimensions. The overlap between the two non-monetary measures decreases (insignificant reduction) while the overlap in two dimensions increases significantly. Interestingly, the overlaps seem to be somewhat larger (not significantly) for younger children than for older ones in both cross-sections. A larger proportion of children are classified as both income poor and materially deprived or socially excluded in 2010 than in 2000. Finally, we find that the largest overlap is between income and material deprivation in 2010. With rising relative income poverty as demonstrated in table 7 and growing income inequality, this could be an indication of those at the lower end of the income distribution not being able to keep up with the others with respect to material possessions.

The overlap between the measures may reasonably be considered low. There is a number of potential explanations behind the modest overlap between monetary and non-monetary indicators of child poverty (see e.g. the discussion in Bradshaw and Finch (2003) covering most of the explanations presented below). One explanation could be that our monetary and non-monetary measures identify different individuals. Children who are socially deprived could in some (observed or unobserved) respects be different from those who are materially deprived. The result could also be an indication of the phenomenon of "birds of a feather flocking together". In socially segregated societies, disadvantaged children will more likely play with disadvantaged peers (due to, for example, social and geographical distance). Our measure of social exclusion will inherently fail to capture social deprivation in segregated societies.

Another reason could be a lagged adjustment of living standards (Saunders et al., 2008). There could be cases in transition between the states deprived/non-deprived which will not show up in our overlap categories (as discussed in section 5). The modest overlap could also be due to a compensating behavior within reconstituted families (divorced parents competing with material gifts since the income of only one parent shows up in our data for reconstituted families) or by grandparents cushioning their grandchildren during periods of economic distress. These and related issues could be explored further using the detailed survey questions to both parents and children in LNU.[25]

Finally, as noted by Saunders et al. (2008): "Income is not the only determinant of the living standards that ultimately affect whether deprivation and exclusion exist... Low income may be a barrier to some forms of inclusion, but there are many other areas where social exclusion is caused by factors other than poverty" (p. 16).

6 Predictive power of measures

In this section, we proceed by exploring the predictive power of our monetary and non-monetary poverty measures. We investigate the size of the overlap between the child poverty status measures and selected adult outcomes. For instance, we ask how many percent of the children

[25]There could also be technical issues with the measures with respect to the index score distributions, for example those discussed in section 3.3.

labeled as income poor are also labeled as income poor as adults.

The analysis is based on a panel of 803 individuals who filled out the child questionnaire in 2000 and who were later re-interviewed as adults in the main LNU survey in the year 2010. It is the same individuals that were analyzed in the cross-section analysis above less the twins since these could not be uniquely matched with the register data from 2010. The outcomes in early adulthood consist of three different dummy variables which are used as proxies for economic status in early adulthood. These include whether or not an individual is income poor in 2010 defined in terms of equivalent disposable household income being below 50 percent of the median in the overall population in 2010, whether or not an individual has any university studies, and, finally, whether he or she is employed in the year 2010.[26] *Any university* indicates a completed university degree or currently studying at the university. An individual is considered *employed* if he or she has an SEI code for current work (socio-economic group for respondent's occupation in 2010). There are 12 missing cases on the employment outcome variable and these individuals are excluded from the analysis. The results are presented in table 12.

The row totals do not add up to 100 as an individual can belong to more than one outcome category. For example, an individual that is labeled as socially excluded in childhood can both have a university degree and be employed. Table 12 reports sample means and the estimates are therefore not corrected for age differences between the respondents. We control for age in the logistic regressions presented further below.

[26]We use income in young adulthood as a proxy for life-time income although we are aware that this could produce inconsistent estimates due to the so-called life-cycle bias (Böhlmark and Lindquist, 2006). We also create an indicator for neither in employment nor in education and training (NEET). In these specifications (delivered upon request) we do, however, not find any significant associations with our child poverty indicators.

Table 12: Selected adult outcomes in 2010 by poverty status in 2000, panel, means and s.e., n=803

	Income poor 2010	Any university	Employed
	(1)	(2)	(3)
Income poor 2000	0.229	0.196	0.621
	(0.062)	(0.065)	(0.080)
Material deprivation	0.152	0.378	0.552
	(0.028)	(0.039)	(0.040)
Social exclusion	0.109	0.374	0.672
	(0.024)	(0.038)	(0.038)
Overlap			
I and M	0.311	0.291	0.606
	(0.104)	(0.111)	(0.114)
I and S	0.221	0.280	0.612
	(0.152)	(0.189)	(0.195)
M and S	0.170	0.526	0.513
	(0.071)	(0.097)	(0.097)

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as belonging to the lowest quintile of the respective index. *Any university* is an indicator variable for whether an individual has a completed university degree or is currently studying at the university. *Employed* indicates whether an individual has an SEI code for current work. 12 individuals are omitted from the analysis due to missing values on the employment outcome variable.

The proportion of children that are income poor in young adulthood, given that they are classified as poor in childhood, is close to 23 percent (table 12, column (1)). Income poverty in childhood seems to be more closely related to income poverty in adulthood than are material deprivation and social exclusion. Among the income poor children, a substantial proportion is employed (62.1 percent). An important point to make here is that the age range in the sample is 20–29; hence, some of the individuals may still be living at home with their parents and may not yet have moved on to study at the upper-secondary level or the university.

Table 12 also shows similar patterns in the adult outcomes of individuals who were classified as materially deprived or socially excluded in childhood. Among those who belonged to the lowest quintile of the material deprivation index distribution, 15.2 percent were classified as income poor as adults. Furthermore, 10.9 percent were income poor in the lowest quintile of the social exclusion index. The proportion that goes on to study at the university is about 37 percent in these two categories and more than half are employed. The proportions of employed in each of the childhood poverty status categories are found within the range 55–67 percent. Amongst all indicators, social exclusion and being employed have the largest overlap (67.2 percent, column (3)).

Moving on to the three overlap categories income poor 2000 and material deprivation (I and M), income poor 2000 and social exclusion (I and S) and material deprivation and social exclusion (M and S), the lower panel of table 12 shows that these seem to overlap with being employed to about 60 percent (except for the last category for which the overlap with being employed is close to 50 percent).

Due to a potential composition bias, we run logistic regressions where we control for age. In what follows, we estimate the relationship between the later life outcomes presented above and our indicators of poverty status in 2000: relative income poverty, material deprivation and social exclusion. As before, the model is estimated by logit regressions and the latent linear response model we estimate is the following:

$$AdultOutcome_i^* = \alpha + \beta Indicator_i + \mathbf{x_i}'\gamma + \epsilon_i, \tag{5}$$

where we only observe $AdultOutcome_i = I(y_i^* > 0)$ for the latent variable $AdultOutcome_i^*$ above. We assume that the error terms are independent and follow a logistic distribution. $AdultOutcome_i$ is a dummy variable of poverty in early adulthood and $\mathbf{x_i}'$ represents a vector of the individual characteristics birth year and gender. The standard errors are robust and clustered at the family level. The estimation results are found in table 13.

Income poverty in childhood seems to be a strong predictor of being poor as a young adult: The odds of being poor are more than twice as large for those who were classified as income poor as children (panel A, column (1)) and less likely to be employed (although insignificant). Being income poor as a child makes one significantly less likely to study at the university (OR=0.435, p<0.10). Material deprivation in childhood is positively associated with being income poor in young adulthood, while social exclusion is negatively associated with the same, although the estimates are insignificant. We do not find any significant relationship between either material deprivation or social exclusion with being employed in 2010 or having university studies (shown in panels B and C, columns (2) and (3)). We exclude the overlapping categories in the logistic regressions as the number of individuals who fall into these categories is too small and including these would produce trivial results.[27]

To summarize, income poverty in childhood seems to be a strong predictor of being poor as an young adult. The odds of being impoverished with respect to income are more than twice as high for those who were classified as income poor as children (OR=2.608, p<0.01). In addition, being income poor in childhood makes an individual less likely

[27] A potential issue when using survey data is that the sample size is too small to identify a true effect which is why we do not consider the overlapping categories in the regression analysis. Table 10 shows the proportions: 1.1–3.2 percent of the sample which corresponds to less than 10 to 25 individuals.

Table 13: Predictive power of monetary and non-monetary measures for selected adult outcomes

	OR (s.e.) (1)	OR (s.e.) (2)	OR (s.e.) (3)	OR (s.e.) (4)
Panel A: Income poor 2010				
Demographics				
Age	0.813***	0.818***	0.809***	0.816***
	(0.044)	(0.046)	(0.044)	(0.046)
Female	0.744	0.753	0.744	0.747
	(0.188)	(0.190)	(0.189)	(0.193)
Indicators				
Income poor 2000	2.608***			2.550**
	(0.933)			(0.929)
Material deprivation		1.221		1.092
		(0.333)		(0.307)
Social exclusion			0.978	0.995
			(0.275)	(0.287)
Observations	803	803	803	803
Panel B: Employed				
Demographics				
Age	1.256***	1.241***	1.258***	1.242***
	(0.042)	(0.043)	(0.042)	(0.043)
Female	1.194	1.180	1.207	1.191
	(0.194)	(0.191)	(0.198)	(0.195)
Indicators				
Income poor 2000	0.875			0.931
	(0.314)			(0.341)
Material deprivation		0.774		0.785
		(0.154)		(0.157)
Social exclusion			1.116	1.093
			(0.220)	(0.216)
Observations	791	791	791	791
Panel C: Any university				
Demographics				
Age	1.010	1.023	1.015	1.026
	(0.030)	(0.031)	(0.030)	(0.032)
Female	1.107	1.112	1.119	1.144
	(0.176)	(0.175)	(0.179)	(0.184)
Indicators				
Income poor 2000	0.435*			0.406**
	(0.191)			(0.174)
Material deprivation		1.233		1.352
		(0.249)		(0.273)
Social exclusion			1.168	1.185
			(0.221)	(0.226)
Observations	803	803	803	803

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from logistic regressions with robust standard errors clustered at the family level. Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as belonging to the lowest quintile of the respective index. *Any university* is an indicator variable for whether an individual has a completed university degree or is currently studying at the university. *Employed* indicates whether an individual has an SEI code for current work.

to study at the university (OR=0.435, $p<0.10$). We do not find any significant relationship between our non-monetary child poverty indicators and the selected outcome variables. The next step is to look at outcomes pertaining to life satisfaction and social networks in adulthood.

7 Discussion

The debate about what poverty means and how welfare should be assessed is age-old. Are income-based indicators more reliable than self-reported deprivation measures and are these competing or complementary? The aim of this study was to broaden the analysis of child poverty by introducing supplementary measures based on children's self-reported level of living to further investigate the general living standard of children in Sweden over time.

Consistent with previous findings, we find that relative income poverty among children increased substantially between year 2000 and 2010, by 8.2 percentage points. Overall, we find that the factor loadings of the material and social indices are stable between the years 2000 and 2010. The results also suggest that the risk factors of child poverty are stable over time. In line with previous findings, we find that children at-risk are those living with single parents and in larger households. Moreover, our results demonstrate that the overlap between the monetary and non-monetary measures is relatively small, which is consistent with the findings of Bradshaw and Finch (2003), Gross-Manos (2015) and Saunders et al. (2008). The modest size of the overlap suggests that these measures are complementary rather than competing, i.e. they capture different dimensions of scarcity.

Our results point to the importance of not only relying on monetary measures but on several multidimensional measures that can more broadly capture welfare. Poverty is a multifaceted phenomenon which necessitates more comprehensive measures of welfare and well-being. Household-centered measures may overlook the needs of children growing up in materially impoverished families since they do not take into account the distribution of income within families. As opposed to household income measures, child-centric measures will be less likely to overlook the possessions and activities that define membership in a community from the viewpoint of children.

Among our three indicators, the monetary measure is the best predictor of adult outcomes. We find that income status in childhood is significantly related to income poverty in adulthood. Moreover, experiences of income poverty in childhood seem to be related to adverse economic outcomes in young adulthood since children who grow up in poverty are less likely to study at the university. Our measure of participation, the social exclusion indicator, is not related to any of our selected adult outcomes and neither is the material deprivation measure. The next step would therefore be to explore other outcomes that could be associated with our non-monetary indicators such as, for example, social networks. With growing income inequality in several European countries, and Sweden being one of them, new measures are needed to study the life trajectories of children growing up in economic and social hardship.

An important policy question is to what extent the Swedish welfare system protects children from poverty. Are those at the bottom part of the distribution able to keep up with others with respect to consumption and participation during periods of economic distress? Children's consumption and participation can suffer directly from cutbacks in social benefits. For example, Hjalmarsson and Mood (2015) find evidence suggesting that children who lack their own room on average receive fewer friendship nominations and are thus at higher risk of social isolation. Moreover, workforce policies directed at parents can, through their detrimental effect on household consumption, also have long-lasting consequences for children's later life educational and labor outcomes. The lack of certain socially perceived necessities in childhood may affect children's position in their society and, consequently, result in a lower earnings potential in the long run.

During the last four decades, Sweden has experienced a significant influx of immigrants, including many children. Since the migration status of parents has been shown to be an important predictor of child poverty (Gustafsson and Österberg, 2016; Lindquist and Sjögren Lindquist, 2012; Galloway et al., 2009), changes in macroeconomic and demographic conditions make it all the more important to follow the life-course trajectories of certain subgroups. Living a life on par with others seems to matter but what is the relevant reference group if poor children only play with other poor children? And what are the long-term consequences of socio-economic segregation?

We suggest that more research should be devoted to studying the well-being and the social networks of poor children longitudinally. The next wave of the LNU survey will be conducted in a couple of years and it will hopefully consist of a new child survey and a follow-up of the individuals studied in this paper. A longitudinal comparative study is already made possible by the Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU) which contains information similar to that in the LNU survey.

It should be mentioned that the findings of this paper are based on normative assumptions of what the adequate standard of living is and on subjective methodological choices (as discussed by for example Kingdon and Knight (2006)), which undeniably complicates the policy conclusions. The results should be interpreted with caution although taken together with previous evidence within the field, the overall findings tend to point to the importance of alternative poverty indicators (Bradshaw and Finch, 2003; Gross-Manos, 2015).

The limitations of our study mainly relate to the reliability and validity of our measures and a power problem. The size of the analysis sample is relatively small, resulting in an efficiency problem. One way of testing the internal validity is to investigate the correlation between non-monetary measures and other non-monetary and monetary measures not used for the indices. We perform several tests showing that our measures are valid but more research in this field is needed to validate the existing findings. With regard to the external validity of the results, the findings of this paper could be generalized to other European countries with extensive welfare states.

Finally, our findings suggest that income-based measures are strongly related; being poor in 2000 makes an individual significantly more likely to be income poor as an adult. An important next step is to investigate who these poor children are. Another related question that it would be interesting to look at is the correlation between our non-monetary measures and other child measures of well-being such as somatic and psychological health, two growing concerns in many European countries today.

A Sensitivity analysis

In this section, we investigate the sensitivity of our findings. We try out alternative methods and definitions. First, we present the correlations between each underlying item and the income poverty indicator conditional on a set of individual and background characteristics (shown in tables A1, A2, A3 and A4). The only variables that are significant, conditional on age, gender etc., are indicators for having an own room and computer in 2010 (see table A2). With regard to social exclusion, having friends at home is weakly significant ($p<0.10$) in 2000.

Next, in order to test the robustness of our results, we set an alternative threshold for material deprivation and social exclusion. Tables A5, A6, A7 and A8 show the results with material deprivation and social exclusion defined as having an index score below 1/2 of the median of the respective index score. Table A5 gives an overview of the results.

The proportion of children labeled as materially deprived and socially excluded in the year 2000 is 45.8 percent and 54.6 percent, respectively, compared to 42.1 percent and 51.8 percent in the year 2010. The largest overlap is between the material and social indices (24.0 percent in 2000 and 21.2 percent in 2010). The overlap between income poverty and material deprivation is 4.0 percent and the overlap between income poverty and social exclusion is 2.4 percent in 2000. These overlaps increased significantly during the period of study (5.0 and 4.9 percentage points, respectively). The results suggest that these overlaps are relatively stable with respect to the choice of threshold. The overlap between the two non-monetary measures decreased, although insignificantly.

Tables A6 and A7 display a larger overlap between the two non-monetary measures than the previous results based on the definition of lowest quintile in the material and social indices. For completeness, the corresponding proportion for the panel are displayed in table A8. Overall, the results are consistent with the findings in the main analysis.

As a supplemental sensitivity test, we utilize an alternative measure, namely a deprivation index score, defined as the number of necessities a child is missing (Bradshaw and Finch, 2003; Saunders et al., 2008). The index score ranges between 0 and 5. Frequencies and percentages are shown in tables C3 and C4. With regard to social activities, the corresponding frequencies and percentages are shown in tables C5 and C6. The results from this approach suggest that material deprivation is positively related to income poverty (table A9), all else equal. We also find evidence that the number of missing social activities is positively related to income poverty (see table A10).

Table A1: Lacking certain necessary items, correlations with income poverty indicator, year 2000

Dependent variable: Income poor					
Room	0.0668				
	(0.045)				
Pet		0.000352			
		(0.019)			
TV			0.0174		
			(0.020)		
Mobile				0.00342	
				(0.019)	
Computer					0.0278
					(0.017)
Age	0.000181	-0.000396	0.000470	-0.0000767	0.0000459
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Girl	0.0150	0.0136	0.0118	0.0137	0.00946
	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)
Number of children in hh	0.0381**	0.0443***	0.0430**	0.0440**	0.0431**
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
Single parent	0.0950***	0.103***	0.102***	0.103***	0.103***
	(0.034)	(0.033)	(0.033)	(0.033)	(0.033)
Constant	-0.0584	-0.0580	-0.0742	-0.0637	-0.0798
	(0.062)	(0.062)	(0.066)	(0.063)	(0.065)
Observations	1288	1288	1288	1288	1288

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from OLS regressions with robust standard errors clustered at the family level.

Table A2: Lacking certain necessary items, correlations with income poverty indicator, year 2010

Dependent variable: Income poor					
Room	0.183**				
	(0.079)				
Pet		0.0379			
		(0.032)			
TV			0.0389		
			(0.032)		
Mobile				0.106	
				(0.084)	
Computer					0.103***
					(0.035)
Age	0.00780	0.00574	0.00721	0.00727	0.0101*
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Girl	0.00782	0.0154	0.00664	0.0117	0.00680
	(0.023)	(0.024)	(0.023)	(0.024)	(0.023)
Number of children in hh	0.0600***	0.0731***	0.0736***	0.0750***	0.0694***
	(0.020)	(0.021)	(0.021)	(0.021)	(0.019)
Single parent	0.188***	0.200***	0.206***	0.204***	0.205***
	(0.049)	(0.049)	(0.049)	(0.049)	(0.047)
Constant	-0.162*	-0.167*	-0.182*	-0.177*	-0.232**
	(0.096)	(0.100)	(0.105)	(0.098)	(0.103)
Observations	910	910	910	910	910

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from OLS regressions with robust standard errors clustered at the family level.

Table A3: Lack of participation, correlations with income poverty indicator, year 2000

Dependent variable: Income poor				
Seldom or never...				
Friends home	0.0259			
	(0.022)			
Home friends		0.0613*		
		(0.033)		
Meet friends			0.00118	
			(0.023)	
Sport				-0.00337
				(0.017)
Age	-0.00119	-0.000743	-0.000363	-0.000331
	(0.003)	(0.003)	(0.003)	(0.003)
Girl	0.0140	0.00973	0.0135	0.0138
	(0.016)	(0.016)	(0.017)	(0.016)
Number of children in hh	0.0434**	0.0424***	0.0443***	0.0444***
	(0.017)	(0.016)	(0.017)	(0.017)
Single parent	0.100***	0.0964***	0.103***	0.103***
	(0.032)	(0.031)	(0.033)	(0.033)
Constant	-0.0512	-0.0566	-0.0584	-0.0581
	(0.062)	(0.061)	(0.065)	(0.062)
Observations	1288	1288	1288	1288

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from OLS regressions with robust standard errors clustered at the family level.

Table A4: Lack of participation, correlations with income poverty indicator, year 2010

Dependent variable: Income poor				
Seldom or never...				
Friends home	0.0427			
	(0.032)			
Home friends		0.0465		
		(0.037)		
Meet friends			-0.00103	
			(0.048)	
Sport				0.0397
				(0.029)
Age	0.00508	0.00559	0.00587	0.00425
	(0.006)	(0.005)	(0.006)	(0.006)
Girl	0.0112	0.0110	0.0116	0.00936
	(0.024)	(0.024)	(0.024)	(0.023)
Number of children in hh	0.0734***	0.0741***	0.0749***	0.0741***
	(0.020)	(0.020)	(0.021)	(0.021)
Single parent	0.204***	0.204***	0.205***	0.202***
	(0.048)	(0.049)	(0.049)	(0.049)
Constant	-0.150	-0.157	-0.152	-0.140
	(0.098)	(0.098)	(0.103)	(0.099)
Observations	910	910	910	910

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from OLS regressions with robust standard errors clustered at the family level.

Table A5: Child poverty according to monetary and non-monetary measures in 2000 (n=1288) and 2010 (n=910), cross-sections, means and s.e., less than 1/2 of median in score

	Income	Material	Social	Overlap		
				I and M	I and S	M and S
2000	0.066	0.458	0.546	0.040	0.024	0.240
	(0.008)	(0.015)	(0.015)	(0.006)	(0.005)	(0.012)
2010	0.148	0.421	0.518	0.089	0.074	0.212
	(0.014)	(0.018)	(0.018)	(0.012)	(0.011)	(0.015)
Difference	0.082	-0.037	-0.028	0.050	0.049	-0.028

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as having an index score below 1/2 of the median of the respective index score.

Table A6: Child poverty according to monetary and non-monetary measures in 2000, cross-section, means and s.e., less than 1/2 of median in score, n=1288

	Income	Material	Social	Overlap		
				I and M	I and S	M and S
All	0.066	0.458	0.546	0.040	0.024	0.240
	(0.008)	(0.015)	(0.015)	(0.006)	(0.005)	(0.012)
All in ages 10-14	0.071	0.563	0.592	0.044	0.023	0.324
	(0.011)	(0.019)	(0.019)	(0.008)	(0.006)	(0.017)
All in ages 15-18	0.058	0.294	0.475	0.033	0.027	0.109
	(0.013)	(0.022)	(0.024)	(0.009)	(0.008)	(0.015)
Girls	0.074	0.499	0.506	0.047	0.027	0.249
	(0.012)	(0.021)	(0.021)	(0.009)	(0.007)	(0.017)
Girls in ages 10-14	0.079	0.615	0.547	0.051	0.022	0.333
	(0.015)	(0.026)	(0.026)	(0.011)	(0.008)	(0.024)
Girls in ages 15-18	0.068	0.336	0.448	0.042	0.034	0.130
	(0.020)	(0.032)	(0.034)	(0.015)	(0.013)	(0.022)
Boys	0.057	0.413	0.589	0.032	0.022	0.230
	(0.011)	(0.021)	(0.021)	(0.008)	(0.007)	(0.018)
Boys in ages 10-14	0.063	0.511	0.636	0.037	0.024	0.315
	(0.015)	(0.027)	(0.026)	(0.011)	(0.009)	(0.025)
Boys in ages 15-18	0.046	0.243	0.507	0.022	0.019	0.083
	(0.015)	(0.030)	(0.035)	(0.011)	(0.009)	(0.020)

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as having an index score below 1/2 of the median of the respective index score.

Table A7: Child poverty according to monetary and non-monetary measures in 2010, cross-section, means and s.e., less than 1/2 of median in score, n=910

	Income	Material	Social	Overlap		
				I and M	I and S	M and S
All	0.148	0.421	0.518	0.089	0.074	0.212
	(0.014)	(0.018)	(0.018)	(0.012)	(0.011)	(0.015)
All in ages 10-14	0.149	0.523	0.569	0.097	0.088	0.281
	(0.020)	(0.025)	(0.025)	(0.017)	(0.016)	(0.022)
All in ages 15-18	0.145	0.313	0.465	0.080	0.058	0.139
	(0.021)	(0.024)	(0.025)	(0.017)	(0.015)	(0.019)
Girls	0.155	0.426	0.489	0.085	0.068	0.206
	(0.020)	(0.025)	(0.025)	(0.016)	(0.015)	(0.021)
Girls in ages 10-14	0.153	0.515	0.558	0.090	0.083	0.279
	(0.028)	(0.036)	(0.035)	(0.022)	(0.023)	(0.032)
Girls in ages 15-18	0.156	0.332	0.416	0.079	0.052	0.128
	(0.030)	(0.034)	(0.035)	(0.023)	(0.020)	(0.025)
Boys	0.140	0.415	0.548	0.094	0.079	0.218
	(0.021)	(0.025)	(0.025)	(0.018)	(0.016)	(0.021)
Boys in ages 10-14	0.145	0.530	0.581	0.104	0.092	0.283
	(0.029)	(0.035)	(0.035)	(0.026)	(0.022)	(0.031)
Boys in ages 15-18	0.135	0.294	0.514	0.082	0.065	0.150
	(0.030)	(0.034)	(0.036)	(0.025)	(0.023)	(0.028)

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as having an index score below 1/2 of the median of the respective index score.

Table A8: Child poverty according to monetary and non-monetary measures in 2000, panel, means and s.e., less than 1/2 of median in score, n=803

	Income	Material	Social	Overlap		
				I and M	I and S	M and S
All	0.064	0.476	0.531	0.043	0.023	0.242
	(0.010)	(0.019)	(0.019)	(0.008)	(0.005)	(0.016)
All in ages 10-14	0.069	0.576	0.580	0.045	0.021	0.327
	(0.012)	(0.023)	(0.023)	(0.010)	(0.006)	(0.021)
All in ages 15-18	0.055	0.300	0.445	0.039	0.025	0.093
	(0.016)	(0.029)	(0.032)	(0.013)	(0.010)	(0.019)
Girls	0.067	0.524	0.491	0.045	0.027	0.258
	(0.014)	(0.026)	(0.026)	(0.010)	(0.008)	(0.022)
Girls in ages 10-14	0.064	0.631	0.538	0.044	0.019	0.344
	(0.017)	(0.031)	(0.032)	(0.012)	(0.008)	(0.030)
Girls in ages 15-18	0.072	0.341	0.412	0.048	0.041	0.113
	(0.026)	(0.042)	(0.044)	(0.019)	(0.017)	(0.028)
Boys	0.060	0.424	0.574	0.040	0.018	0.224
	(0.014)	(0.027)	(0.027)	(0.011)	(0.007)	(0.022)
Boys in ages 10-14	0.074	0.518	0.624	0.046	0.024	0.308
	(0.019)	(0.033)	(0.033)	(0.015)	(0.010)	(0.030)
Boys in ages 15-18	0.035	0.254	0.482	0.028	0.006	0.072
	(0.018)	(0.039)	(0.045)	(0.017)	(0.006)	(0.024)

Notes: Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. Material deprivation and social exclusion is defined as having an index score below 1/2 of the median of the respective index score.

Table A9: Risk factors of income poverty in childhood, number of missing necessary items

	2000		2010	
Number of missing necessary items=1	0.993	0.634	1.348	1.348
	(1.127)	(0.714)	(0.539)	(0.550)
Number of missing necessary items=2	2.017	1.375	1.868	1.995*
	(2.115)	(1.439)	(0.745)	(0.835)
Number of missing necessary items=3	1.477	0.876	3.068**	1.997
	(1.562)	(0.971)	(1.545)	(1.087)
Number of missing necessary items=4	3.035	1.707	9.474***	6.580***
	(3.182)	(1.931)	(5.813)	(4.559)
Number of missing necessary items=5	8.780**	3.591	6.924***	8.979**
	(9.718)	(4.333)	(5.033)	(8.050)
Age		1.014		1.079
		(0.068)		(0.059)
Girl		1.366		1.056
		(0.401)		(0.227)
Number of children in hh		1.595***		1.513***
		(0.251)		(0.206)
Single parent		4.805***		4.285***
		(1.816)		(1.441)
Observations	1288	1288	910	910
Pseudo R^2	0.041	0.121	0.056	0.146

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from logistic regressions with robust standard errors clustered at the family level. Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population.

Table A10: Relative risk factors of income poverty in childhood, number of missing social activities

	2000		2010	
Number of missing social activities=1	1.145	1.054	1.457	1.322
	(0.361)	(0.345)	(0.372)	(0.356)
Number of missing social activities=2	1.637	1.235	1.116	0.957
	(0.761)	(0.572)	(0.441)	(0.361)
Number of missing social activities=3	2.897**	1.867	1.638	1.479
	(1.273)	(0.874)	(0.644)	(0.680)
Number of missing social activities=4	2.568*	1.863	5.144***	4.151**
	(1.381)	(1.123)	(3.071)	(2.454)
Age		0.967		1.024
		(0.049)		(0.050)
Girl		1.233		1.130
		(0.366)		(0.234)
Number of children in hh		1.723***		1.595***
		(0.241)		(0.196)
Single parent		4.378***		4.148***
		(1.591)		(1.359)
Observations	1288	1288	910	910
Pseudo R^2	0.016	0.105	0.018	0.127

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from logistic regressions with robust standard errors clustered at the family level. Income poverty is defined in terms of equivalent disposable household income being below 1/2 of the median in the overall population. *Number of missing social activities* is based on dummies indicating whether or not an individual has reported missing a social activity (i.e. having responded either "Seldom" or "Never" to the question: "How many days during a normal week do you..." with the following options: "Every day", "Several times a week", "Once a week", "Seldom", "Never"). The reference category consists of individuals with zero missing social activities.

B Questionnaire items

This section presents a selection of the questionnaire items that were used in the two waves 2000 and 2010 of the Swedish Level-of-Living Survey (LNU, 2010).

1. (Wave 1, 2000) Do you have any of the following: own room, pet, own TV, own VCR, own computer games, own CD-player, own mobile phone, own computer, or none of these?

2. (Wave 1, 2010) Do you have any of the following: own room; pet, own TV, own mobile phone, own computer, or none of these?

3. Which of the following places/activities did you visit/participate in this summer: family summer house, family vacation in Sweden, family vacation abroad, trip with friends, stay with relatives, ”kollo”, camp, foreign language course, summer job, or none of these?

4. How well does this statement match? Options: Does not match at all, Matches poorly, Matches roughly and Matches exactly. Coded as 1 (Does not match at all) to 4 (Matches exactly).

    - I am almost always in a good mood
    - I find it hard to sit still and concentrate
    - I rarely start fights
    - I am often tense and nervous
    - I have no worries
    - I often feel sad or down
    - I can cope with a lot
    - I get angry easily
    - I am mostly happy with myself
    - I am often grumpy and annoyed
    - I dare to express my own opinion
    - I am satisfied with my looks
    - I have a positive outlook on the future

5. During the past 6 months, how often have you had the following: headache, stomachache, troubles sleeping, or feeling stressed? Options: Every day, Several times a week, Once a week, A couple of times a month, or Seldom. Coded as 1 (Seldom) to 4 (Every day).

6. (Wave 1, 2000) Do you feel safe in the following places?

   - Outside in my neighborhood
   - On your way to school
   - In the classroom
   - During breaks
   - On your way home from school
   - None of the above

7. (Wave 2, 2010) Do you feel safe in the following places?

   - Outside in my neighborhood, at daytime
   - Outsider in my neighborhood, at night
   - On your way to and from school
   - In the classroom
   - During breaks
   - None of the above

8. How many days during a normal week do you... Options: Every day, Several times a week, Once a week, Seldom, Never.

   - ... read books
   - ... follow the news on TV, on the radio or in the newspaper
   - ... use the Internet
   - ... play computer or TV-games
   - ... have friends at home
   - ... visit friends in their home
   - ... spend time with friends in some other place (e.g. outside)
   - ... participate in some organized sports activity
   - ... participate in some organized activity other than sports such as the scouts, theater or chess

- ... have time that is free from duties or responsibilities (for example relax and listen to music)

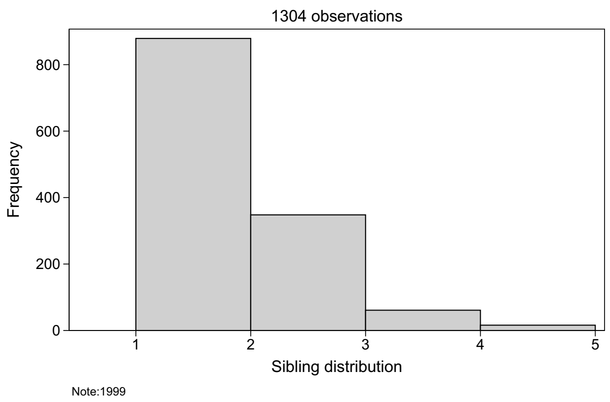
9. If you suddenly needed 100 kronor for tomorrow, for example to go to the cinema, would you be able to get the money? Options: Yes, No, Don't know.

10. Do you get money from home? Options: Yes, I get x kronor per week; Yes, I get x kronor per month; I don't get any.

C Figures and tables

Figure C.1: Sibling distributions, 2000 and 2010

(a)



(b)

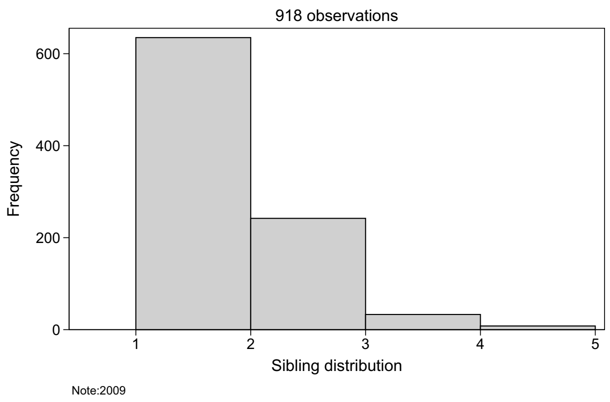


Table C1: Do you have any of the following..., as a percentage of the sample (n=1304 in 2000 and n=918 in 2010), unweighted

	2000		2010	
Necessity	Do not have	Have	Do not have	Have
Room	10.81	89.19	8.71	91.29
Pet	56.29	43.71	50.44	49.56
TV	48.39	51.61	41.18	58.82
Mobile phone	58.05	41.95	4.03	95.97
Computer	74.39	25.61	33.01	66.99
Have not (things)	98.08	1.92	99.46	0.54

Table C2: How many days a normal week do you..., as a percentage of the sample (n=1304 in 2000 and n=918 in 2010), unweighted

Activity	Every day	Several times a week	Once a week	Seldom	Never	Missing values
2000						
Read	17.87	26.07	17.18	27.45	11.20	0.23
News	18.63	36.43	16.64	18.40	9.66	0.23
Play	15.87	34.28	18.33	21.55	9.89	0.08
Internet	11.20	27.76	17.48	21.63	21.78	0.15
Friends home	5.75	45.55	23.93	22.09	2.38	0.31
Home friends	6.13	54.68	21.63	15.80	1.69	0.08
Sport	5.52	44.56	15.57	8.21	25.84	0.31
Other activities	0.92	6.06	15.11	14.95	62.12	0.84
Meet friends	34.28	36.58	12.42	12.35	3.91	0.46
Leisure	10.12	38.11	26.69	21.63	3.07	0.38
2010						
Read	13.18	25.60	14.81	32.57	13.51	0.33
News	14.38	33.01	21.02	21.35	9.69	0.54
Play	29.74	30.50	11.33	18.19	9.91	0.33
Internet	55.56	30.50	4.79	5.56	3.27	0.33
Friends home	2.72	40.31	28.00	25.05	3.59	0.33
Home friends	2.18	47.06	28.00	20.92	1.63	0.22
Sport	6.10	45.86	13.51	8.39	26.03	0.11
Other activities	1.09	7.19	14.16	11.98	64.81	0.76
Meet friends	34.53	38.67	12.75	11.33	2.29	0.44
Leisure	6.86	38.34	26.80	23.64	3.27	1.09

Table C3: Number of missing items in frequency and percent, 2000

Number of missing necessary items	**n/%**
0	65
	5.0
1	226
	17.5
2	341
	26.5
3	390
	30.3
4	214
	16.6
5	52
	4.0
Total	1288
	100.0

Table C4: Number of missing items in frequency and percent, 2010

Number of missing necessary items	**n/%**
0	210
	23.1
1	335
	36.8
2	232
	25.5
3	94
	10.3
4	28
	3.1
5	11
	1.2
Total	910
	100.0

Table C5: Number of social activities in frequency and percent, 2000

Number of missing social activities	**n/%**
0	567
	44.0
1	408
	31.7
2	191
	14.8
3	86
	6.7
4	36
	2.8
Total	1288
	100.0

Table C6: Number of social activities in frequency and percent, 2010

Number of missing social activities	**n/%**
0	384
	42.2
1	272
	29.9
2	148
	16.3
3	86
	9.5
4	20
	2.2
Total	910
	100.0

Table C7: Equivalence scale, HEK, Statistics Sweden

One person	1,00
Two adults	1,51
First child	0,52
Later children	0,42
Children older than 19 and other adults in the household	0,60

Chapter 2

The Aspirations-attainment Paradox of Immigrant Children: A Social Networks Approach*

1 Introduction

Although higher education is free in Sweden, children with an immigrant background lag behind children of native-born parents in educational performance; on average they have lower grades and are more likely to have incomplete grades or dropout. Empirical findings in the field of educational inequality suggest a number of plausible mechanisms for this result and one important factor is individual aspirations and expectations of higher education (see, for example, Guyon and Huillery (2016) and Jonsson and Rudolphi (2011) for a literature review). Importantly, immigrant children may face specific challenges in turning aspirations into achievement, for instance, sanctions by peers for succeeding in school, structural barriers on the labor market and occupational discrimination.

*I am grateful to Eskil Wadensjö, Matthew Lindquist, Tuomas Pekkarinen, Karin Hederos, Manja Gärtner, Elin Molin and Lena Lindahl for valuable comments. I also want to thank Barry R. Chiswick and seminar participants at the Economics Department at George Washington University, D.C. for constructive comments. This paper uses the Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU, Kalter et al. (2016a,b)).

In spite of these obstacles (or perhaps in part because of them), children of immigrants tend to have higher aspirations than their native majority peers. A significant body of research (Kao and Tienda, 1995; Heath and Brinbaum, 2007; Jonsson and Rudolphi, 2011) has found that ethnic minority or immigrant children generally have more positive attitudes towards education than their native-born counterparts.[1] For instance, black students in the US have been shown to perform worse at school than do white students but still have more positive attitudes toward school than their white peers (Akerlof and Kranton, 2002). This phenomenon has been called "the aspiration-attainment paradox of immigrants" (see, for example, Mickelson (1990) for a discussion).

In this paper, I explore "the aspiration-attainment paradox" by comparing the discrepancies between aspirations for a university degree and the expectations of getting one between children with immigrant parents and children of native-born. Drawing on the theory of Ray (2006), Genicot and Ray (2017) and Dalton et al. (2016) on the "aspirations window" and "aspirations failure", I use the mismatch between educational aspirations and expectations, what I will refer to as "the aspirations-expectations gap" (or more simply "the gap") as a potential mechanism behind the aspirations-attainment gap among immigrant students.[2]

A closely related topic is the concept of "lost talent", a term coined by Hanson (1994) in a seminal paper on the mismatch of aspirations and expectations among American youths showing early signs of academic potential.[3] Inspired by Hanson (1994), I study the observable characteristics of the pool of students in a representative sample of eight graders in Sweden who are showing signs of early academic potential and who

[1] Jonsson and Rudolphi (2011) do not study attitudes *per se*, but interpret actual transitions to academic tracks as positive attitudes.

[2] See also Genicot and Ray (2009).

[3] Hanson (1994) finds that not race but social class is the strongest predictor of lost talent. One of the critics of this literature, Mickelson (1990), argues that this is a consequence of researchers' inability to distinguish between abstract and concrete attitudes. Abstract attitudes are general beliefs about education, for instance the generally held belief that education is important for socioeconomic mobility, while concrete attitudes are formed through actual experiences. According to Mickelson (1990), concrete rather than abstract attitudes determine school performance.

are expressing an aspirations-expectations gap. Finally, I test whether children of immigrants are more likely to belong to this category than are children of native-born parents.

The empirical analysis is based on two datasets: the Swedish Level-of-Living Survey 2010 – Immigrants and their children (LNU-UFB) and the Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU, Kalter et al. (2016a,b)). Both datasets are comprised of nationally representative samples of Swedish students and include an oversampling of children with an immigrant background. The stratified samples of LNU-UFB 2010 and CILS4EU allow detailed analyses of the social integration of immigrant children specifically, a group of great interest given the increased importance of immigration in Western countries. The survey data in LNU-UFB 2010 is combined with rich register data on the background characteristics of parents, such as region of birth.[4]

The analysis is structured as follows. First, I investigate students' aspirations and expectations with respect to their parents' immigration status. The outcome variables *educational aspirations* and *educational expectations* are drawn from the two following questions found in the LNU survey: "Would you like to continue to go to school after the upper secondary level, that is, attend a university or university college?" and "Do you think you actually will continue to go to school after the upper secondary level?" and the corresponding questions in CILS4EU: "What is the highest level of education you wish to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)" and "What is the highest level of education you think you will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)". The variable *aspirations-expectations gap* is constructed using the variables *educational aspirations* and *educational expectations* and is defined as having aspirations for a university degree

[4]Apart from Rudolphi (2014), the LNU child survey has previously been used in a study by Jonsson and Östberg (2009) and the governmental report of Mood and Jonsson (2013). The study Olsson (2009) also uses Child-LNU data to look at the role of social relations for disadvantaged adolescents.

but not expecting to get one.

I try to account for potential differences using information at the family, friendship, and classroom level. By using the multilevel-structured dataset CILS4EU, I try to gauge the influence of the gender, immigrant status and socioeconomic background composition within an individual's network of best friends on the three outcome variables educational aspirations, expectations and the aspirations-expectations gap. As a final step, I explore the observable characteristics of students scoring higher than the mean or median of the sample on a standardized cognitive test in grade 8 and who are expressing an aspirations-expectations gap (henceforth referred to as "lost talent").

This study contributes to the emerging economic literature on aspirations (Goux et al., 2014; Carlana et al., 2015; Guyon and Huillery, 2016) and disparities in life courses of individuals. To the best of my knowledge, this is the first study that explores the predictors of "lost talent" among children with foreign-born parents in a European context.[5] A handful of studies have tried to explain differences in aspirations or expectations among different socio-economic or ethnic groups (Salikutluk, 2016; Hanson, 1994; Rudolphi, 2014; Heath and Brinbaum, 2007).[6] This study contributes to the existing literature by studying the gap between aspirations and expectations from a social network approach using self-reported friendship links. Unlike the studies of Rudolphi (2014) and Guyon and Huillery (2016) focusing on low-SES children, this paper utilizes a dataset that includes an oversampling of foreign-born children which facilitates a broader analysis of disadvantage. The interaction between immigrant background and gender is of particular interest.

It also contributes to the literature on dropout decision (Goux et al., 2014; Mora and Oreopoulos, 2011) by exploring the gap in aspirations

[5]The only paper on lost talent that I am aware of is the study of Hanson (1994).

[6]Salikutluk (2016) tests the explanatory power of different explanations for ethnic disparities in aspirations for upper-secondary education using survey data on immigrant youth in Germany. Based on a survey of 1,052 individuals, the results show that the theories of immigrant optimism, blocked opportunities and social capital contribute to explain the ethnic gap in aspirations.

and expectations among low-performing students at risk of dropout after compulsory school. A closely related paper is that of Guyon and Huillery (2016) which estimates the influence of aspirations on school outcomes and empirically tests the aspirations failure model of Ray (2006). They find a social gradient in aspirations failure (operationalized using survey questions about high school track choice, awareness of existing tracks and self-perceived academic potential), validating previous findings (e.g. Hanson (1994)). In contrast to Guyon and Huillery (2016) and Salikutluk (2016), which are based on either relatively small or unrepresentative survey samples, this study uses two independent and nationally representative samples of Swedish youths combined with detailed friendship network data.

Aspirations are determined through social interactions. The most relevant social networks studies for the purposes of this paper are Guyon and Huillery (2016), Burgess and Umaña-Aponte (2011) and Mora and Oreopoulos (2011) of which the latter two estimate the impact of the social network on individual educational aspirations (for example whether or not to drop out from school).[7] So far, research on social networks and educational decisions has been confined to general peer effects and less attention has been paid to the interaction of immigrant status and gender. This paper fills the existing gap by studying the influence of friends' characteristics on educational plans.

Based on two independent and nationally representative samples, I find that children with an immigrant background generally have higher aspirations and expectations than the majority group. Overall, I do not find any evidence of a significant immigrant-non-immigrant gap in aspirations and expectations: immigrant children's aspirations and expectations are not less aligned than those of their native-majority peers. This results suggest that immigrant-native disparities in school outcomes are

[7] Burgess and Umaña-Aponte (2011) find significant effects of the socio-economic background of friends for own educational aspirations and expectations. See also Roth and Salikutluk (2012) on aspirations and social networks of mothers. The results of Mora and Oreopoulos (2011) suggest that the influence of non-reciprocating friends' dropout plans for an individual's decision to drop out is small and insignificant.

not driven by an aspirations-expectations gap.

I find significant gender differences: girls are more likely to express an aspirations-expectations gap and be labeled as lost talent. I find that gender and language proficiency are the strongest predictors of lost talent. Moreover, having only female friends makes one less likely to belong to the aforementioned category.

The rest of this paper is structured as follows. In section 2, I give an overview of previous research and the relevant terms and concepts. Data and definitions are presented in section 3. In sections 4–6, I show the results and discuss their robustness. Finally, in section 7, I discuss the policy implications of my findings and give some concluding comments.

2 Previous literature

2.1 Aspirations, expectations and human capital formation

Educational aspirations and expectations are important since they can help explain and predict individual differences in educational choices.[8] According to human capital theory (Becker, 1964; Mincer, 1974; Schultz, 1960; Björklund et al., 2014), individuals make educational choices based on the calculations of the future wage returns from investments in human capital. Expectations reflect an individual's plans for investment in human capital. Given that individuals base their decisions on calculations of future wage returns, those with the highest rates of return to education should also have the highest educational expectations (see, for example, Morgan (1998)).

2.2 Mismatched aspirations and expectations

A highly relevant study for the purpose of this paper is the study of Hanson (1994) which looks at the mismatch between educational aspi-

[8] See, for example, Feliciano and Rumbaut (2005), Jacob and Wilder (2010) and Portes and Rumbaut (2001).

rations and expectations to measure the amount of "lost talent" among American youths measured in senior years of high-school. The sample is restricted to individuals with high educational expectations and above average scores on standardized Mathematics and reading tests. Hanson (1994) finds that 16 percent of the sample of youths who aspire to a college degree do not expect to attain one. Furthermore, she finds no significant effect of race in logistic regression models predicting lost talent. The strongest predictor of lost talent is social class.

The educational aspirations and expectations of Swedish children have previously been studied by Rudolphi (2014) who looks at the consistency between wanting to continue to go to school after upper secondary level and thinking that one will actually attend university studies in a sample of compulsory school students in Sweden (LNU, n=620). The results reveal that students generally show a consistency between high aspirations and high expectations. Moreover, girls tend to show more consistency than boys. The study does not look specifically at immigrant children.[9]

2.3 Social determinants of aspirations and expectations

A much less explored topic within the literature on aspirations and expectations is the role of peer effects for students' educational plans. Previous studies on social networks and peer effects have shown that reference groups and friends are important determinants of scholastic achievement (e.g. Calvó-Armengol et al. (2009)). The theoretical paper of Ray (2006) incorporates the social dimension of aspirations in his so-called "aspirations-based view of individual behavior", arguing that

[9]The studies of Halleröd (2011) and Alm (2011) examine the relationship between different outlooks in adolescence and later outcomes in life using Swedish data. The findings of Halleröd (2011) indicate that there is a relationship between children's expectations at the ages 12–13 and outcomes later in adult life: children who had a more pessimistic view of their future (approach to the future, future outlooks, expectations, beliefs about the future) were more at risk of economic hardship and weak labor market attachment. The results of Alm (2011) show that indifference in adolescence is positively correlated with economic hardship and a low educational attainment later in life.

individual preferences and behavior depend *both* on historical experience *and* the experiences of individuals that are similar or close to him or her (socially and spatially). Furthermore, aspirations are determined through social interactions and are transmitted to children from parents, friends, classroom peers and adults in the community in which they live (Appadurai, 2004). The empirical papers of Burgess and Umaña-Aponte (2011) and Mora and Oreopoulos (2011) previously mentioned estimate the impact of a friendship network on individual educational aspirations and drop out intentions using cross-sectional network data.

The effects of parental tutoring on dropout behavior have, for example, been demonstrated by Goux et al. (2014) who use a randomized control trial on parents' aspirations. The treated sample, the parents of low-performing students with unrealistic aspirations, was provided with extra counseling with respect to their children's transition to high school. The intervention was not planned to improve these students' school results but to attune their aspirations to their school performance so as to reduce the risk of drop out in high school due to unrealistic educational plans. Goux et al. (2014) find that parental tutoring reduces dropout rates when they target parents of low-performing pupils with unrealistic aspirations. A similar RCT has previously been conducted by Avvisati et al. (2014) where the treatment consisted of informational meetings between parents and the school head. The parents were given advice on how to assist their children with their school work and the findings indicate that parental involvement had a significant impact on student behavior.

As schools with a high proportion of foreign-born students tend to be located in areas of concentrated economic disadvantage with neighborhoods composed of adults with low educational and labor market aspirations, studying the role of social networks is key for understanding the determinants of ethnic disparities in educational decisions.[10] Another relevant study is Carlana et al. (2015) which presents positive causal estimates of the influence of motivational meetings on the choice

[10]See, for example, "the memberships theory of inequality" of Durlauf (2006).

of high school program among high performing immigrant boys in Italy. In 2011, the Italian Ministry of Education initiated an educational program "to induce students to undertake educational decisions congruous to their potentialities". The intervention was designed as a randomized control trial, sampling schools and students in northern Italy, specifically targeting high performing immigrant students. The purpose was to adjust students' aspirations before their choice of high school program and make high performing immigrant students more likely to consider an academic track in upper-secondary school.

2.4 The aspirations gap and poverty traps

The concept of aspirations can also be found in the more recent inequality literature, for example in the theoretical papers of Ray (2006), Genicot and Ray (2017) and Dalton et al. (2016), which explore the link between aspirations and poverty. Dalton et al. (2016) develop a model according to which external constraints make poor individuals more susceptible to behavioral poverty traps or so-called "aspirations failure". Within this framework, individuals can face both internal (identity) or external constraints (credit/budget constraints) and Dalton et al. (2016) refer to this as a behavioral bias in setting aspirations.[11] For example, the rate of return to higher eduction of immigrant children may be lower than that of their native-born peers. Immigrant children may be well-aware of the benefits of higher eduction but the individual returns are perceived as low due to, for example, labor market discrimination and lack of role models in their community or neighborhood.

Genicot and Ray (2017) introduce the concept of an "aspirations window" to describe the group of individuals who serve as a reference point, the social frame that shapes an individual's aspirations. The authors argue that aspirations and the social environment in which they are determined should be incorporated into standard economic theory. In their paper, they relate aspirations to the income distribution, in-

[11] See also the sociological literature on internal/external locus of control.

vestment and growth on a macro level arguing that optimal aspirations are those "that lie at a moderate distance from the individual's current economic standard, large enough to incentivize but not so large as to induce frustration". A more recent contribution to this literature is the empirical study by Guyon and Huillery (2016) which tests their model against real data.

On the same topic, Ray (2006) presents a model where individual behavior is determined by the gap between an individual's current economic standard and the aspired one. According to this idea, individuals who have small aspirations gaps are less motivated to raise their standard of living. The same applies to individuals with wide gaps: they have small incentives to change their standard of living since the necessary investment is too large. Ray (2006) cautions that if the aspirations window is too wide, it can result in what he describes as "the curse of frustrated aspirations", a state in which the incentives to make an investment effort are low and the cost of narrowing the gap is high relative to the benefits. This implies that the investment efforts are smallest among individuals with relatively high or low aspiration gaps.[12]

3 Data and definitions

This paper makes use of two datasets, both oversampling children with an immigrant background: the Swedish Level-of-Living Survey 2010 – Immigrants and their children (LNU-UFB) and the Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU,

[12] The incidence of aspirations failure depends on the degree of polarization in a society. Ray (2006) presents two types of societies where the first is connected and the other is polarized. The aspirations window is wider in societies where the perceived mobility is high. Regardless of whether the poor include the rich in their aspirations window, increased polarization will lead to aspiration failure. Thus, aspirations can both incentivize and create frustration: if too high, aspirations can discourage effort investments in, for example, education. Furthermore, frustration can give rise to what sociologist and anthropologists call an "oppositional culture" (see, for example, Fordham and Ogbu (1986), which is expressed through weak scholastic achievements and misbehavior.

Kalter et al. (2016a,b)). Both datasets consists of a nationally representative samples of Swedish children and are described in detail below.

3.1 The Swedish Level-of-Living Survey (LNU)

The Swedish Level-of-Living Survey (LNU) is a panel survey of the regular level of living of the Swedish population and has been conducted around every tenth year since 1968. In 2010, the sample was extended with a subsample of the foreign-born population in Sweden, a survey called the Swedish Level-of-Living Survey 2010 – Immigrants and their children (LNU-UFB). It consists of foreign-born individuals with a permanent residence permit in Sweden and their children. The respondents have been living in Sweden for at least five years. The respondents' children were either born in Sweden or abroad and are 10 to 18 years old and living at home.

The LNU-UFB survey has the same design as the LNU of 2010. Both surveys were carried out by Statistics Sweden during the years 2010 to 2012 and included interviews with a total of 1,357 respondents in the ages 10 to 18 living at home. The surveys were run simultaneously and the contents of the questionnaires were identical which means that LNU-UFB has a reference group consisting of the children of a representative sample of the Swedish population. LNU-UFB contains responses from a total of 437 respondents. The children filled out a questionnaire by listening to recorded questions with a tape recorder. The child survey consists of questions in the following areas: children's material and financial resources, health, household work, neighborhood characteristics and education.

The LNU child sample is restricted to children in the ages 13–18 (grade 7 and above) living at home. Descriptive statistics for the analysis samples are provided in tables 1 and 2. The sample contains 874 child respondents, with one, two or no native-born parent. Each child is paired with a parent included in either LNU or LNU-UFB. In order to match the dataset from the LNU-UFB to the parents, all identical twins have been removed (four pairs) since it is impossible to distinguish between same sex identical twins. LNU and LNU-UFB contain data on respondents' income, employment biography, education history, and health. LNU-UFB is based on a stratified sample of foreign-born individuals; hence, the survey results are weighted by the parent's region of birth and age (a representative sample of foreign born in the age span 18–75, who have lived in Sweden for at least 5 years). LNU-UFB provides information on the the region of origin of the parent and his or her partner.

I match the LNU-UFB sample with register data from LISA (Longitudinal integration database for health insurance and labor market studies) to obtain additional information on the parents' background, for example the region of birth of the partner.[13] LISA (formerly known as LOUISE) was constructed by Statistics Sweden, the Social Insurance Agency and the Swedish Agency for Innovative Systems and consists of annual registers since 1990. It includes all individuals aged 16 and above registered as living in Sweden as of December 31 each year.

3.2 The Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU)

The second dataset used in this study, CILS4EU is a new, longitudinal cohort survey conducted in four countries: the UK (only England), Germany, the Netherlands, and Sweden. CILS4EU is a multileveled survey containing rich information on family, teacher, school and classroom. It includes five sub-questionnaires directed at students, parents and teachers: "Youth main", "Youth classmates","Parents", "Teachers" and "Youth friends". In this study, I make use of "Youth main", "Youth classmates" and "Parents". The sample employs a two-stage stratified cluster design, interviewing students in sampled school classes. While the sample is designed to be nationally representative, it features a deliberate overweighting of schools with many children of immigrant background.

[13] Information on the partner is missing in LNU 2010, which is why I resort to the register data on partner's country of origin.

The first wave was conducted in the school year 2010–2011 when participating students were in the eighth grade (aged 14–15). The number of respondents in the main questionnaire in Sweden in the school year 2010–2011 was 5,025. Amongst these, a total of 4,804 students took both the language test and the cognitive test. The network analysis sample is constructed in the following way. In order to calculate the average characteristics in an individual's friendship network, I remove all those that have missing values on any of the variables female, foreign, parents' education, educational aspirations and expectations. Next, I add the friendship network data and thereafter I am left with a total of 4,364 observations. Finally, I match these data with the parent questionnaire which contains information on parents' aspirations and expectations for their children's educational attainment.

The second wave of CILS4EU was administered in 2011–2012 when the respondents attended ninth grade (aged 15–16). The survey questions regarding aspirations and expectations are identical in the two waves. Information on cognitive and language test results is found in the first wave of the survey, while self-reported grades in the core subjects Maths, Swedish and English are included in the second wave. Due to attrition and item non-response, the sample size shrinks to 3,631 individuals from wave 1 to wave 2.[14] The relevant variables for this study are presented in tables 1 and 2 in section 3.7.

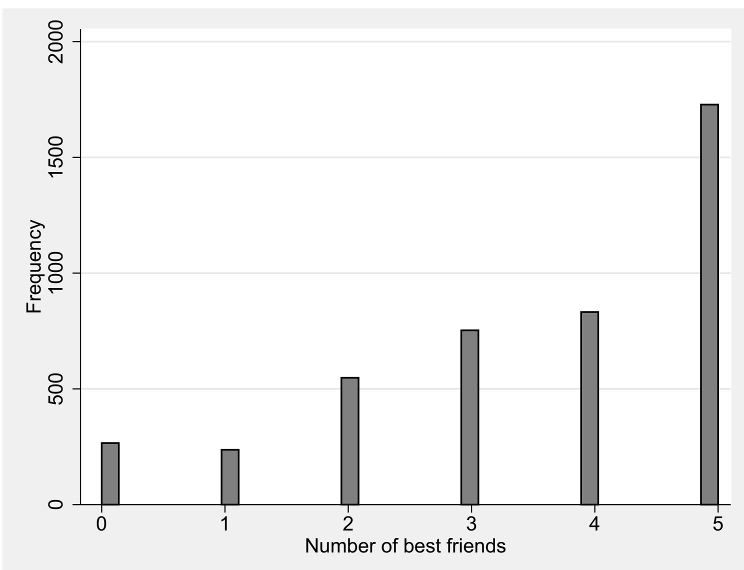
3.3 Friendship network

I use the Swedish sociometric classroom data (n=4,794) which was collected in the first wave of CILS4EU. In many of the cases, the friendship network questionnaire was administered during a class with the homeroom teacher. Friendship is defined on the basis of the question "Who are your best friends in this class?", to which the student could nominate a maximum of five individuals. A link between two students exists if an individual nominated another as a "best" friend.

[14]The number of unmatched individuals is 1,633 (total from wave 1 and wave 2). In total, 900 individuals are lost due to attrition.

Students who were absent on the day of the network questionnaire or who refused to participate were excluded from the school class roster and the set of potential friend nominees. Individuals with no friends have been dropped from the friendship network analysis (in total 266 individuals from the analysis sample of non-missing cases defined above).[15] Furthermore, individuals with missing values on any of the main explanatory variables female, foreign background, higher educated parents and educational aspirations and expectations have been removed from the analysis based on friendship network data. Figure 1 shows the distribution of number of friends and figure 2 displays the characteristics of best friends.

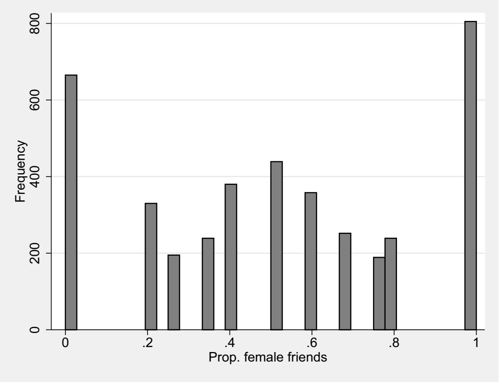
Figure 1: Number of best friends in grade 8, CILS4EU



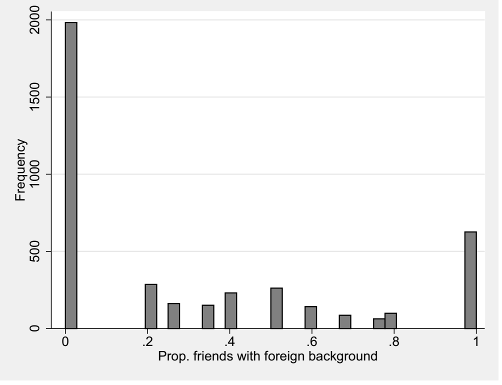
[15]None of these "isolated" individuals filled out the main questionnaire; hence, I am unable to explore their observable characteristics.

Figure 2: Characteristics of best friends in grade 8, CILS4EU

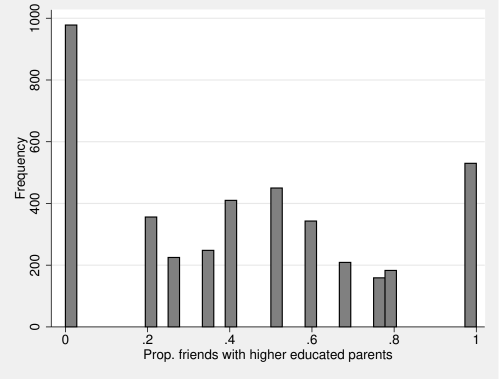
(a)



(b)



(c)



3.4 Definitions of immigrant children

The analyses in this paper are based on two separate datasets with varied details on the birthplace of the respondents' parents. The advantage of the LNU data over the CILS4EU dataset is that it contains more detailed background variables. Using the LNU survey and register data, it is possible to identify the region of birth of both parents. The LNU-UFB survey also contains information on the parents' self-reported migration history, along with other useful background statistics. The CILS4EU dataset, however, only includes self-reported information by parents and children on whether the parents were born in or outside of Sweden.

In line with previous literature on immigration (Borjas, 2011; Portes and MacLeod, 1999), I use two commonly applied definitions of immigrant children. Throughout the main analysis of this paper I define children of immigrants as children with both parents born abroad regardless of own birthplace. The reference category consists of children with at least one parent born in Sweden. I refer to this category as *native-majority children*. I use the terms *immigrant children* and *children of immigrants* interchangeably. In the sensitivity analyses, I will also look separately at the outcomes of children who have themselves migrated. Ethnic groups are defined by parental birth region, as is common in the literature on ethnic differentials (see, for example, Szulkin and Jonsson (2007)).

In the analyses based on LNU data, the child's region of birth is based on the mother's region of birth. If there are two biological parents in the household, I use the mother's place of birth to define the child's ethnicity. If the mother was born in Sweden but the father is foreign-born, the father's region of birth defines the origin of the child. In case the household consists of a lone biological father, I use his region of birth.[16] I can distinguish eight regions of birth in the LNU-UFB dataset: *Sweden*, *Nordic countries*, *EU15+*, *Other European countries/Not EU15+*,

[16]Using register data, it is possible to distinguish between first- and second-generation immigrants. I discuss alternative definitions in Appendix A.1.

Middle East, *Africa*, *Asia* and *Latin America* but due to a small sample size and multicollinearity, I aggregate the regions into three categories: *Sweden*, *Europe* and *non-Europe*.[17]

3.5 Educational aspirations and expectations

I distinguish educational aspirations from educational expectations. Aspirations are defined as idealistic goals and refer to individuals' hopes about the future regardless of constraints while expectations are what individuals think will happen when taking into account their constraints (Morgan, 2006; Jacob and Wilder, 2010).[18] The variables *educational aspirations* and *educational expectations* are drawn from the two following questions in the LNU-UFB 2010 questionnaire:

1. Would you like to continue to go to school after the upper secondary level, that is, attend a university or university college? (Yes, absolutely; Yes, probably; No, probably not; No, absolutely not)

2. Do you think you will actually continue to go to school after the upper secondary level, that is, attend a university or university college? (Yes, absolutely; Yes, probably; No, probably not; No, absolutely not)

The outcome variable *aspirations-expectations gap* is defined as having aspirations for a university degree and but not expecting to get one. In the analysis that is based on LNU data, the gap is coded "1" if an individual has responded "Yes, absolutely" or "Yes, probably" to the question "Would you like to continue to go to school after the upper

[17]The variable indicating the region of birth of the partner of the interviewee in the LNU survey does not include the category *Middle East*. Children whose origin is based on the partner of the interviewee will have *Asia* and not *Middle East* as their region of origin.

[18]Educational expectations are dynamic, i.e. they are subject to constant revision and updating (Morgan, 1998). The acquisition of new information on academic ability or on the costs and benefits of higher education may alter children's educational expectations (Jacob and Wilder, 2010).

secondary level, that is, attend a university or university college?" and "No, probably not" or "No, absolutely not" to the question "Do you think you will actually continue to go to school after the upper secondary level?"). The corresponding questions in the CILS4EU survey (first and second wave) are:

1. What is the highest level of education you wish to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)

2. What is the highest level of education you think you will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)

In the analysis utilizing CILS4EU data, the aspirations-expectations gap is coded "1" if an individual has responded "College/university" to question 1 above *and* less than university, i.e. any of the options "Don't know", "No degree", "Compulsory school", and "Upper secondary school" to question 2. In both samples, individual aspirations and expectations are measured close to a crucial transition point (from compulsory school to upper-secondary school). The Swedish school system applies no formal tracking during the first nine years of compulsory school. At the end of middle school (last term in grade 9) students decide on their educational careers and what upper-secondary program to choose. Grade nine is a crucial transition point in the education system as students move from compulsory school to high school. The GPA in the ninth grade determines the set of feasible programs in high school and a pass in all core subjects is required for eligibility to secondary education.

3.6 Cognitive and language tests

The CILS4EU data include individual scores on both a cognitive test and a language test. These two tests were administered in the first wave of the survey during the school year 2010–2011. The language test is a test of proficiency in the Swedish language. More precisely, it is a test of a child's lexicon of antonyms. The test includes 30 items with four alternatives each (for more information, see Kruse and Konstanze (2016)).

While the language test is used to assess children's verbal competencies, the cognitive test is "language free" and does not require any language skills. It is a 7 minute multiple-choice test of graphical puzzles including 27 items with properties similar to Raven's Progressive Matrices (Raven, 2003). The maximum score of this test is 27 and the minimum is 0. The distribution of test scores by parents' immigration status is shown in figures 3 and 4.

Figure 3: Destination language test score distributions in grade 8 by parents' immigration status, CILS4EU

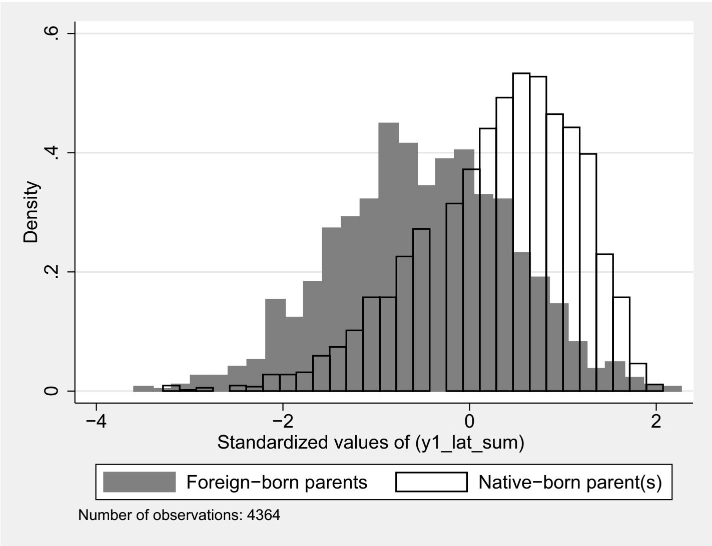
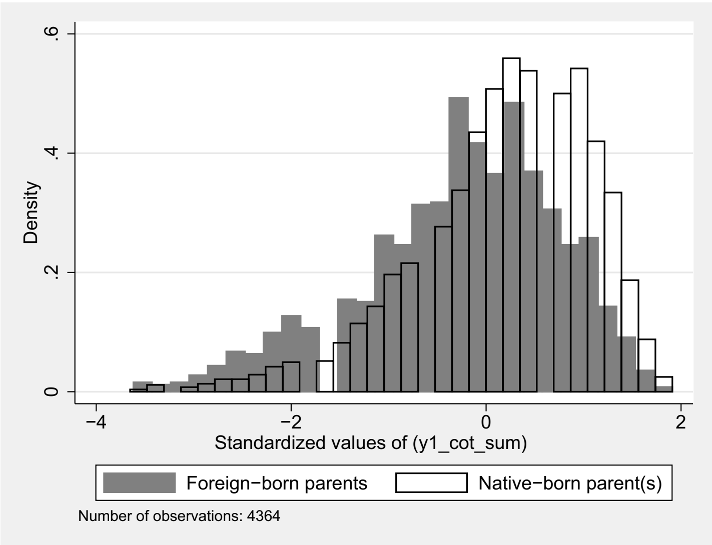


Figure 4: Cognitive ability test score distributions in grade 8 by parents' immigration status, CILS4EU



3.7 Explanatory variables

The explanatory variables are sorted into three categories: individual characteristics, family characteristics and friendship network variables. Descriptive statistics are presented in tables 1 and 2.

I use a binary variable indicating the gender of the child (1=female). The age variable in the LNU 2010 dataset is the age of the student at the time of the survey (either 2010, 2011 or 2012). The average age of children in the LNU 2010 sample is approximately 16. Children in CILS4EU are in the age span 14–15 (wave 1) and 15–16 (wave 2). In the CILS4EU sample, I use a dummy of high skill occupation as a proxy for higher educated parents (1=if at least one parent has a high skill occupation). I use this variable rather than parents' self-reported years of education since less than 62 percent (n=3,104) of the respondents' parents participated in the survey and because the proportion of missing values is high among those that did take part.[19] In the analysis sample, about 43 percent are coded as managers and professionals.

In the analysis that is based on LNU data, I use the parents' self-reported level of education which should reduce the measurement error in the education variables. Parents' highest level of education is coded into three categories: compulsory school or less, high-school or less and university studies. Moreover, I distinguish three different types of families: intact families, reconstituted families and single-parent families. The proportion of children living in intact families is about 70 percent. I also use a variable indicating the number of individuals in the household drawn from survey answers.

School performance is measured by individual self-reported grades from the last school report in the core subjects Maths, Swedish and English. The response options are: Excellent, Pass with Distinction, Pass, and Fail and these are coded from 0 (Fail) to 3 (Excellent). These options are used to create a grade sum for each individual, ranging

[19] Engzell (2016) discusses the problems with using the parents' education in CILS4EU.

from 0 to 9.[20] The survey question regarding school grades is found in the second wave of the survey conducted during the respondents' final year in secondary school (compulsory school). Students' school grades in ninth grade will determine the set of attainable high school tracks (e.g. academic or vocational) and are thus crucial for their future academic career.[21] I use household characteristics (e.g. country of origin and parental occupation) from both surveys and Swedish registers. I standardize the achievement test scores (language and cognitive ability) for comparability and ease of interpretation.

Since I lack information on school performance for the LNU sample, I use students' self-assessed school performance, measured using the question: "If you compare yourself to your peers, how well do you think you do at school? (Best in class, Among the best, Better than the majority, About as good as most people, Not as good as most people)". The response options are coded as dummies.

I use each individual's self-reported friendship network (described in section 3.3 above) to calculate the average characteristics of the explanatory variables female, foreign background and higher educated parents and university aspirations among his or her best friends. I also calculate the corresponding means at the classroom and school level. Using the network information, I create dummy variables for having best friends who all have the following characteristics: female, immigrant, higher educated parents and university aspirations. In addition to the variables listed above, I also use parents' aspirations and expectations of their child's education which are drawn from the following two questions found in CILS4EU:

1. What is the highest level of education you wish your child to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)

[20] As a robustness test I also use indicator variables for Fail in each core subject and standardized grades in each subject. The results from these estimations display a similar picture (results are delivered upon request).

[21] The LNU survey also includes program in high-school (vocational and academic) and whether or not the individual has finished school.

2. What is the highest level of education you think your child will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)

Using these questionnaire items, I create the variable *parent discrepancy* indicating whether the parent wishes the child to get a college/university education but expects him or her to get less than a college/university education.

Table 1: Descriptive statistics, LNU 2010

Variable	Mean	Std. Dev.	Min.	Max.	N
Demographics					
Age	15.919	1.678	12	19	874
Female	0.509	0.5	0	1	874
Grade	9.041	1.16	7	12	874
Parental education					
Compulsory school or less	0.054	0.226	0	1	870
High-school or less	0.286	0.452	0	1	870
University studies	0.66	0.474	0	1	870
Self-assessments					
Best in class	0.035	0.183	0	1	869
Among the best	0.334	0.472	0	1	869
Better than the majority	0.221	0.415	0	1	869
About as good as most people	0.379	0.485	0	1	869
Not as good as most people	0.032	0.177	0	1	869
Family characteristics					
Intact family	0.706	0.456	0	1	874
Reconstituted family	0.142	0.349	0	1	874
Single parent family	0.146	0.354	0	1	874
Household members	4.261	1.221	2	11	874
Educational aspirations and expectations					
University aspirations	0.768	0.423	0	1	874
University expectations	0.787	0.41	0	1	874
Aspirations-expectations gap	0.026	0.16	0	1	874

Table 2: Descriptive statistics, CILS4EU (wave 1 and 2)

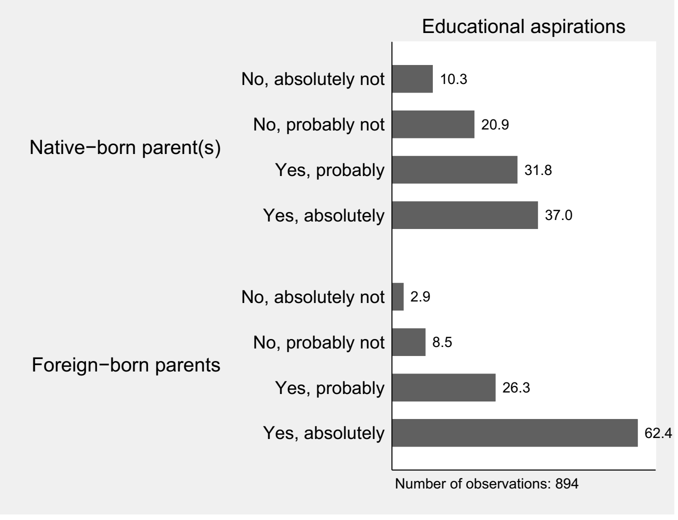
Variable	Mean	Std. Dev.	Min.	Max.	N
Demographics					
Female	0.514	0.5	0	1	4364
Foreign-born parents	0.305	0.46	0	1	4364
Parental education					
Higher educated parents	0.434	0.496	0	1	4364
Academic potential					
Language test score (std)	0.078	0.954	-3.524	2.266	4346
Cognitive test score (std)	0.055	0.971	-3.526	1.911	4334
School achievement					
Incomplete grades: Maths	0.068	0.251	0	1	3601
Incomplete grades: Swedish	0.035	0.185	0	1	3595
Incomplete grades: English	0.045	0.207	0	1	4364
Educational aspirations and expectations					
University aspirations	0.667	0.471	0	1	4364
University expectations	0.522	0.5	0	1	4364
Aspirations-expectations gap	0.177	0.382	0	1	4364
Parent's aspirations and expectations					
Parent consistency	0.307	0.461	0	1	4364
Parent discrepancy	0.225	0.418	0	1	4364
Friendship network characteristics					
Prop. female friends	0.51	0.337	0	1	4091
Prop. friends with foreign background	0.31	0.371	0	1	4091
Prop. friends with higher educated parents	0.425	0.331	0	1	4091
Prop. university aspirations friends	0.651	0.317	0	1	4091

4 Aspirations and expectations

4.1 Accounting for differences in aspirations and expectations

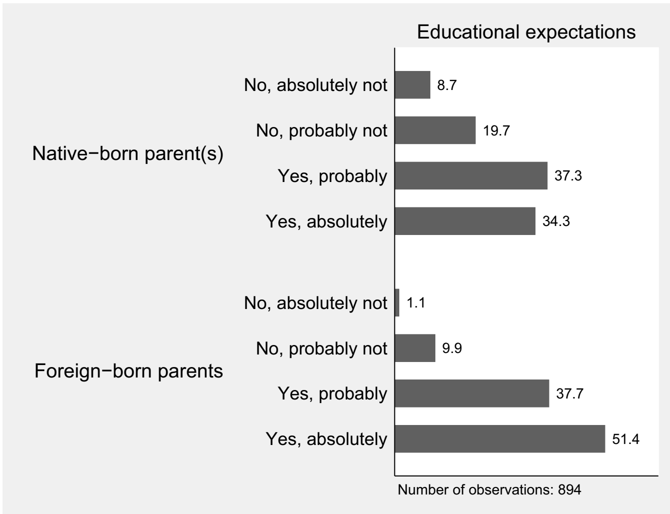
In this subsection, I examine the educational aspirations and expectations between children with two foreign-born parents and children with at least one native-born parent. Figure 5 reports the fraction of children with native versus foreign-born parents that answered each category to the question: "Would you like to continue to go to school after the upper secondary level, that is, attend a university or university college?". This figure shows that children with foreign-born parents have answered "Yes, absolutely" to a larger extent than children with native-born parents (62.4 compared to 37.0 percent) and the difference is significant.[22] Children with foreign-born parents seem to show more "certainty" in their answers while children with native-born parents are more evenly distributed across the different categories.

Figure 5: Aspirations by parents' immigration status, LNU 2010



[22] $p<0.05$ two-tailed t-tests of the differences between the other categories show that they are not significant.

Figure 6: Expectations by parents' immigration status, LNU 2010



Turning to figure 6 and the question: "Do you think you will actually continue to go to school after the upper secondary level?", we see that children with foreign-born parents have replied "Yes, absolutely" to a larger extent than children with native-born parents (51.4 compared to 34.3 percent) and the difference is significant.[23] Once more, children with foreign-born parents show more "certainty" in their answers; however, the differences between the two groups are smaller than their differences in aspirations.

A first glance at the data shows that children of immigrants have both higher aspirations and expectations than their peers, but are they more or less consistent in their aspirations and expectations as compared to the reference group? Contingency tables can be a useful way of measuring the inconsistencies between aspirations and expectations. The diagonal shows the proportion of individuals who answered consistently in tables 3 and 4. Full consistency corresponds to 100 percent in all diagonal cells. Table 3 shows educational expectations by educational aspirations among children with native-born parents. This table shows

[23] $p<0.05$ two-tailed t-tests of the differences between the other categories show that they are not significant.

how the children responded to the expectations question, given what they answered to the aspirations question. For example, given that they answered “No, absolutely not” to the aspirations question, 71 percent of the children with native-born parents answered “No, absolutely not” to the expectations question. The diagonal elements in table 3 are all larger than 70 percent for children with native-born parents.

Table 3: Expectations by aspirations (%) among children with native-born parents, frequencies (weighted) in parentheses

	Aspirations				
Expectations	No, absolutely not	No, probably not	Yes, probably	Yes, absolutely	Total
No, absolutely not	**71**	5	0	1	9
	(40.47)	(6.34)	(0)	(1.33)	(48.14)
No, probably not	24	**72**	7	0	20
	(13.75)	(83.42)	(12.50)	(0)	(109.67)
Yes, probably	5	23	**76**	21	37
	(3.01)	(26.36)	(134.95)	(42.96)	(207.28)
Yes, absolutely	0	0	17	**78**	34
	(0)	(0)	(29.40)	(161.50)	(190.90)
Total	100	100	100	100	100
	(57.23)	(116.12)	(176.86)	(205.79)	(556)

Note: In order to adjust for family size we use the weights provided in the technical report by SCB (see details in SCB (2012)).

Table 4: Expectations by aspirations (%) among children with foreign-born parents, frequencies (weighted) in parentheses

	Aspirations				
Expectations	No, absolutely not	No, probably not	Yes, probably	Yes, absolutely	Total
No, absolutely not	**37**	0	0	0	1
	(3.38)	(0)	(0)	(0)	(3.38)
No, probably not	6	**74**	9	2	10
	(.60)	(19.84)	(7.19)	(3.80)	(31.43)
Yes, probably	57	16	**75**	24	38
	(5.26)	(4.29)	(62.50)	(47.79)	(119.85)
Yes, absolutely	0	10	17	**74**	51
	(0)	(2.79)	(13.81)	(146.74)	(163.34)
Total	100	100	100	100	100
	(9.25)	(26.93)	(83.50)	(198.32)	(318)

Note: In order to adjust for family size we use the weights provided in the technical report by SCB (see details in SCB (2012)).

Turning to children with foreign-born parents, we see a similar pattern in table 4 where the diagonal elements are larger than 70 percent except for one particular case: among the children with foreign-born parents who answered “No, absolutely not” to the aspirations question, a significant proportion have replied “Yes, probably” to the expectations question. Note, however, that the sample contains 318 individuals with foreign-born parents and only a small fraction of the children answered “No, absolutely not” (as shown in figure 5).

Figure 7 reports children’s responses to the question: “What is the highest level of education you wish to get?” and figure 8 shows the distributions of the responses to the question: “What is the highest level of education you think you will actually get?”. In line with the results presented above based on the LNU dataset, children of immigrants tend to have higher aspirations and expectations than their peers. Overall, children of immigrants do not show any signs of higher or lower inconsistency than their native-majority peers.

Next, we turn to the CILS4EU dataset. Tables 7 and 8 present the aspirations and expectations of children in grade 8 by parents’ immigration status. The results presented in the tables below validate the findings above: children of immigrants have both significantly higher aspirations (76.5 percent versus 62.4 percent, t-test α=0.05) and expectations (59.0 percent versus to 49.1 percent, t-test α=0.05) than children with native-born parents.

Figure 7: Aspirations in grade 8 by parents' immigration status, CILS4EU

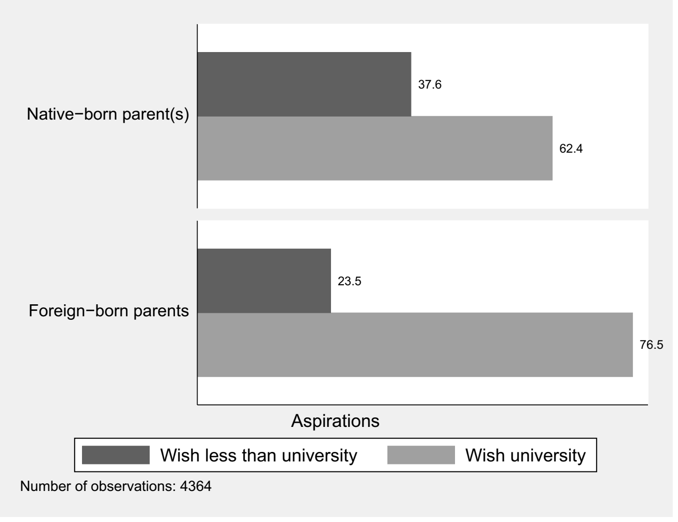


Figure 8: Expectations in grade 8 by parents' immigration status, CILS4EU

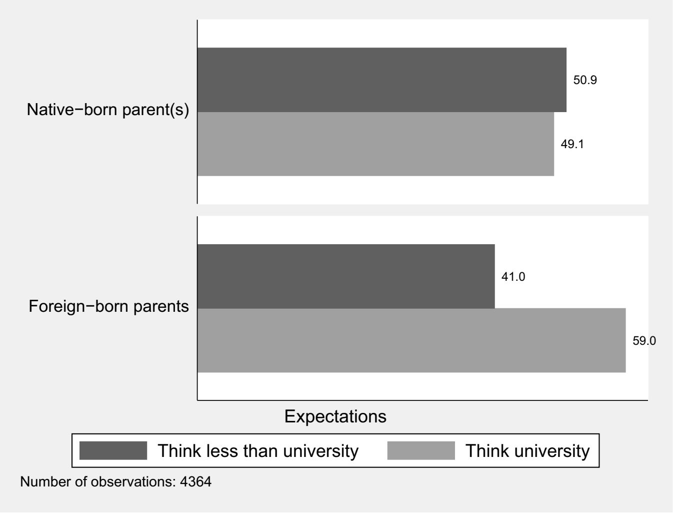


Figure 9: Aspirations-expectations in gap grade 8 by parents' immigration status, CILS4EU

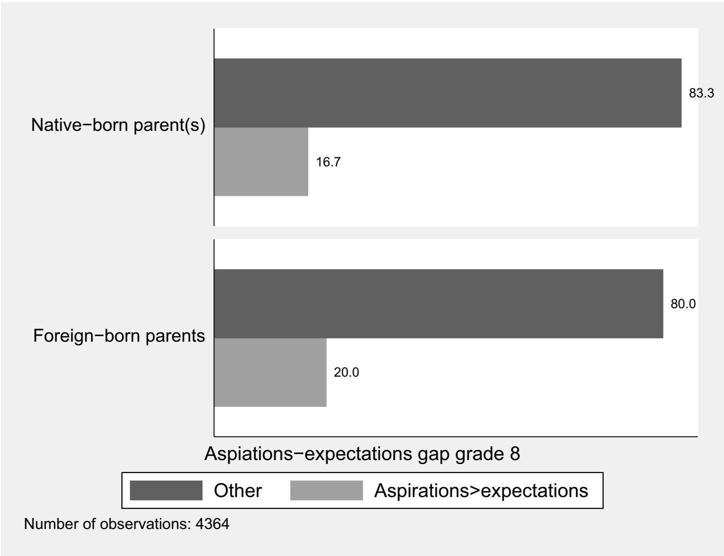
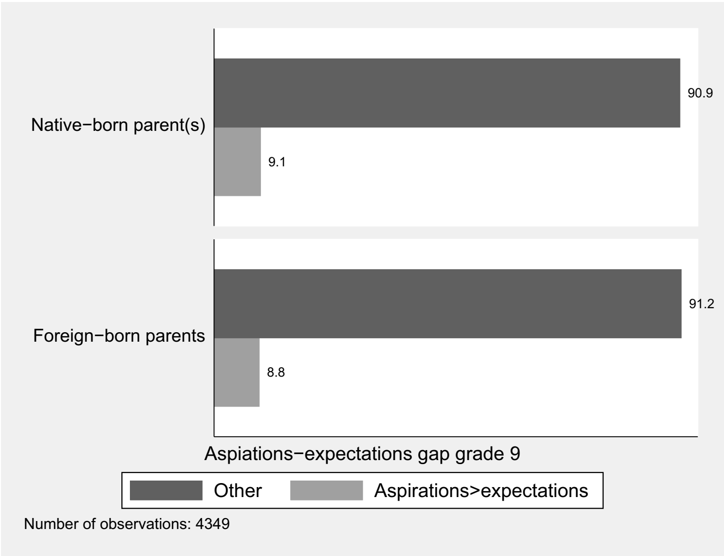


Figure 10: Aspirations-expectations in gap grade 9 by parents' immigration status, CILS4EU



In sum, the above analysis above seems to indicate that there is a significant difference in the aspirations and expectations among children with native-born parents and children with foreign-born parents. Children with foreign-born parents have, on average, both higher educational aspirations and expectations than their native-majority counterparts before controlling for individual and background characteristics. Next, I will try to account for the immigrant-native gap using rich sets of control variables found in the LNU and CILS4EU datasets.

The following analysis is performed on two separate datasets. While the LNU dataset includes finer categories of the respondent's region of birth, it lacks information on school performance and social networks. I start by creating binary variables indicating aspirations and expectations for a university degree. The different sets of control variables in the LNU survey and matched administrative records fall into the categories: individual characteristics, family characteristics, and schooling variables. The unit of analysis is the child. I estimate the following linear probability model (LPM) by OLS:

$$\begin{aligned} y_i = \alpha + \beta_1 immstat_i + \beta_2 female_i + \beta_3 immstat_i \times female_i \\ + \sum_{j=1}^{2} \beta_{4j} educ_{ij} + \sum_{j=1}^{4} \beta_{5j} selfass_{ij} + \sum_{j=1}^{3} \beta_{6j} famtype_{ij} \\ + \beta_7 hhsize_i + \epsilon_i, \end{aligned} \tag{1}$$

where y_i is a dummy indicating the outcome of child i in educational aspirations, educational expectations or the aspirations-expectations gap, α is a constant, $immstat_i$ is a dummy indicating parents' immigration status (if the individual has two foreign-born parents and irrespective of own birthplace) and $female_i$ is a dummy representing gender. Standard errors are robust and clustered at the family level since the sample includes siblings. As the LNU data lacks information on individual school performance, I instead include a measure of self-assessed school performance. This measure is drawn from the question "If you compare yourself to your peers, how well do you think you do at school?" with the response options: "Best in class", "Among the best", "Better than the majority", "About as good as most people", and "Not as good as most people". The term $selfass_{ij}$ denotes indicators of self-assessed performance. The reference category consists of individuals who answered "Not as good as most people". The term $educ_{ij}$ denotes a set of indicators of the highest education of both parents (interviewee and partner) and the categories include: compulsory school or less, high-school or less and university studies. Observations are coded as missing if both the interviewee and the partner have missing values on the relevant variable. $famtype_{ij}$ stands for a set of covariates representing intact family, reconstituted family, single parent household or other. Each response category of the family type question has been coded as a dummy variable. $hhsize_i$ is a continuous variable indicating the number of members in the household.

In tables 5 and 6, I present the results from OLS regressions on the three outcome variables listed above. The models are estimated for a sample of children in the ages 12–19.[24] The coefficient of interest is β_1 which captures the discrete change from having at least one native-born parent to having two foreign-born parents. Children with immigrant parents have significantly higher aspirations than their native majority peers; they are 17.8 percentage points (ppt) more likely to report having aspirations for a university degree.

In model (2) in table 5, I enter all the covariates listed in section 3.7. Hence, β_1 is now interpreted as the independent effect of parents' immigration status once all the above factors have been controlled for. The sample size is only marginally reduced due to missing values on the covariates but the magnitude is unchanged, implying that the results are robust to including individual and family characteristics.

[24]Alternative model specifications can be found in the sensitivity analysis in Appendix A.1. Table A1 presents both the log odds and average marginal effects.

Table 5: Aspirations and expectations by region of origin, LNU

	Educational aspirations			Educational expectations		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Foreign-born parents	0.178***	0.255***		0.157***	0.227***	
	(0.029)	(0.054)		(0.028)	(0.054)	
European			0.0841			0.0755*
			(0.053)			(0.043)
non-European			0.214***			0.186***
			(0.049)			(0.047)
Age (demeaned)		-0.00682	-0.00661		-0.0129	-0.0125
		(0.009)	(0.009)		(0.009)	(0.009)
Female		0.216***	0.185***		0.217***	0.189***
		(0.040)	(0.034)		(0.038)	(0.033)
Foreign-born parents × Female		-0.171***			-0.157**	
		(0.062)			(0.065)	
Parents' highest educ=University		0.180***	0.188***		0.191***	0.198***
		(0.037)	(0.038)		(0.036)	(0.036)
Self-assessement						
Best in class		0.396***	0.369***		0.356***	0.331***
		(0.118)	(0.117)		(0.113)	(0.112)
Among the best		0.353***	0.350***		0.285***	0.281***
		(0.094)	(0.094)		(0.096)	(0.096)
Better than the majority		0.375***	0.375***		0.314***	0.314***
		(0.095)	(0.094)		(0.095)	(0.095)
About as good as most people		0.227**	0.229**		0.178*	0.180*
		(0.095)	(0.094)		(0.094)	(0.094)
Reconstituted family		0.0248	0.0326		0.00904	0.0158
		(0.046)	(0.047)		(0.045)	(0.045)
Single parent family		-0.0174	-0.0138		-0.0101	-0.00448
		(0.052)	(0.052)		(0.051)	(0.051)
Household members		0.0149	0.0103		0.00872	0.00570
		(0.014)	(0.014)		(0.014)	(0.015)
Constant	0.703***	0.115	0.144	0.730***	0.219*	0.240**
	(0.018)	(0.111)	(0.110)	(0.017)	(0.114)	(0.114)
Observations	876	867	867	874	865	865
Adjusted R^2	0.040	0.149	0.146	0.033	0.145	0.142

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regressions with robust standard errors clustered at the family level. In models (1)–(3) the dependent variable is a dummy defined as having aspirations for a university degree (i.e. having responded "Yes, absolutely" or "Yes, probably" to the question "Would you like to continue to go to school after the upper secondary level, that is, attend a university or university college?". The dependent variable in models (4)–(6) is a dummy defined as having expectations for a university degree (i.e. having responded "Yes, absolutely" or "Yes, probably" to the question "Do you think you will actually continue to go to school after the upper secondary level, that is, attend a university or university college?").

To assess whether the relationship differs by gender, I also include an interaction term between the indicators for having two foreign-born parents and being female. Due to the inclusion of the interaction term, the reference category is now native-majority boys. The interaction term indicates by how much the influence of being an immigrant student differs between girls and boys and, ceteris paribus, the "net effect" of having two immigrant parents is less positive for girls than boys as the interaction coefficient β_1 is -17.1. Interestingly, the results display a significant gender gap: all else equal, immigrant girls are 30 ppt more likely to have aspirations for a university degree than native-majority boys. Moreover, they are 5 ppt more likely to express university aspirations than immigrant boys, although this difference is insignificant (F-test, α=0.05, column (2)). Native-majority girls are significantly more likely than native-majority boys to report university aspirations (21.6 ppt, $p<0.01$). Girls with two foreign-born parents are 8.4 ppt more likely to have university aspirations than native-majority girls (not significant).

Unsurprisingly, children with at least one higher educated parent are more likely to wish to study at the university than their peers (18.0 ppt, $p<0.01$). Self-assessments of own scholastic ability seems to matter too. Individuals who consider themselves to belong to the upper part of the ability distribution among their peers tend to report university aspirations to a larger extent (ranging between 39.6 to 22.7 ppt, $p<0.01$) than the reference group consisting of individuals who have responded "Not as good as most people". The positive influence seems to grow with higher self-assessment.

In models (3) and (6), the binary outcome variable $immstat_i$ is replaced by three dummy variables indicating region of origin: "Sweden", "Europe" and "non-Europe".[25] Moreover, the results are shown conditional on gender and socioeconomic background. The β_1 coefficient now indicates the differential between children with a European or non-European origin and children with at least one native-born parent. Chil-

[25] Figure D.1 in Appendix D.1 shows the distribution of region of origin in the LNU sample.

dren with parents of European origin are not significantly different in their university aspirations than their native-majority peers. Children with parents born in a non-European country are, however, 21.4 ppt more likely to have university aspirations than their peers ($p<0.01$).

Moving on to educational expectations and model (4), β_1 is the raw difference in educational expectations between children with two immigrant parents and children with at least one parent born in Sweden with the same gender, similar socioeconomic and family backgrounds and self-assessments of scholastic performance. The immigrant-non-immigrant gap is also positive but smaller when we look at the educational expectations in model (4) as compared to aspirations in columns (1) and (2). The probability of thinking that you will attend university is 15.7 ppt higher among children with foreign-born parents than in the reference category ($p<0.01$). The estimate increases in the analysis sample (15.7 ppt versus 22.7 ppt). The direction and relevance of the estimates are similar to those in the models of aspirations (models (1)–(3)). The gender differential is present also with respect to university expectations. Both immigrant and native-majority girls are significantly more likely to report expectations for a university degree (28.7 ppt and 21.7 ppt).

The immigrant-non-immigrant differential is significant and larger for children with a non-European origin (around 18.6 ppt, $p<0.01$) as compared to children of European decent. Both non-European girls and boys have higher aspirations than their native-majority counterparts (not shown here). University expectations are more likely among girls than among native-majority boys (21.7 ppt higher among native-majority girls and 28.7 ppt higher among immigrant girls). In addition, the gap in aspirations between non-European boys and native-majority boys is larger than the gap between non-European girls and native-majority girls (not shown here). Family type and household size do not seem to matter for aspirations and expectations (the reference category is intact family and other).

Moving on to models (1)–(3) in table 6 the dependent variable is the aspirations-expectations gap which is defined as having aspirations for a university education but not expecting to get one. The β_1 coefficient is close to zero and insignificant. The proportion of children expressing a gap is only 2.6 percent (displayed in the descriptive table in section 3.7) which explains the low explanatory power of the model. I find no significant differences in the immigrant-non-immigrant aspirations-expectations gap presented in models (1), (2) and (3), suggesting that immigrant children are not more likely to have expectations falling short of aspirations than their native-majority peers. Model (3) also shows that, all else equal, native-majority girls are significantly less likely to express a gap as compared to their male native-majority peers. Due to the small sample size, these results need to be interpreted with caution, however.

In sum, children with foreign-born parents seem to have both higher educational aspirations and expectations than their counterparts with native-born parents. After controlling for parents' highest education, there is still a significant gap in both aspirations and expectations. An important piece of the puzzle is still missing – academic potential and performance – factors that will be added in the subsequent analysis of section 4.2. The remaining gap might be explained by some subgroups having unrealistically high aspirations and expectations with respect to their academic performance or potential. Another possible explanation is unobserved heterogeneity among students such as behavioral factors, motivation, parental preferences towards higher education.

In the next step, I broaden the analysis by using the CILS4EU dataset which includes self-reported school results and friendship links. As before, I try to account for differences in aspirations and expectations among children with foreign-born and native-born parents but this time *conditional* both on academic potential and school performance. Then, I add sociometric information and different socio-economic and schooling factors found in CILS4EU. Due to possible sorting across schools, in what follows I will include classroom fixed-effects in all regression models.

4.2 The role of school performance and friendship network

Previous research shows that foreign-born children and children of immigrants lag behind children of native-born parents in educational performance in several European countries, and Sweden is no exception (Schnepf, 2007).[26] Foreign-born students in Sweden are less likely to be eligible to attend upper secondary school than their native-born counterparts.[27] Importantly, immigrant children constitute a heterogeneous group. Given attained school grades, they tend to make more ambitious study choices than their native-majority peers (see Arai et al. (2000), Jonsson and Rudolphi (2011) and Heath and Brinbaum (2014)). The school performance of children born in Sweden with immigrant parents is varying by ethnic origin and those who decide to continue to higher education often outperform the majority population, while those who fail in secondary school have low labor market prospects (Jonsson and Rudolphi, 2011).

Figure 11 shows the distributions of grades by parents' immigration status (irrespective of own birthplace).[28] Children with immigrant parents are more likely to have non-complete grades in core subjects. The largest difference between the two groups is in English and the second largest difference is in Maths where 9.3 percent of the sample of children with immigrant parents have reported Fail on their last school report (versus 5.7 percent among their native-majority peers).

[26]See also Heath and Brinbaum (2007) and Heath and Brinbaum (2014).

[27]Arai et al. (2000) show that children born abroad have lower marks, attain lower levels of education and show higher risks of unemployment than their native-born counterparts.

[28]Children who have themselves immigrated are included in the sample of children with immigrant parents, which could explain a large part of the immigrant-non-immigrant differential displayed in figure 11. In the following regression analysis, I control for language proficiency, among other things.

Table 6: The aspirations-expectations gap by region of origin, LNU

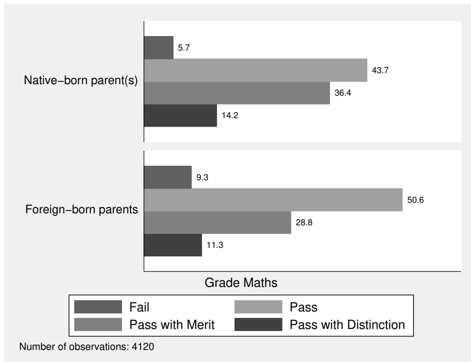
	Aspirations-expectations gap		
	Model 1	Model 2	Model 3
Foreign-born parents	0.00312	0.0430	
	(0.011)	(0.034)	
European			0.0143
			(0.026)
non-European			0.0242
			(0.021)
Age (demeaned)		-0.00126	-0.00105
		(0.004)	(0.004)
Female		-0.0178	-0.0259**
		(0.013)	(0.013)
Foreign-born parents × Female		-0.0428	
		(0.036)	
Parents' highest educ=University		-0.00250	-0.00174
		(0.013)	(0.013)
Self-assessement			
Best in class		-0.0259	-0.0318
		(0.037)	(0.038)
Among the best		-0.00669	-0.00833
		(0.037)	(0.037)
Better than the majority		-0.0256	-0.0259
		(0.038)	(0.038)
About as good as most people		-0.00295	-0.00337
		(0.038)	(0.038)
Reconstituted family		0.0218	0.0229
		(0.019)	(0.019)
Single parent family		-0.0170	-0.0152
		(0.016)	(0.015)
Household members		-0.00739	-0.00738*
		(0.005)	(0.004)
Constant	0.0252***	0.0741	0.0781
	(0.007)	(0.048)	(0.048)
Observations	874	865	865
Adjusted R^2	-0.001	0.004	0.001

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

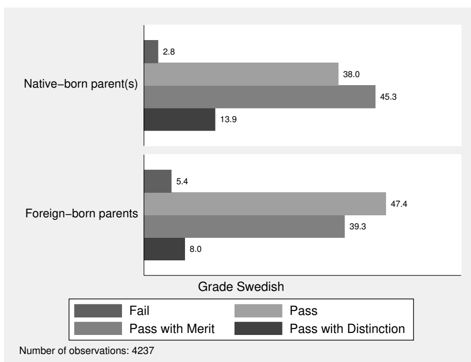
Note: OLS regressions with robust standard errors clustered at the family level. In models (1)–(3) the dependent variable is a dummy for the aspirations-expectations gap which is defined as having aspirations for a university degree but not expecting to get one (i.e. having responded “Yes, absolutely” or “Yes, probably” to the aspirations question and “No, probably not” or “No, absolutely not” to the expectations question.

Figure 11: Grade distributions in core subjects by parents' immigration status, self-reports in grade 9, CILS4EU

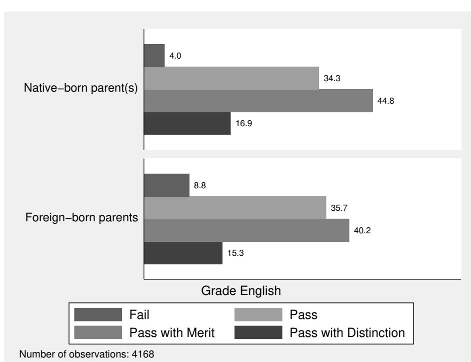
(a)



(b)



(c)



Next, I turn to the CILS4EU dataset. This dataset includes friendship network data and extensive survey information on parents and friends. I start by estimating the following regression:

$$\begin{aligned} y_{ict_0} &= \alpha + \beta_1 immstat_i + \beta_2 female_i + \beta_3 immstat_i \times female_i \\ &+ \beta_5 educ_i + \sum_{j=1}^{2} \beta_{4j} testscore_{ji} + \beta_6 pardisc_i + \mathbf{x}_{\boldsymbol{it_0}}^{friend}\gamma + \epsilon_{ict_1}, \end{aligned} \tag{2}$$

where y_{ict} is a dummy either indicating the outcome variable university aspirations or university expectations of individual i in grade 8 denoted by t_0 and class c. α is a constant, $immstat_i$ is a dummy indicating if the individual has two foreign-born parents irrespective of own birthplace and $testscore_{ji}$ denotes individual test scores on cognitive and language tests performed in grade 8 (wave 1). Parental level of education is proxied by parents' occupational class and $educ_i$ is a dummy denoting high skill occupations and coded 1 if at least one parent has an occupation belonging to the category managers and professionals.[29] Parent discrepancy, represented by the term $pardisc_i$, is a dummy indicating whether the parent wishes the child to get a college/university education but expects him or her to get less than a college/university education, and ϵ_{ict_0} is the error term.

The characteristics of friends, denoted by $\mathbf{x}_{\boldsymbol{it_0}}^{friend}$, are four dummy variables indicating whether or not an individual has friends who all have the following characteristics: female, foreign-born parents, higher educated parents and university aspirations.[30]

[29] The dummy for managers and professionals is coded 1 if either parent's occupation belongs to the categories >999 & <3000 of ISCO 2008. Parents' occupational class is drawn from the children's reports of their parents' occupation. The variable is based on the student questionnaire item: "Think about your mother's job. If she is not currently working, think about her last job. What is the name of her job? Additionally, please describe what she does in her job.". I also use the corresponding question for father's occupation. An alternative approach is to create three categories based on ISCO 2008: "high skill": 1 and 2, "mid skill": 3,4 and 7 and "low skill": 5,6,8 and 9.

[30] In alternative specifications, the vector includes the mean characteristics of best friends. Moreover, I also include the average peer characteristics at the classroom and school level, represented by the vectors $\bar{\mathbf{x}}_{\boldsymbol{it_0}}^{class}$ and $\bar{\mathbf{x}}_{\boldsymbol{it_0}}^{school}$. Alternative specification

Due to potential sorting across classrooms and schools as well as different grading practices across schools, I include classroom fixed-effects in all models (N.B. I use the terms school class and classroom interchangeably). Moreover, by including classroom fixed-effects, I control for the educational environment such as teacher and classmate quality. The classroom dummies absorb across classroom and school differences, i.e. I only compare students in the same classroom. FE_{ct_0} denotes fixed-effects at the classroom level and the indicator is based on the composition of students on the day of the network survey in grade 8. Unless a student relocates or actively decides to change classes, students in Sweden tend to have the same classmates all through grades 7–9 of compulsory school.

Next, I match the first wave of CILS4EU with the second wave that also contains self-reported grades in Maths, Swedish and English in grade 9 in the last semester (not final grades). Thus, I am able to investigate differences in aspirations and expectations between children of foreign-born and children of native-born parents *conditional* on academic performance. I proceed by estimating the following regression:

$$\begin{aligned} y_{ict_1} = \alpha &+ \beta_1 immstat_i + \beta_2 female_i + \beta_3 immstat_i \times female_i \\ &+ \beta_4 educ_i + \sum_{j=1}^{2} \beta_{5j} testscore_{ji} + \beta_6 pardisc_i + \beta_7 gradesum_i \\ &+ \mathbf{x}_{\boldsymbol{it_0}}^{friend} \gamma + \nu FE_c + \epsilon_{ict_1}, \end{aligned} \tag{3}$$

where y_{it} is a dummy indicating either the outcome variable educational aspirations or educational expectations of individual i in grade 9, class c, and wave 2 as denoted by t_1. The dependent variable is a dummy defined as having aspirations for a university degree, i.e. having reported "College/university" on the questionnaire item "What is the highest level of education you wish to get?". The terms α, $immstat_i$, $educ_i$, $testscore_{ji}$ and $pardisc_i$ are defined as above. As before, $\mathbf{x}_{\boldsymbol{it_0}}$ represents a vector of covariates at the friendship level where friends are defined according

results are either presented in Appendix A.1 or available upon request.

to friendship nominations at t_0 (wave 1). Since I only use the friendship data in t_0, I treat the friendship network as static. The term $grade_{jit_1}$ represents an individual's grade in Maths, English and Swedish. To correct for potential similarity of individuals within clusters, the standard errors are clustered at the classroom level. Table 7 reports OLS regression coefficients from models of university aspirations.[31]

In table 7, I present the estimations of the outcome variables aspirations in grade 8 (models (1)–(3)) and aspirations in grade 9 (models (4)–(7)). Recall that $immstat_i$ is a dummy, hence β_1 captures the change in likelihood as the variable changes from 0 to 1. Model (1) shows the raw difference in aspirations between children with at least one native-born parent and children with two foreign-born parents in grade 8 for the full sample. Immigrant children are 10.7 ppt ($p<0.01$) more likely to express university aspirations than their native-majority peers.

Model (2) shows the corresponding results for the analysis sample. The coefficient is only slightly higher (10.7 versus 11.7), indicating that the result is robust to sample changes. Unconditional on individual, friends and family characteristics, children of immigrant background are significantly more likely to want to study at the university than their peers.

In model (3), I partial out the influence of gender, parents' highest level of education, academic potential (proxied by cognitive and language ability tests), parents' aspirations-expectations discrepancy and the characteristics of friends. The network variables include dummies for whether or not an individual has friends who all have the following characteristics: female, foreign-born parents, higher educated parents and university aspirations. The coefficient for the dummy indicating immigration status indicates that immigrant boys are 25.7 ppt more likely to have university aspirations than native-majority boys. The interaction term indicates by how much the influence of being an im-

[31] I also run multileveled logit regressions with random-effects at the classroom level and standard errors clustered at the classroom level. These models are estimated using Stata's melogit command for mixed multilevel logit models.

migrant student differs between girls and boys. The influence of immigration status is less positive for girls as compared to boys but not significantly (F-test, α=0.05, column (3)). Both native-majority and immigrant girls are significantly more likely to report university aspirations than native-majority boys (approximately 10.8 and 28.9 ppt, respectively).[32] Furthermore, the gender difference seems to be larger within the native-majority group than within the immigrant group.

Individuals with at least one higher educated parent (proxied by both parents' occupational class) are significantly more likely to wish to attend university (10.5 ppt more likely). Language proficiency seems to matter more than cognitive ability: all else equal, a standard deviation (std=4.85) increase in the language test score of an individual is, on average, associated with a 11.6 ppt increase in the probability of having university aspirations. The estimate of the influence of the cognitive ability test score is also significant but smaller: 4.0 ppt (std=4.72).

To determine the importance of the composition of an individual's social networks, I also include a selection of observable characteristics of an individual's friendship network. Having only female friends is negatively associated with university aspirations. However, the coefficient is small and insignificant.[33] Other friends' characteristics seem to be positively correlated with individual aspirations, for instance the estimate is positive for the indicators for only having friends with foreign-born parents (4.41 ppt) and only friends with university aspirations (1.52 ppt). All estimates are insignificant at conventional levels, suggesting that friendship characteristics are not major determinants of aspirations in grade 8. A reason for this could be that the fixed-effects at the classroom level have captured much of the variance.[34]

[32]The coefficient for girls with foreign-born parents is: 0.257+0.108-0.0756=0.289, F-test, α=0.05, column (3).

[33]In alternative specifications, I have used the proportion of friends with certain observable characteristics. These estimates are both very small and statistically insignificant.

[34]The results from fixed-effects logistic regressions in Appendix A.1 show a similar picture.

Table 7: OLS coefficients from regressions of aspirations in grade 8 and 9, respectively, CILS4EU

	Aspirations grade 8			Aspirations grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	0.107***	0.117***	0.257***	0.0946***	0.133***	0.235***	0.234***
	(0.021)	(0.022)	(0.028)	(0.021)	(0.021)	(0.027)	(0.027)
Female			0.108***			0.120***	0.115***
			(0.021)			(0.019)	(0.020)
Foreign-born parents × Female			−0.0756**			−0.0796**	−0.0814***
			(0.033)			(0.031)	(0.031)
Higher educated parents			0.105***			0.0644***	0.0641***
			(0.016)			(0.014)	(0.014)
Language test score (std)			0.116***			0.0310***	0.0319***
			(0.010)			(0.010)	(0.010)
Cognitive test score (std)			0.0400***			0.0146	0.0144
			(0.010)			(0.010)	(0.010)
All friends: female			−0.0107				0.0253
			(0.025)				(0.020)
All friends: foreign-born parents			0.0441				0.0466
			(0.034)				(0.032)
All friends: higher educ parents			0.0152				−0.00678
			(0.026)				(0.025)
All friends: university aspirations			−0.0390*				−0.0228
			(0.021)				(0.019)
Grade sum						0.0721***	0.0723***
						(0.005)	(0.005)
Classroom FEs	✓	✓	✓	✓	✓	✓	✓
Observations	4364	4075	4075	4354	3381	3381	3381
Adjusted R^2	0.007	0.009	0.102	0.005	0.013	0.184	0.184

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regressions. Standard errors are clustered at the classroom level. All regressions include classroom fixed-effects. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having aspirations for a university degree ("What is the highest level of education you wish to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)").

Next, I present the results for the same individuals, but now their aspirations and expectations have been measured one year later in grade 9. Model (4) shows the raw difference between children with immigrant parents and at least one native-born parent in the same classroom in the full sample (9.46 ppt). The analysis sample in model (5) consists of 3,381 individuals. The estimate of having two foreign-born parents increases somewhat to 13.3 ppt, indicating some degree of selection from the reduced sample size.

Moving on to model (6), we can see that the differential is higher when controls are entered (23.5 ppt, $p<0.01$). The classroom fixed-effects imply that I am comparing individuals in the same classroom with similar individual characteristics, academic potential, school performance and social background.[35] Model (6) also holds constant for grade sum measured by adding up the grades in each core subject. Thus, I adjust for the presence of individuals with unrealistic aspirations and expectations. Given the same academic potential and similar school results, children of immigrants have significantly higher aspirations than their native-majority peers.[36]

Language test scores are still important. The association between aspirations and language tests scores is weaker in grade 9 than in grade 8, but still significant as compared to the previous influence of cognitive ability which disappears (11.6 ppt versus 3.1 ppt). Moreover, the grade sum in the core subjects Maths, English and Swedish are positively related to university aspirations: all else equal, a one point increase in the grade sum (moving from a "Pass" to a "Pass with Distinction" in a core subject) is associated with a 7.2 ppt increase in the likelihood of having university aspirations ($p<0.01$).

The results from regressions including friends' characteristics are presented in model (7). Overall, the estimates have the same direction as in

[35] In alternative specifications of model (6), we instead hold constant for having passed all core subjects (based on self-reported grades from the last school report in grade 9).

[36] As previously mentioned, the grades are based on self-reported grades from the last school report in grade 9.

models (3) and (6). The results suggest that the influence of the observable characteristics of friends is insignificant. The university aspirations among boys with two foreign-born parents is now 23.4 ppt (p<0.01) higher than that of the base category which consists of native-majority boys. Furthermore, native-majority girls and immigrant girls are more likely to report university aspirations than is the base category: the coefficient for immigrant girls is 26.8 ppt (F-test, α=0.05, column (6)) and for native-majority girls it is 11.5 ppt. Holding constant for the characteristics of an individual's social network, the immigrant-non-immigrant differential is still present and significant.

Following the same procedure as above, I estimate the corresponding regressions for the outcome variable educational expectations and the results are reported in table 8. The dependent variable is a dummy defined as having expectations for a university degree, i.e. having reported "College/university" on the questionnaire item "What is the highest level of education you think you will actually get?".

Model (1) in table 8 presents the raw difference in university expectations between children of immigrants and native-born children for the full sample in grade 8. The coefficient of particular interest, β_1, indicates that immigrant children are 7.14 ppt more likely to want to attend university than their native-majority peers (p<0.01). The coefficient is larger and still highly significant in the analysis sample in model (2) (8.02 ppt versus 7.14 ppt).

Model (3) shows the results conditional on the set of explanatory variables in the first wave of CILS4EU. The signs and the relevance are similar to the models of university aspirations in table 7. All else equal, models (1)–(3) suggest that children of immigrants report expectations for higher education in grade 8 to a larger extent than their native-majority peers.

The outcome variable in models (4)–(7) is educational aspirations in grade 9. Similarly to the model of expectations in grade 8, the estimate for having immigrant parents increases when covariates are added to the model of expectations in grade 9 (13.5 ppt versus 24.6 ppt). Unlike the cognitive ability test scores which lose significance in grade 9 expectation models, language ability remains highly significant in both model (6) and model (7).

I enter the full set of explanatory variables in model (7) and I am now comparing children in the same class with similar individual and family characteristics, school performance and academic potential (proxied by language and cognitive tests in grade 8) and friendship network characteristics. As expected, the grade sum in core subjects is positively related to expectations for higher education (model (7)). With regard to the friendship level variables, all except having only friends with higher educated parents turn out to be insignificantly associated with individual expectations ($p<0.01$).

To compare the fit of the network model and the full-sample model, I perform a log-likelihood test (of whether the models are nested) where the null hypothesis states that there is no significant difference between the two models. The test indicates that I can reject the null hypothesis and conclude that the network model provides a better fit to the data.

To summarize the tables for aspirations and expectations, children of immigrant parents are more likely to aspire to university studies and to expect to study at the university than their native-majority peers. Both immigrant and native-majority girls are more likely to aspire to and expect university studies than native-majority boys (F-tests, α=0.05, columns (6)–(7)).

Table 8: OLS coefficients from regressions of expectations in grade 8 and 9, respectively, CILS4EU

	Expectations grade 8			Expectations grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	0.0714***	0.0802***	0.224***	0.0981***	0.135***	0.246***	0.245***
	(0.021)	(0.023)	(0.028)	(0.022)	(0.023)	(0.028)	(0.028)
Female			0.0710***			0.119***	0.114***
			(0.021)			(0.019)	(0.019)
Foreign-born parents × Female			−0.0667*			−0.0793**	−0.0806**
			(0.035)			(0.034)	(0.033)
Higher educated parents			0.102***			0.106***	0.105***
			(0.017)			(0.015)	(0.015)
Language test score (std)			0.122***			0.0292***	0.0288***
			(0.010)			(0.010)	(0.010)
Cognitive test score (std)			0.0593***			0.0135	0.0137
			(0.009)			(0.009)	(0.009)
All friends: female			0.0277				0.0239
			(0.028)				(0.021)
All friends: foreign background			0.0381				0.0231
			(0.040)				(0.041)
All friends: higher educ parents			−0.0231				−0.0522*
			(0.029)				(0.028)
All friends: university aspirations			−0.0110				0.0135
			(0.024)				(0.020)
Grade sum						0.0899***	0.0902***
						(0.005)	(0.005)
Classroom FEs	✓	✓	✓	✓	✓	✓	✓
Observations	4364	4075	4075	4353	3377	3377	3377
Adjusted R^2	0.003	0.003	0.098	0.005	0.011	0.224	0.225

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regressions. Standard errors are clustered at the classroom level. All regressions include classroom fixed-effects. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having expectations for a university degree ("What is the highest level of education you think you will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)").

5 The aspirations-expectations gap

In this subsection, I examine whether children of immigrants are less consistent in their aspirations and expectations than their native-majority peers. I treat the outcome variables aspirations and expectations as ordinal since the difference between "Yes, absolutely" and "Yes, probably" is not necessarily the same as the difference between "No, probably not" and "No, absolutely not". Furthermore, the error terms of the two models may be correlated. Simply subtracting the one from the other will be inappropriate which is why I consider the following two alternative approaches.

The first approach involves dichotomizing the underlying variables aspirations and expectations and running multileveled logit regressions on a binary outcome variable defined as having aspirations for a university degree but not expecting to get one. A drawback with this method is that it could lead to a loss of important information from the model. The alternative strategy is to estimate the model using the bivariate ordered probit model, thus making full use of the categorical property of the aspirations and expectations variables in the LNU dataset. The latter approach is less suitable for the CILS4EU data and, for comparability, the former is therefore more appropriate. Hence, in what follows I dichotomize the aspirations-expectations gap. I present the results from the alternative approach in Appendix A.1. I follow the same procedure as in section 4.2 above and estimate the following regression:

$$\begin{aligned} y_{ict} &= \alpha + \beta_1 immstat_i + \beta_2 female_i + \beta_3 immstat_i \times female_i \\ &+ \beta_4 educ_i + \sum_{j=1}^{2} \beta_{3j} testscore_{ji} + \beta_5 pardisc_i + \beta_6 gradesum_i \\ &+ \mathbf{x}_{\boldsymbol{it_0}}^{friend} \boldsymbol{\gamma} + \nu FE_{ct_0} + \epsilon_{ict}, \end{aligned} \tag{4}$$

where y_{ict} is the aspirations-expectations gap of individual i in class c in t_0 (wave 1) or t_1 (wave 2). The outcome variable y_{ict} is a dummy indicating whether an individual has aspirations for a university degree but does not expect to get one, i.e. having responded "College/university" to the question "What is the highest level of education you wish to get?" and having replied any of the options "Don't know", "No degree", "Compulsory school" or "Upper secondary school" to the question "What is the highest level of education you think you will actually get?". All other variables are defined as above. The OLS regression results are presented in table 9. Models (1) and (2) report the baseline regression results of the outcome variable aspirations-expectations gap in grade 8 on the dummy $immstat_i$ including class fixed-effects. Standard errors are robust clustered at the classroom level.

Children who have two foreign-born parents are 3.12 ppt more likely to express a gap than the native-majority group (the unconditional average of the aspirations-expectations gap among native-majority children is 0.167). The estimation results also reveal that the positive association between parents' immigration status and the aspirations-expectations gap disappears once covariates are entered into the model (table 9, model (3)). The adjusted R^2 increases but only marginally.

Gender seems to play a non-negligible role since the coefficient for gender is bordering on statistical significance ($p<0.10$). Native-majority girls are 2.72 ppt more likely to express a gap than are native-majority boys, all else equal. Immigrant girls are also significantly more likely to have mismatched aspirations and expectations than native-majority boys (4.28 ppt, F-test, $\alpha=0.05$, column (3)). However, the gender differential is not significant within the immigrant group (1.86 ppt, F-test, $\alpha=0.05$, column (3)).

In models (4)–(7), we turn to the aspirations-expectations gap in grade 9. Interestingly, the gap is no longer present in the baseline regressions of models (4) and (5), suggesting that individuals adjust their aspirations over time. Children with higher educated parents are less likely to report an aspirations-expectations gap (4.0–4.1 ppt, models (6) and (7)). Moreover, the grade sum is negatively associated with reporting a gap.

Table 9: OLS coefficients from regressions predicting the aspirations-expectations gap in grade 8 and 9, respectively, CILS4EU

	Aspirations-expectations gap grade 8			Aspirations-expectations gap grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	0.0312**	0.0316*	0.0242	−0.00503	−0.00629	−0.00934	−0.00846
	(0.015)	(0.016)	(0.021)	(0.012)	(0.015)	(0.019)	(0.019)
Female			0.0272*			0.0102	0.0103
			(0.016)			(0.013)	(0.013)
Foreign-born parents × Female			−0.00864			−0.0207	−0.0210
			(0.027)			(0.025)	(0.025)
Higher educated parents			−0.00763			−0.0407***	−0.0402***
			(0.013)			(0.012)	(0.012)
Language test score (std)			−0.00928			−0.00215	−0.00120
			(0.008)			(0.008)	(0.008)
Cognitive test score (std)			−0.0146**			−0.000467	−0.000799
			(0.007)			(0.007)	(0.007)
All friends: female			−0.0322				0.00229
			(0.021)				(0.017)
All friends: foreign-born parents			0.0180				0.0178
			(0.035)				(0.029)
All friends: higher educ parents			0.0140				0.0343*
			(0.021)				(0.021)
All friends: university aspirations			−0.0200				−0.0260*
			(0.020)				(0.014)
Grade sum						−0.0187***	−0.0188***
						(0.003)	(0.003)
Classroom FEs	✓	✓	✓	✓	✓	✓	✓
Observations	4364	4075	4075	4349	3377	3377	3377
Adjusted R^2	0.001	0.001	0.003	−0.000	−0.000	0.018	0.019

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regressions. Standard errors are clustered at the classroom level. All models include classroom fixed-effects. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having aspirations for a university degree (i.e. having responded "College/university" to the question "What is the highest level of education you wish to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)" but not expecting to get one (i.e. having responded less than "College/university" to the question "What is the highest level of education you think you will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)" .

Due to the low response rate among parents, the results from regressions including the parent discrepancy indicator are presented in a separate table. Table 10 suggests that parent discrepancy is an important predictor of both aspirations and expectations. Having a parent with expectations that fall short of aspirations is negatively related to individual aspirations and expectations for higher education ($p<0.01$). The coefficient remains negative and significant in all specifications. Children's aspirations-expectations gaps are also significantly associated with their parents' aspirations as demonstrated in the two right-most columns of table 10.

Returning to summarize table 9, children of immigrants are significantly more likely to express an aspirations-expectations gap in grade 8. However, the gap diminishes over time and once covariates have been entered into the model. Overall, neither immigrant boys nor immigrant girls are more likely to have mismatched aspirations and expectations than are their native-majority peers. The results validate the findings in section 4.1. The next question is whether individuals with non-complete grades are more likely to have unrealistically high aspirations and whether children of immigrants are more likely to belong to this category.

Table 10: OLS coefficients from models of aspirations, expectations and the aspirations-expectations gap in grade 8 and 9, respectively, including parent discrepancy, CILS4EU

	Aspirations		Expectations		Aspirations-expectations gap	
	Grade 8	Grade 9	Grade 8	Grade 9	Grade 8	Grade 9
Foreign-born parents	0.226***	0.176***	0.201***	0.244***	0.0202	−0.0567**
	(0.038)	(0.033)	(0.042)	(0.035)	(0.032)	(0.024)
Female	0.0968***	0.106***	0.0679**	0.136***	0.0217	−0.00916
	(0.026)	(0.022)	(0.027)	(0.024)	(0.020)	(0.016)
Foreign-born parents × Female	−0.0665	−0.0534	−0.0607	−0.119***	−0.00805	0.0323
	(0.045)	(0.038)	(0.050)	(0.044)	(0.040)	(0.034)
Higher educated parents	0.110***	0.0568***	0.119***	0.0937***	−0.0212	−0.0344**
	(0.019)	(0.019)	(0.022)	(0.020)	(0.018)	(0.016)
Language test score (std)	0.124***	0.0142	0.117***	0.0107	−0.00343	−0.00425
	(0.014)	(0.013)	(0.014)	(0.014)	(0.012)	(0.011)
Cognitive test score (std)	0.0205*	0.000393	0.0433***	0.00929	−0.0166	−0.00934
	(0.012)	(0.013)	(0.012)	(0.013)	(0.011)	(0.010)
Parent discrepancy	−0.0400**	−0.0436**	−0.116***	−0.0714***	0.0629***	0.0343**
	(0.019)	(0.018)	(0.020)	(0.020)	(0.018)	(0.016)
All friends: female	−0.0192	−0.00957	0.0219	−0.00440	−0.0389	−0.00312
	(0.032)	(0.025)	(0.036)	(0.028)	(0.025)	(0.023)
All friends: foreign-born parents	0.0989*	0.0427	0.0328	0.0326	0.0731*	−0.00102
	(0.051)	(0.050)	(0.052)	(0.057)	(0.044)	(0.038)
All friends: higher educ parents	−0.00147	−0.0323	−0.0263	−0.0834**	0.00419	0.0409
	(0.035)	(0.028)	(0.038)	(0.034)	(0.027)	(0.025)
All friends: university aspirations	−0.0520*	−0.0407*	0.00366	0.0124	−0.0540**	−0.0458**
	(0.028)	(0.024)	(0.030)	(0.025)	(0.024)	(0.018)
Grade sum		0.0709***		0.0880***		−0.0187***
		(0.006)		(0.006)		(0.005)
Classroom FEs	✓	✓	✓	✓	✓	✓
Observations	2438	2139	2438	2135	2438	2135
Adjusted R^2	0.097	0.166	0.106	0.227	0.012	0.030

Standard errors in parentheses

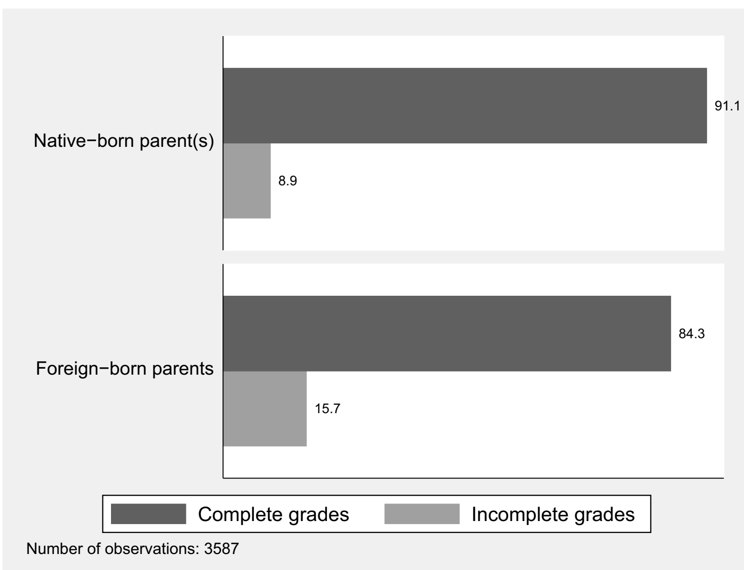
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regressions. Standard errors are clustered at the classroom level. All models include classroom fixed-effects. Variable definitions are found in section 3.7.

5.1 Sub-sample analysis

In this subsection, I look more closely at individuals with non-complete grades. To examine potential subgroup differences, I run separate analyses on individuals with complete and incomplete grades. I create a non-complete grades dummy that is based on self-reported grades from the last school report (1=at least one Fail in any of the core subjects) which is used as a proxy for school performance. The reference category consists of individuals with at least Pass in all core subjects. Figure 11 in section 4.2 reports the self-reported grades in the core subjects Maths, Swedish and English. Distributions of school performance are shown in figure 12 below.

Figure 12: Complete/incomplete grades in grade 9 by parents' immigration status, CILS4EU



Next, I investigate whether individuals with non-complete grades are more likely to have unrealistically high aspirations in grade 9. Table 11, Panel A, shows that within the subgroup of individuals with incomplete grades, children of immigrants do not differ significantly from the native-majority children. The coefficients for the immigration status of parents in column (1) and gender in columns (2)–(3) are both positive but none of the estimates is significant. While column (1) reports the "raw" differential including fixed effects, the estimated models in columns (2) and (3) account for individual and social network characteristics.

Turning to Panel B and the subgroup of students with at least Pass in all core subjects, boys of foreign background are approximately 3.0 ppt (column (2)) less likely to have mismatched aspirations and expectations than boys of native-majority background, conditional on parental education and language proficiency. This estimate is insignificant, however.

The set of explanatory variables is expanded in column (3). In addition to the variables listed above, the regression model in column (3) also consists of friends' characteristics including foreign background, female and higher educated parents. Among children with complete grades, those with at least one higher educated parent are 4.21 ppt less likely to express an aspirations-expectations gap ($p<0.01$, column (3)). Language test scores are significantly and negatively associated with reporting an aspirations-expectations gap in grade 9.

Table 11: Subgroup analysis of the aspirations-expectations gap in grade 9, OLS coefficients and standard errors in parentheses

	Aspirations-expectations gap		
	(1)	(2)	(3)
Panel A: Non-complete grades			
Foreign-born parents	0.0201	0.00993	−0.0206
	(0.042)	(0.120)	(0.115)
Female		0.0244	0.0170
		(0.108)	(0.108)
Foreign-born parents × Female		−0.0205	−0.0293
		(0.128)	(0.135)
Higher educated parents		−0.0425	−0.0291
		(0.082)	(0.084)
Language test score (std)		0.0317	0.0410
		(0.031)	(0.031)
Classroom FEs	✓	✓	✓
Observations	351	351	351
Adjusted R^2		−0.007	0.006
Panel B: At least Pass in all core subjects			
Foreign-born parents	−0.00834	−0.0300	−0.0284
	(0.012)	(0.020)	(0.020)
Female		−0.00297	−0.00345
		(0.012)	(0.013)
Foreign-born parents × Female		−0.0116	−0.0110
		(0.025)	(0.025)
Higher educated parents		−0.0421***	−0.0417***
		(0.012)	(0.012)
Language test score (std)		−0.0231***	−0.0223***
		(0.008)	(0.008)
Classroom FEs	✓	✓	✓
Observations	3034	3034	3034
Adjusted R^2		0.008	0.009

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Linear probability models (LPM) with classroom fixed-effects and standard errors clustered at the classroom level. While column (1) displays the "raw" immigrant-non-immigrant difference, column (2) includes a set of individual-level explanatory variables. The model in column (3) also controls for friends' average characteristics including foreign background, female, higher educated parents and university aspirations as defined in section 3.7.

6 "Lost talent" among immigrant youths?

Following Hanson (1994), I define lost talent as expressing an aspirations-expectations gap and scoring higher than the mean of the sample on the cognitive ability test administered in grade 8. The cutoff is produced using the analysis sample in previous sections (n=4,075). The distribution is skewed to the left and the median is greater than the mean (19.0 versus 17.9). The minimum score on the cognitive ability test for the analysis sample is 0 and the maximum is 27. In column (1) the threshold is set at a test score higher than the mean score in the analysis sample (henceforth referred to as definition A) while in column (2), lost talent is defined as scoring higher than the median in the analysis sample (henceforth referred to as definition B). According to definition A, 9.99 percent of the sample irrespective of parental migration status are labeled as lost talent in grade 8 and 6.55 according to definition B. In grade 9, the proportions are lower: 5.77 and 3.73 percent, respectively.

Table 12 shows OLS coefficients for models predicting lost talent among a representative sample of eight and ninth graders in Sweden. All models have very low adjusted R^2-levels. I omit the fixed-effects to keep more variation, i.e. I do not confine the analysis to variation within classrooms, since the number of individuals labeled as lost talent per classroom is too small.

Column (1) reports that according to definition A, children with immigrant parents are 1.7 ppt less likely to belong to the category of lost talent ($p<0.10$). Covariates are added to the model in column (2) and the results indicate that neither boys nor girls with immigrant parents are significantly more likely to be labeled as lost talent than the reference group (native-majority boys).[37] All else equal, native-majority girls are significantly more likely to belong to the lost talent category than are native-majority boys (2.61 ppt, $p<0.05$, column (2)). The result is, however, not robust with respect to alternative definitions (A and B

[37] Immigrant girls are 1.61 ppt more likely to be labeled as lost talent according to column (2). However, we cannot reject the null from an F-test that the means are the same (α=0.05).

and in grade 8 and 9).

According to definition B and unconditioned on covariates, there is a significant immigrant-non immigrant differential in lost talent (1.89 ppt, $p<0.05$, column (3)). Thus, native-majority students are more likely to be classified as lost talent. The gap diminishes, however, as covariates are added to the model (column (4)). Columns (5)–(8) reveal a similar pattern. Overall, the immigrant-non-immigrant disparity is negative and insignificant. Language proficiency is a significant and consistent predictor of lost talent. Moreover, only having university aspiring best friends also seems to be important, although the estimate is only significant in column (8) (1.34 ppt, $p<0.05$). Apart from having only university aspiring friends, there is a another network indicator that turns out to have a significant influence on the outcome variable: having only female friends is negatively associated with lost talent both in models (2) and (3). The estimated association is approximately 2 ppt ($p<0.10$ in column (2) and $p<0.05$ in column (3)).

To summarize table 12, the results suggest that immigrant children align their aspirations and expectations according to their school results and over time. Conditional on school performance and academic potential, I find no indication of immigrant children being more likely to be labeled as lost talent in Sweden. I find that native-majority girls are more at risk of being labeled as lost talent in grade 8 than are their male native-majority peers according to definition A. The result is, however, not robust to changing the cutoff definition.

Table 12: Predictors of lost talent, alternative definitions, CILS4EU

	Grade 8				Grade 9			
	Cutoff A		Cutoff B		Cutoff A		Cutoff B	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Foreign-born parents	−0.0170*	0.00394	−0.0189**	−0.00979	−0.0142	0.00298	−0.0142	−0.00293
	(0.010)	(0.015)	(0.008)	(0.012)	(0.009)	(0.012)	(0.009)	(0.009)
Female		0.0261**		0.0111		0.0144		0.000995
		(0.013)		(0.010)		(0.009)		(0.008)
Female × Foreign-born parents		−0.0139		0.00806		−0.0220		−0.00653
		(0.019)		(0.016)		(0.015)		(0.013)
Higher educated parents		−0.00941		−0.0102		−0.0126		−0.00355
		(0.010)		(0.009)		(0.009)		(0.007)
Language test score (std)		0.0285***		0.0276***		0.0102*		0.0106**
		(0.005)		(0.004)		(0.005)		(0.004)
All friends: female		−0.0241*		−0.0249**		−0.000246		−0.00377
		(0.013)		(0.010)		(0.010)		(0.007)
All friends: foreign-born parents		0.0184		0.0204*		−0.00348		0.00201
		(0.015)		(0.012)		(0.013)		(0.010)
All friends: higher educ parents		−0.0196		0.00334		0.0145		0.0112
		(0.014)		(0.013)		(0.012)		(0.010)
All friends: university aspirations		0.00200		0.00161		−0.00199		−0.0134**
		(0.011)		(0.010)		(0.008)		(0.007)
Grade sum						−0.00552**		−0.00211
						(0.002)		(0.002)
Constant	0.105***	0.0922***	0.0711***	0.0637***	0.0618***	0.0836***	0.0618***	0.0523***
	(0.006)	(0.009)	(0.005)	(0.008)	(0.005)	(0.013)	(0.005)	(0.011)
Observations	4075	4075	4075	4075	3377	3377	3377	3377
Adjusted R^2	0.000	0.008	0.001	0.010	0.000	0.002	0.000	0.001

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Linear probability model (LPM) with standard errors are clustered at the classroom level. Variable definitions are found in section 3.7. The dependent variable is a dummy for lost talent which is defined as scoring higher than the mean or the median of the sample on the cognitive ability test administered in grade 8 and expressing an aspirations-expectations gap. In columns (1)–(2) and (5)–(6) the threshold is defined as a cognitive ability test score higher than the mean in the analysis sample. In columns (3)–(4) and (7)–(8) the threshold is defined as a test score higher than the median in the analysis sample.

7 Discussion

The issue of educational aspirations and expectations is important from a policy perspective, since expectations are strong predictors of educational attainment (see for example Feliciano and Rumbaut (2005); Jacob and Wilder (2010); Portes and Rumbaut (2001)), which in turn is key for the economic and social integration of children with an immigrant background (Bratsberg et al., 2011; Card, 2005).

In this study, I explore a potential mechanism for immigrant-native disparities in school results, namely the aspirations-expectations gap. In line with previous research (Guyon and Huillery, 2016; Salikutluk, 2016; Hanson, 1994; Rudolphi, 2014; Heath and Brinbaum, 2007) and based on two independent and nationally representative samples, I find that children of foreign-born parents tend to have higher aspirations and expectations than their native-majority peers. Conditional on a set of background factors, individual academic performance and academic potential, they are on average 25–30 ppt more likely to have university aspirations and express university expectations than their peers. One interpretation of these findings is that children of immigrants value higher education more than their native-majority counterparts: Many seem to be well-aware of the importance of education for moving up the social ladder.

Part of the differential could also be explained by measurement error in the explanatory variable parental education proxied by occupational status. Immigrants are more likely to be overeducated (Joona et al., 2014) and the variable used in this study is likely not fully capturing the relative social class of children with immigrant parents.

A handful of recent studies have further investigated this issue (e.g. Ichou (2014) and Engzell (2016)) by testing whether a better measure would be to use the social class in the country of origin as some immigrant groups are positively selected on both observables (e.g. educational attainment) and unobservables (e.g. “motivation” and “drive”).[38]

[38] See the discussion in, for example, Ichou (2014) and Engzell (2016).

Thus, an explanation behind the relatively high aspirations and expectations of immigrant students could be that they aspire to or expect to attain the social status of their parents in the country of origin. Another potential mechanism behind the immigrant-non-immigrant disparities in aspirations, expectations and educational choice could be a strategy to avoid discrimination: immigrant students may aim higher because they want to reduce the risk of discrimination in low-skill occupations (Rudolphi, 2014).[39]

Overall, I do not find any evidence of a significant immigrant-native aspirations-expectations gap; immigrant children's aspirations and expectations are not less aligned than those of their native-majority peers. This result suggest that immigrant-native disparities in school outcomes are not driven by an aspirations-expectations gap.

In contrast to the findings of Rudolphi (2014) and Salikutluk (2016), I find that both immigrant and native-majority girls are significantly more likely to express a gap in grade 8 than are native-majority boys. The results also display a significant gender differential in the outcome variable lost talent, a category defined as students scoring higher than the mean or median of the sample on the cognitive ability test and who are reporting an aspirations-expectations gap. I find that native-majority girls are significantly more likely to be labeled as lost talent.

The gender composition of an individual's closest friends also seems to matter. Having only female friends is negatively related to showing signs of academic potential and expressing an aspiration-expectations gap. In line with Hanson (1994), I find that the educational aspirations (or educational values) of friends constitute an important predictor of lost talent.[40] Clearly, the result from the lost talent analysis hinges on the definition of lost talent which concerns two main factors: (i) the

[39]See Carlsson and Rooth (2007) on ethnic labor market discrimination by occupation.

[40]The definition of the lost talent is somewhat different in Hanson (1994) as compared to this study which limits the comparability between the two studies. The reference category in Hanson (1994) consists of students who both aspire to and expect to attain a college degree. Moreover, the study of Hanson (1994) is based on a sample of American high school seniors.

relevance of the threshold, and (ii) whether the variable cognitive test scores constitutes an appropriate indicator of school talent and academic potential.

Based on these findings, an important avenue for future research is the role of teachers' and parents' aspirations and expectations for student outcomes, such as, for instance, the decision to drop out. Among those who decide to drop out, the lion's share are children of immigrant background. Another important policy question is whether aspirations and expectations are set efficiently. For example, Guyon and Huillery (2016) find evidence of significant biases in aspirations among low-SES students who tend to have lower aspirations and are more likely to have fatalistic views. Two categories of students are therefore of particular interest from a policy perspective: low aspiring but high-achieving low SES-students and high-aspiring but low-achieving low SES-students.

As of today, causal studies of the role of individual aspirations for school outcomes are scarce, yet the field is growing (Goux et al., 2014; Avvisati et al., 2014; Carlana et al., 2015).[41] The existing evidence suggests that teachers' and parents' aspirations play an important role in the formation of individual aspirations and in educational choice. It is argued that setting realistic aspirations can have significant effects on individual life outcomes and that interventions aimed at low-performing but high aspiring or high-performing but low-aspiring students could be relatively inexpensive as compared to reduced classroom size, for instance.

An important question is: Who should be targeted? I find that parents' aspirations play an important role in children's educational plans. Mismatched parental expectations, i.e. having a parent who is expressing an aspirations-expectations gap, is both a statistically and economically significant predictor of the individual aspirations-expectations gap. However, a widely recognized issue with targeting parents is selection, i.e. those who need the educational program the most are more likely to opt out (see, for example, Goux et al. (2014)) and as an additional

[41] See a detailed review of the literature in Fryer Jr (2016).

point longterm interventions are expensive and cost-efficiency could, in some regards, be questionable.

One way of empirically testing the importance of the gap in aspirations and expectations is to track those identified as “lost talent” as they move through the educational system. Are they more likely to drop out after comprehensive school? What is their highest level of attained education as adults? Such an approach is possible by matching the data used in this study with comprehensive administrative data on students' educational outcomes.

A potential issue with using survey data is individual non-response. Those who took part in the survey are perhaps more likely to have high educational aspirations and value education higher than the absentees. It is not unlikely that the respondents are positively selected on these characteristics. If immigrant students with low aspirations are more likely to shirk, the estimates of the immigrant-non-immigrant gap will be exaggerated.

To sum up, dropouts and students with incomplete grades constitute a highly ranked issue on the political agenda. Understanding the mechanisms underlying the decision to drop out is essential for effective policy formation. Children's aspirations and expectations are not formed in a vacuum and the roles of teachers' and parents' aspirations for students' outcomes are two important avenues for future research.

A Model specification

A.1 Robustness checks

In this section, I check if the results are robust to changing model specifications. My preferred model is the OLS fixed-effects model. As a robustness test I also estimate an OLS random-effects model. The random or fixed intercepts handle the clustered nature of my data. I perform a Hausman test to see whether the fixed and random-effects are significantly different. The test result shows that I can reject the null, i.e. a fixed-effects model is more suitable for the data.

The fixed-effects model is preferable to the random-effects model since the purpose of this paper is to account for differences in aspirations, expectations and the aspirations-expectations gap, and not to estimate variance components. A fixed-effects estimation allows me to disentangle the influence of classroom-specific factors from the influence of individual factors and reduces the omitted variable bias. Put differently, the fixed-effects model takes account of the correlation among individuals who belong to the same cluster, in this case the classroom.

As the results may be sensitive to the functional form of the model I present the results from separate logit and probit regressions. The latent response model corresponding to equation (1) is:

$$y_i^* = \alpha + \beta_1 immstat_i + \beta_2 age_i + \beta_3 female_i + \beta_4 immstat_i \times female_i$$
$$+ \sum_{j=1}^{2} \beta_{5j} educ_{ji} + \sum_{j=1}^{3} \beta_{6j} selfass_{ji} + \sum_{j=1}^{3} \beta_{7j} famtype_{ji} + \beta_7 hhsize_i + \epsilon_i,$$

where we only observe $y_i = I(y_i^* > 0)$ for the latent variable y_i^*. Moreover, I estimate the corresponding unconditional and conditional logit and probit models. Since odds ratios are not comparable across nested models, I present the result in the form of average marginal effects whenever possible. Table A1 shows the results from logistic regressions on the LNU data.[42] In contrast to the marginal effects at means where

[42] See Mood (2010) for a discussion on comparing odds ratios across nested models.

all covariates are set to their average value, the average marginal effects uses all the data. For binary variables, the coefficient indicates that the predicted probabilities change as the variable goes from 0 to 1. With regard to continuous variables, the average marginal effect measures the instantaneous rate of change. The average marginal effect of a continuous variable such as age indicates by how many units (ppt) the probability of having aspirations for a university education changes if the explanatory variable changes by one year. Average marginal effects are less useful when models include interaction terms and in those cases I instead use odds ratios. Table A2 shows the results from probit regressions without fixed-effects using the LNU data.

Due to the incidental parameters problem of binary choice models, unconditional logit and probit may be erroneous. Estimating these models with classroom dummies may produce inconsistent estimates (of both the fixed-effects estimate and the other coefficients). The conditional fixed-effect logit model deals with this problem; however, the classroom-effect is not estimated in the fixed-effect logit (xtlogit command in Stata). The functional form of the logit allows for elimination of the classroom-specific term in the conditional fixed-effects logit case but there is the problem of interpreting the effects: marginal effects cannot be estimated unless one assumes that the constants are 0.

Another alternative to the unconditional logit and probit models is to use the probit model with random-effects where marginal effects can be estimated at constants equaling null. However, this model does not allow for a correlation between the classroom-specific effect and any of the explanatory variables. As such, it does not handle the endogeneity issue. Table A3 shows the odds ratios from random-effects probit regressions. Tables A4, A5 and A6 show the results from random-effects logistic regressions of aspirations, expectations and the gap. There is no command in Stata for conditional fixed-effects probit estimation. Tables A7, A8 and A9 show the results from fixed-effects logistic regressions.

Tables A10, A11 and A12 present the results from multilevel logit regressions. It is not possible to calculate average marginal effects using the Stata command melogit due to the mixed design of the model with both random (individual effects) and fixed effects (explanatory variables). However, predicted probabilities can be calculated separately using marginsplots for specific categories of the independent variables and then analyzed using odds ratios. The results in this section are presented both as log odds and odds ratios for ease of interpretation. Overall, the results from the different specifications display a similar picture and are largely confirmatory.

Table A1: Odds ratios and average marginal effects from logistic regressions of aspirations, expectations and the gap by region of origin, LNU

	Educational aspirations		Educational expectations		Aspirations-expectations gap	
	Model 1		Model 2		Model 3	
	OR	AME	OR	AME	OR	AME
Foreign-born parents	4.361***	0.173***	3.821***	0.152***	3.009*	0.0252
	(1.754)	(0.040)	(1.553)	(0.038)	(1.803)	(0.021)
Age (demeaned)	0.962	-0.00650	0.922	-0.0128	0.952	-0.00125
	(0.054)	(0.009)	(0.054)	(0.009)	(0.149)	(0.004)
Female	3.192***	0.184***	3.459***	0.188***	0.458	-0.0266**
	(0.706)	(0.033)	(0.798)	(0.032)	(0.256)	(0.013)
Foreign-born parents × Female	0.515		0.561		0.238	
	(0.282)		(0.339)		(0.295)	
Parents' highest educ=University	2.736***	0.176***	3.075***	0.188***	0.922	-0.00210
	(0.576)	(0.037)	(0.643)	(0.036)	(0.462)	(0.013)
Self-assessment						
Best in class	7.147***	0.218***	6.910***	0.200***	0.277	-0.0197
	(5.231)	(0.045)	(5.112)	(0.042)	(0.381)	(0.013)
Among the best	5.565***	0.254***	4.155***	0.204***	0.792	-0.00580
	(2.621)	(0.057)	(1.928)	(0.058)	(0.810)	(0.025)
Better than the majority	6.707***	0.255***	5.365***	0.217***	0.279	-0.0232
	(3.276)	(0.048)	(2.563)	(0.047)	(0.370)	(0.018)
About as good as most people	2.787**	0.155**	2.258*	0.120**	0.867	-0.00364
	(1.286)	(0.061)	(0.991)	(0.059)	(0.919)	(0.027)
Reconstituted family	1.183	0.0274	1.081	0.0122	2.187	0.0255
	(0.330)	(0.045)	(0.304)	(0.043)	(1.249)	(0.023)
Single parent family	0.910	-0.0159	0.948	-0.00842	0.417	-0.0169
	(0.274)	(0.051)	(0.291)	(0.049)	(0.391)	(0.014)
Household members	1.067	0.0107	1.027	0.00416	0.716	-0.00854
	(0.104)	(0.016)	(0.100)	(0.015)	(0.170)	(0.006)
Constant	0.141***		0.224**		0.189	
	(0.086)		(0.134)		(0.311)	
Observations	867	867	865	865	865	865
McFadden's Adj. R-squared	0.142	0.142	0.145	0.145	0.072	0.072
Log-likelihood	-479215.112	-479215.112	-457514.704	-457514.704	-108793.156	-108793.156

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Logistic regressions with robust standard errors clustered at the family level. In model 1, the dependent variable is a dummy defined as having aspirations for a university degree (having responded "Yes, absolutely" or "Yes, probably" to the question "Would you like to continue to go to school after the upper secondary level, that is, attend a university or university college?". The dependent variable in model 2 is a dummy defined as having expectations for a university degree (having responded "Yes, absolutely" or "Yes, probably" to the question "Do you think you will actually continue to go to school after the upper secondary level, that is, attend a university or university college?"). In model 3, the dependent variable is a dummy for the aspirations-expectations gap which is defined as having aspirations for a university degree but not expecting to get one (having responded "Yes, absolutely" or "Yes, probably" to the aspirations question and "No, probably not" or "No, absolutely not" to the expectations question. The reference category consists of children with at least one native-born parent.

Table A2: Odds ratios and average marginal effects from probit regressions of aspirations, expectations and the gap by region of origin, LNU

	Educational aspirations		Educational expectations		Aspirations-expectations gap	
	Model 1		Model 2		Model 3	
	OR	AME	OR	AME	OR	AME
Foreign-born parents	2.315***	0.168***	2.121***	0.148***	1.753**	0.0287
	(0.494)	(0.039)	(0.461)	(0.036)	(0.470)	(0.020)
Age (demeaned)	0.977	-0.00657	0.951	-0.0136	0.978	-0.00130
	(0.031)	(0.009)	(0.031)	(0.009)	(0.061)	(0.004)
Female	2.009***	0.186***	2.084***	0.191***	0.699	-0.0283**
	(0.260)	(0.033)	(0.275)	(0.032)	(0.160)	(0.012)
Foreign-born parents × Female	0.658		0.711		0.520	
	(0.190)		(0.225)		(0.241)	
Parents' highest educ=University	1.800***	0.174***	1.923***	0.187***	0.978	-0.00130
	(0.219)	(0.037)	(0.232)	(0.036)	(0.200)	(0.012)
Self-assessment						
Best in class	3.367***	0.229***	3.174***	0.208***	0.542	-0.0213*
	(1.405)	(0.042)	(1.325)	(0.041)	(0.312)	(0.012)
Among the best	2.884***	0.265***	2.345***	0.210***	0.902	-0.00582
	(0.804)	(0.057)	(0.658)	(0.060)	(0.405)	(0.025)
Better than the majority	3.170***	0.264***	2.695***	0.222***	0.570	-0.0238
	(0.908)	(0.048)	(0.768)	(0.049)	(0.307)	(0.017)
About as good as most people	1.877**	0.161***	1.620*	0.122**	0.988	-0.000693
	(0.512)	(0.061)	(0.433)	(0.062)	(0.449)	(0.026)
Reconstituted family	1.108	0.0286	1.054	0.0141	1.450	0.0268
	(0.180)	(0.044)	(0.171)	(0.043)	(0.348)	(0.021)
Single parent family	0.940	-0.0176	0.975	-0.00676	0.704	-0.0162
	(0.165)	(0.051)	(0.173)	(0.048)	(0.255)	(0.014)
Household members	1.043	0.0119	1.021	0.00568	0.856	-0.00899
	(0.057)	(0.016)	(0.056)	(0.015)	(0.082)	(0.006)
Constant	0.304***		0.407**		0.338	
	(0.108)		(0.145)		(0.232)	
Observations	867	867	865	865	865	865
McFadden's Adj. R-squared	0.143	0.143	0.146	0.146	0.077	0.077
Log-likelihood	-478698.130	-478698.130	-457103.955	-457103.955	-108173.173	-108173.173

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Probit regressions with robust standard errors clustered at the family level. In model 1, the dependent variable is a dummy defined as having aspirations for a university degree (having responded "Yes, absolutely" or "Yes, probably" to the question "Would you like to continue to go to school after the upper secondary level, that is, attend a university or university college?". The dependent variable in model 2 is a dummy defined as having expectations for a university degree (having responded "Yes, absolutely" or "Yes, probably" to the question "Do you think you will actually continue to go to school after the upper secondary level, that is, attend a university or university college?"). In model 3, the dependent variable is a dummy for the aspirations-expectations gap which is defined as having aspirations for a university degree but not expecting to get one (having responded "Yes, absolutely" or "Yes, probably" to the aspirations question and "No, probably not" or "No, absolutely not" to the expectations question. The reference category consists is children with at least one native-born parent.

Table A3: Odds ratios from random-effects probit models of aspirations, expectations and the gap in grade 8 and 9, respectively, CILS4EU

	Aspirations		Expectations		Aspirations-expectations gap	
	Grade 8	Grade 9	Grade 8	Grade 9	Grade 8	Grade 9
Foreign-born parents	2.221***	2.283***	1.956***	2.213***	1.080	0.961
	(0.173)	(0.214)	(0.145)	(0.199)	(0.087)	(0.097)
Female	1.348***	1.553***	1.206***	1.519***	1.116*	1.037
	(0.072)	(0.100)	(0.063)	(0.095)	(0.065)	(0.075)
Foreign-born parents × Female	0.883	0.892	0.857*	0.843	0.951	0.875
	(0.088)	(0.113)	(0.079)	(0.098)	(0.097)	(0.115)
Higher educated parents	1.433***	1.347***	1.391***	1.515***	0.939	0.790***
	(0.066)	(0.076)	(0.061)	(0.082)	(0.046)	(0.050)
Language test score (std)	1.415***	1.144***	1.397***	1.127***	0.974	0.992
	(0.042)	(0.043)	(0.040)	(0.041)	(0.030)	(0.041)
Cognitive test score (std)	1.126***	1.052	1.193***	1.041	0.931**	0.996
	(0.030)	(0.035)	(0.031)	(0.034)	(0.026)	(0.037)
All friends: female	0.920	1.036	1.046	1.032	0.866**	0.997
	(0.056)	(0.079)	(0.062)	(0.075)	(0.057)	(0.080)
All friends: foreign-born parents	1.225***	1.046	1.148*	0.984	1.033	1.075
	(0.096)	(0.099)	(0.084)	(0.089)	(0.079)	(0.103)
All friends: higher educ parents	1.012	1.018	0.996	0.884	0.938	1.155
	(0.072)	(0.089)	(0.068)	(0.074)	(0.071)	(0.104)
All friends: university aspirations	1.254***	1.132*	1.196***	1.148**	1.013	0.931
	(0.072)	(0.074)	(0.063)	(0.072)	(0.055)	(0.064)
Grade sum		1.332***		1.379***		0.892***
		(0.024)		(0.024)		(0.017)
Observations	4075	3381	4075	3377	4075	3377
Log-likelihood	−2285.864	−1473.354	−2539.672	−1637.783	−1888.582	−1096.194

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Random-effects probit regressions estimated using the xtprobit command in Stata.

Table A4: Odds ratios from random-effects logistic models of aspirations in grade 8 and 9, respectively, CILS4EU

	Aspirations grade 8			Aspirations grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	1.907***	2.001***	3.858***	1.449***	2.178***	4.428***	4.188***
	(0.160)	(0.177)	(0.514)	(0.114)	(0.239)	(0.707)	(0.694)
Female			1.638***			2.203***	2.124***
			(0.145)			(0.238)	(0.237)
Foreign-born parents × Female			0.820			0.833	0.841
			(0.141)			(0.190)	(0.192)
Higher educated parents			1.837***			1.674***	1.663***
			(0.143)			(0.167)	(0.166)
Language test score (std)			1.785***			1.222***	1.228***
			(0.090)			(0.080)	(0.080)
Cognitive test score (std)			1.218***			1.075	1.079
			(0.054)			(0.062)	(0.062)
All friends: female			0.875				1.094
			(0.091)				(0.148)
All friends: foreign-born parents			1.393**				1.095
			(0.187)				(0.186)
All friends: higher educ parents			1.024				1.056
			(0.123)				(0.164)
All friends: university aspirations			1.469***				1.258**
			(0.143)				(0.145)
Grade sum						1.707***	1.698***
						(0.057)	(0.057)
Observations	4364	4075	4075	4354	3381	3381	3381
Log-likelihood	−2704.027	−2500.710	−2285.852	−2833.177	−1816.393	−1470.843	−1467.634

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Random-effects logit regressions estimated using the xtlogit command in Stata.

Table A5: Odds ratios from random-effects logistic models of expectations in grade 8 and 9, respectively, CILS4EU

	Expectations grade 8			Expectations grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	1.451***	1.489***	3.039***	1.414***	1.839***	4.030***	3.933***
	(0.111)	(0.118)	(0.375)	(0.108)	(0.180)	(0.609)	(0.614)
Female			1.363***			2.088***	2.040***
			(0.116)			(0.217)	(0.220)
Foreign-born parents × Female			0.778			0.776	0.778
			(0.119)			(0.158)	(0.159)
Higher educated parents			1.715***			2.042***	2.046***
			(0.123)			(0.191)	(0.192)
Language test score (std)			1.738***			1.203***	1.205***
			(0.084)			(0.075)	(0.076)
Cognitive test score (std)			1.340***			1.062	1.068
			(0.057)			(0.059)	(0.059)
All friends: female			1.078				1.063
			(0.105)				(0.135)
All friends: foreign-born parents			1.250*				0.990
			(0.151)				(0.156)
All friends: higher educ parents			0.994				0.832
			(0.112)				(0.122)
All friends: university aspirations			1.347***				1.301**
			(0.116)				(0.142)
Grade sum						1.781***	1.777***
						(0.057)	(0.057)
Observations	4364	4075	4075	4353	3377	3377	3377
Log-likelihood	−2962.101	−2764.690	−2539.116	−2945.748	−2068.819	−1633.198	−1629.471

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Random-effects logit regressions estimated using the xtlogit command in Stata.

Table A6: Odds ratios from random-effects logistic models of the aspirations-expectations gap in grade 8 and 9, respectively, CILS4EU

	Aspirations-expectations gap grade 8			Aspirations-expectations gap grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	1.246**	1.238*	1.149	0.970	0.998	0.966	0.941
	(0.109)	(0.141)	(0.164)	(0.114)	(0.124)	(0.176)	(0.181)
Female			1.215*			1.082	1.077
			(0.127)			(0.146)	(0.150)
Foreign-born parents × Female			0.918			0.761	0.762
			(0.164)			(0.191)	(0.192)
Higher educated parents			0.898			0.637***	0.628***
			(0.078)			(0.079)	(0.078)
Language test score (std)			0.954			0.985	0.990
			(0.052)			(0.078)	(0.078)
Cognitive test score (std)			0.883**			0.987	0.983
			(0.044)			(0.069)	(0.069)
All friends: female			0.776**				1.003
			(0.091)				(0.154)
All friends: foreign-born parents			1.056				1.153
			(0.143)				(0.211)
All friends: higher educ parents			0.894				1.305
			(0.123)				(0.224)
All friends: university aspirations			1.024				0.868
			(0.100)				(0.116)
Grade sum						0.807***	0.808***
						(0.030)	(0.030)
Observations	4364	3796	4075	4349	3377	3377	3377
Log-likelihood	−2033.951	−1422.293	−1888.730	−1316.800	−1139.609	−1098.698	−1097.010

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Random-effects logit regressions estimated using the xtlogit command in Stata.

Table A7: Odds ratios from fixed-effects logistic models of aspirations in grade 8 and 9, respectively, CILS4EU

	Aspirations grade 8			Aspirations grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	1.695***	1.804***	3.755***	1.551***	2.348***	4.476***	4.459***
	(0.162)	(0.182)	(0.533)	(0.143)	(0.308)	(0.816)	(0.815)
Female			1.716***			2.103***	2.049***
			(0.157)			(0.241)	(0.243)
Foreign-born parents × Female			0.746*			0.774	0.753
			(0.133)			(0.185)	(0.180)
Higher educated parents			1.739***			1.537***	1.531***
			(0.140)			(0.161)	(0.161)
Language test score (std)			1.838***			1.252***	1.258***
			(0.096)			(0.088)	(0.088)
Cognitive test score (std)			1.211***			1.061	1.062
			(0.056)			(0.067)	(0.067)
All friends: female			0.940				1.178
			(0.112)				(0.191)
All friends: foreign-born parents			1.307				1.511
			(0.248)				(0.398)
All friends: higher educ parents			1.092				0.959
			(0.155)				(0.186)
All friends: university aspirations			0.814*				0.870
			(0.089)				(0.129)
Grade sum						1.683***	1.686***
						(0.060)	(0.060)
Observations	4308	4003	4003	4312	3177	3177	3177
Log-likelihood	−2121.483	−1932.434	−1746.496	−2241.338	−1324.658	−1035.668	−1033.601

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Fixed-effects logistic regressions estimated using xtlogit in Stata.

Table A8: Odds ratios from fixed-effects logistic models of expectations in grade 8 and 9, respectively, CILS4EU

	Expectations grade 8			Expectations grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	1.354***	1.405***	2.881***	1.528***	1.998***	4.266***	4.253***
	(0.118)	(0.128)	(0.375)	(0.136)	(0.230)	(0.726)	(0.725)
Female			1.407***			1.993***	1.947***
			(0.124)			(0.218)	(0.220)
Foreign-born parents × Female			0.736*			0.710	0.703*
			(0.116)			(0.151)	(0.150)
Higher educated parents			1.599***			1.862***	1.852***
			(0.118)			(0.181)	(0.180)
Language test score (std)			1.784***			1.222***	1.224***
			(0.089)			(0.082)	(0.082)
Cognitive test score (std)			1.316***			1.051	1.053
			(0.059)			(0.063)	(0.063)
All friends: female			1.135				1.121
			(0.126)				(0.166)
All friends: foreign-born parents			1.196				1.226
			(0.201)				(0.283)
All friends: higher educ parents			0.893				0.689**
			(0.117)				(0.124)
All friends: university aspirations			0.959				1.170
			(0.097)				(0.162)
Grade sum						1.769***	1.776***
						(0.060)	(0.060)
Observations	4344	4055	4055	4311	3298	3298	3298
Log-likelihood	−2349.495	−2168.771	−1975.535	−2342.992	−1536.249	−1164.510	−1161.053

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Fixed-effects logistic regressions estimated using xtlogit in Stata.

Table A9: Odds ratios from fixed-effects logistic models of the aspirations-expectations gap in grade 8 and 9, respectively, CILS4EU

	Aspirations-expectations gap grade 8			Aspirations-expectations gap grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign-born parents	1.235*	1.238*	1.193	0.940	0.936	0.901	0.896
	(0.135)	(0.141)	(0.184)	(0.140)	(0.150)	(0.190)	(0.189)
Female			1.218*			1.103	1.100
			(0.132)			(0.157)	(0.160)
Foreign-born parents × Female			0.918			0.785	0.778
			(0.172)			(0.209)	(0.207)
Higher educated parents			0.945			0.640***	0.643***
			(0.085)			(0.084)	(0.085)
Language test score (std)			0.939			0.984	0.988
			(0.053)			(0.082)	(0.082)
Cognitive test score (std)			0.906*			1.012	1.012
			(0.047)			(0.076)	(0.076)
All friends: female			0.800				1.044
			(0.110)				(0.195)
All friends: foreign-born parents			1.113				1.188
			(0.228)				(0.328)
All friends: higher educ parents			1.105				1.448*
			(0.179)				(0.317)
All friends: university aspirations			0.869				0.743*
			(0.106)				(0.132)
Grade sum						0.802***	0.801***
						(0.033)	(0.033)
Observations	4106	3796	3796	3373	2630	2630	2630
Log-likelihood	−1551.434	−1422.293	−1414.652	−930.517	−783.482	−750.332	−747.804

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Fixed-effects logistic regressions estimated using xtlogit in Stata.

Table A10: Log odds and odds ratios from multileveled random-effects logistic regressions of aspirations in grade 8 and 9, respectively, CILS4EU

	Aspirations grade 8						Aspirations grade 9							
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR
Foreign-born parents	0.645***	1.907***	0.693***	2.001***	1.350***	3.858***	0.371***	1.449***	0.778***	2.178***	1.488***	4.428***	1.432***	4.188***
	(0.090)	(0.171)	(0.099)	(0.198)	(0.143)	(0.553)	(0.078)	(0.113)	(0.111)	(0.243)	(0.172)	(0.761)	(0.173)	(0.727)
Female					0.493***	1.638***					0.790***	2.203***	0.753***	2.124***
					(0.102)	(0.166)					(0.122)	(0.268)	(0.123)	(0.262)
Foreign-born parents × Female					-0.198	0.820					-0.183	0.833	-0.173	0.841
					(0.187)	(0.153)					(0.240)	(0.200)	(0.240)	(0.202)
Higher educated parents					0.608***	1.837***					0.515***	1.674***	0.509***	1.663***
					(0.080)	(0.147)					(0.097)	(0.163)	(0.097)	(0.161)
Language test score (std)					0.580***	1.785***					0.201***	1.222***	0.206***	1.228***
					(0.054)	(0.097)					(0.066)	(0.081)	(0.066)	(0.081)
Cognitive test score (std)					0.197***	1.218***					0.0720	1.075	0.0756	1.079
					(0.048)	(0.059)					(0.060)	(0.065)	(0.060)	(0.065)
All friends: female					-0.133	0.875							0.0896	1.094
					(0.111)	(0.097)							(0.126)	(0.138)
All friends: foreign-born parents					0.332**	1.393**							0.0908	1.095
					(0.147)	(0.204)							(0.179)	(0.196)
All friends: higher educ parents					0.0238	1.024							0.0540	1.056
					(0.121)	(0.124)							(0.152)	(0.161)
All friends: university aspirations					0.385***	1.469***							0.230**	1.258**
					(0.114)	(0.168)							(0.111)	(0.139)
Grade sum											0.534***	1.707***	0.529***	1.698***
											(0.041)	(0.070)	(0.041)	(0.069)
Constant	0.551***	1.735***	0.583***	1.791***	-0.258***	0.773***	0.432***	1.540***	1.016***	2.761***	-2.125***	0.119***	-2.174***	0.114***
	(0.055)	(0.096)	(0.057)	(0.101)	(0.086)	(0.066)	(0.050)	(0.077)	(0.062)	(0.170)	(0.176)	(0.021)	(0.179)	(0.020)
var(_cons[classid])														
Constant	0.239***	1.271***	0.256***	1.292***	0.143***	1.154***	0.204***	1.227***	0.239***	1.270***	0.114*	1.121*	0.0901	1.094
	(0.052)	(0.067)	(0.056)	(0.072)	(0.052)	(0.060)	(0.065)	(0.080)	(0.060)	(0.076)	(0.059)	(0.067)	(0.056)	(0.062)
Observations	4364	4364	4075	4075	4075	4075	4354	4354	3381	3381	3381	3381	3381	3381
Log-likelihood	-2704.027	-2704.027	-2500.710	-2500.710	-2285.852	-2285.852	-2833.177	-2833.177	-1816.393	-1816.393	-1470.843	-1470.843	-1467.634	-1467.634

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Multilevel logistic regressions. Standard errors are clustered at the classroom level. All regressions include a random effect estimate. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having aspirations for a university degree ("What is the highest level of education you wish to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)").

Table A11: Log odds and odds ratios from multileveled random-effects logistic regressions of expectations in grade 8 and 9, respectively, CILS4EU

	Expectations grade 8						Expectations grade 9							
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR
Foreign-born parents	0.372***	1.451***	0.398***	1.489***	1.112***	3.039***	0.347***	1.414***	0.609***	1.839***	1.394***	4.030***	1.369***	3.933***
	(0.075)	(0.108)	(0.081)	(0.121)	(0.130)	(0.394)	(0.077)	(0.109)	(0.100)	(0.183)	(0.159)	(0.639)	(0.159)	(0.625)
Female					0.310***	1.363***					0.736***	2.088***	0.713***	2.040***
					(0.096)	(0.131)					(0.109)	(0.229)	(0.112)	(0.228)
Foreign-born parents × Female					-0.251	0.778					-0.254	0.776	-0.250	0.778
					(0.158)	(0.123)					(0.213)	(0.165)	(0.212)	(0.165)
Higher educated parents					0.539***	1.715***					0.714***	2.042***	0.716***	2.046***
					(0.077)	(0.132)					(0.093)	(0.191)	(0.093)	(0.190)
Language test score (std)					0.553***	1.738***					0.185***	1.203***	0.186***	1.205***
					(0.050)	(0.087)					(0.062)	(0.075)	(0.062)	(0.075)
Cognitive test score (std)					0.292***	1.340***					0.0604	1.062	0.0658	1.068
					(0.043)	(0.058)					(0.052)	(0.055)	(0.052)	(0.056)
All friends: female					0.0750	1.078							0.0607	1.063
					(0.115)	(0.123)							(0.116)	(0.123)
All friends: foreign-born parents					0.223*	1.250*							-0.0104	0.990
					(0.129)	(0.162)							(0.172)	(0.170)
All friends: higher educ parents					-0.00636	0.994							-0.183	0.832
					(0.121)	(0.121)							(0.152)	(0.127)
All friends: university aspirations					0.298***	1.347***							0.263**	1.301**
					(0.098)	(0.132)							(0.109)	(0.141)
Grade sum											0.577***	1.781***	0.575***	1.777***
											(0.039)	(0.070)	(0.039)	(0.070)
Constant	-0.0270	0.973	-0.00201	0.998	-0.791***	0.453***	0.137***	1.147***	0.634***	1.886***	-2.861***	0.0572***	-2.899***	0.0551***
	(0.055)	(0.053)	(0.055)	(0.055)	(0.086)	(0.039)	(0.052)	(0.060)	(0.061)	(0.114)	(0.192)	(0.011)	(0.195)	(0.011)
var(_cons[classid])														
Constant	0.263***	1.301***	0.256***	1.292***	0.173***	1.189***	0.211***	1.236***	0.283***	1.327***	0.179***	1.197***	0.172***	1.187***
	(0.048)	(0.062)	(0.047)	(0.061)	(0.044)	(0.052)	(0.056)	(0.070)	(0.063)	(0.084)	(0.065)	(0.077)	(0.064)	(0.076)
Observations	4364	4364	4075	4075	4075	4075	4353	4353	3377	3377	3377	3377	3377	3377
Log-likelihood	-2962.101	-2962.101	-2764.690	-2764.690	-2539.116	-2539.116	-2945.748	-2945.748	-2068.819	-2068.819	-1633.198	-1633.198	-1629.471	-1629.471

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Multilevel logistic regression. Standard errors are clustered at the classroom level. All regressions include a random effect estimate. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having expectations for a university degree ("What is the highest level of education you think you will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)").

Table A12: Log odds coefficients and odds ratios from regressions predicting the aspirations-expectations gap in grade 8 and 9, respectively, CILS4EU

	Aspirations-expectations gap grade 8						Aspirations-expectations gap grade 9							
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR	logodds	OR
Foreign-born parents	0.220***	1.246***	0.223**	1.250**	0.0940	1.099	-0.0307	0.970	-0.00185	0.998	-0.169	0.845	-0.192	0.825
	(0.084)	(0.105)	(0.091)	(0.114)	(0.104)	(0.114)	(0.116)	(0.112)	(0.124)	(0.124)	(0.136)	(0.115)	(0.151)	(0.124)
Female					0.167*	1.182*					0.000870	1.001	-0.00424	0.996
					(0.092)	(0.108)					(0.114)	(0.114)	(0.119)	(0.119)
Higher educated parents					-0.108	0.897					-0.453***	0.636***	-0.467***	0.627***
					(0.086)	(0.077)					(0.124)	(0.079)	(0.125)	(0.078)
Language test score (std)					-0.0464	0.955					-0.0135	0.987	-0.00897	0.991
					(0.054)	(0.052)					(0.079)	(0.078)	(0.079)	(0.079)
Cognitive test score (std)					-0.125***	0.882***					-0.0116	0.988	-0.0159	0.984
					(0.047)	(0.042)					(0.070)	(0.069)	(0.070)	(0.069)
All friends: female					-0.253*	0.777*							0.00541	1.005
					(0.131)	(0.102)							(0.154)	(0.155)
All friends: foreign-born parents					0.0517	1.053							0.135	1.145
					(0.154)	(0.163)							(0.183)	(0.210)
All friends: higher educ parents					-0.111	0.895							0.271	1.312
					(0.131)	(0.117)							(0.171)	(0.225)
All friends: university aspirations					0.0241	1.024							-0.141	0.869
					(0.099)	(0.101)							(0.133)	(0.116)
Grade sum											-0.214***	0.807***	-0.213***	0.808***
											(0.037)	(0.030)	(0.037)	(0.030)
Constant	-1.630***	0.196***	-1.635***	0.195***	-1.580***	0.206***	-2.322***	0.0981***	-2.135***	0.118***	-0.930***	0.395***	-0.933***	0.393***
	(0.055)	(0.011)	(0.058)	(0.011)	(0.087)	(0.018)	(0.074)	(0.007)	(0.066)	(0.008)	(0.173)	(0.068)	(0.174)	(0.068)
var(_cons[classid])														
Constant	0.0823*	1.086*	0.116**	1.123**	0.0993*	1.104*	0.0478	1.049						
	(0.046)	(0.050)	(0.053)	(0.059)	(0.053)	(0.058)	(0.068)	(0.072)						
Observations	4364	4364	4075	4075	4075	4075	4349	4349	3377	3377	3377	3377	3377	3377
Log-likelihood	-2033.951	-2033.951	-1899.488	-1899.488	-1888.844	-1888.844	-1316.800	-1316.800	-1139.609	-1139.609	-1099.288	-1099.288	-1097.592	-1097.592

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Multilevel logistic regression. Standard errors are clustered at the classroom level for all except models (4)-(6). All except models (4)-(6) include a random effect estimate. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having aspirations for a university degree ("What is the highest level of education you wish to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)") and not expecting to get one ("What is the highest level of education you think you will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)").

B Ordered logit and probit models

As previously mentioned, dichotomizing the dependent variable may lead to a loss of important information from the model. The primary reason for dichotomizing the dependent variables is comparability between the two samples. Moreover, the character of the CILS4EU data makes it less suitable for an ordered model which is why the following sensitivity analysis is based on the LNU data. In order to see whether any interesting information is lost from dichotomizing the dependent variables in the LNU data, I also perform ordered logit and probit regressions. In contrast to OLS which assumes that a movement from 1 to 2 on the aspirations/expectations scale is equivalent to a movement from 3 to 4, the ordered logit and probit models take account of the thresholds of the underlying continuous latent variable.

First, I estimate the two models separately. In the LNU questionnaires, the respondents have been asked if they would like to continue to go to school after the upper secondary level and whether they think they will actually continue to go to school after the upper secondary level with the ordered response options "Yes, absolutely", "Yes, probably", "No, probably not" and "No, absolutely not".[43] The results from ordered logit and probit regressions are presented in table B1. The coefficients of the variable foreign-born parents from the two models are positive and significant (the magnitude of the coefficients cannot be compared since they are on different scales). Having foreign-born parents makes one significantly more likely to belong to the upper categories of the dependent variables aspirations and expectations and, overall, the models display a similar picture.

The bivariate ordered probit model takes into account the multiple ordered response categories (there are 16 mutually exclusive outcomes). The bivariate ordered probit model is an extension of the bivariate probit model. The results are presented in table B2. There are too few obser-

[43] In the CILS4EU questionnaire they have been asked to specify the level of education they think or wish they will get.

vations in the lowest and highest categories to get meaningful results out of an ordered logit or probit model of the aspirations-expectations gap. The bivariate model is the correct specification since the "rho" parameter is statistically significant in the baseline model with an immigrant dummy. This means that the error terms in the two equations are correlated. The signs of the estimated coefficients for the immigrant dummy are positive for both aspirations and expectations indicating that the latent variable y_i^* increases with this regressor. The lower panel of the table shows the estimates of the thresholds.

Tables B3 and B4 show the predicted joint probabilities from bivariate ordered regressions (SUR) of aspirations and expectations for children with native-born parent(s) and children with foreign-born parents (unconditional on background variables). The table cells add up to 100 percent. As suggested by the results from the ordered logit and probit regression results, children with immigrant parents are more likely to belong to the lower-right corner category of the table. An important next step is to investigate whether the results hold for different definitions of immigrant children.

Table B1: Ordered logit and probit regressions, LNU 2010

	Aspirations		Expectations	
	Ordered logit	Ordered probit	Ordered logit	Ordered probit
	(1)	(2)	(3)	(4)
Foreign-born parents	1.127***	0.638***	0.938***	0.546***
	(0.252)	(0.141)	(0.205)	(0.118)
Age (demeaned)	0.026	0.013	0.066	0.027
	(0.044)	(0.025)	(0.044)	(0.025)
Female	0.867***	0.538***	1.046***	0.634***
	(0.160)	(0.093)	(0.164)	(0.094)
Parents' highest educ=University studies	0.854***	0.489***	0.918***	0.515***
	(0.177)	(0.101)	(0.179)	(0.101)
Self-assessment=Best in class	2.995***	1.769***	3.035***	1.819***
	(0.693)	(0.374)	(0.621)	(0.339)
Self-assessment=Among the best	1.929***	1.142***	1.911***	1.151***
	(0.389)	(0.224)	(0.335)	(0.196)
Self-assessment=Better than the majority	1.915***	1.145***	1.819***	1.133***
	(0.399)	(0.231)	(0.328)	(0.194)
Self-assessment=About as good as most people	1.140***	0.683***	1.167***	0.740***
	(0.382)	(0.220)	(0.322)	(0.189)
Reconstituted family	0.093	0.035	0.128	0.072
	(0.217)	(0.126)	(0.217)	(0.126)
Single parent family	-0.071	-0.068	-0.057	-0.028
	(0.252)	(0.151)	(0.275)	(0.157)
Household members	0.008	0.011	-0.050	-0.032
	(0.077)	(0.046)	(0.074)	(0.044)
Observations	867	867	865	865
McFadden's Adj. R-squared	0.0871	0.0881	0.0898	0.0907

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Coeffients from ordered logit and probit regressions. Robust standard errors clustered at the family level.

Table B2: Bivariate ordered probit regression, LNU 2010

	Aspirations
Aspirations	
Foreign-born parents	0.621***
	(5.83)
Expectations	
Foreign-born parents	0.520***
	(5.20)
athrho	
Constant	1.499***
	(17.14)
cut11	
Constant	-1.270***
	(-17.35)
cut12	
Constant	-0.490***
	(-8.68)
cut13	
Constant	0.333***
	(6.11)
cut21	
Constant	-1.390***
	(-17.52)
cut22	
Constant	-0.586***
	(-10.08)
cut23	
Constant	0.423***
	(7.75)
Observations	874

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Predicted joint probabilities from bivariate ordered regressions (SUR) of aspirations and expectations with immigrant dummy, children with native-born parent(s)

	Aspirations			
Expectations	No, absolutely not	No, probably not	Yes, probably	Yes, absolutely
No, absolutely not	0.0626	0.0189	0.0008	0.0000
No, probably not	0.0366	0.1155	0.0433	0.0011
Yes, probably	0.0028	0.0744	0.2258	0.0820
Yes, absolutely	0.0000	0.0012	0.0485	0.2864

Table B4: Predicted joint probabilities from bivariate ordered regressions (SUR) of aspirations and expectations with immigrant dummy, children with foreign-born parents

	Aspirations			
Expectations	No, absolutely not	No, probably not	Yes, probably	Yes, absolutely
No, absolutely not	0.0175	0.0099	0.0007	0.0000
No, probably not	0.0110	0.0580	0.0357	0.0016
Yes, probably	0.0008	0.0356	0.1800	0.1108
Yes, absolutely	0.0000	0.0005	0.0370	0.5009

C Definitions of immigrant children

In this section, I check if the results are robust to changing variable definitions. In tables C1, C2 and C3, I define immigrant children as children who were born abroad. The reference category consists of boys who are native-born and/or have native-born parents. Conditional on individual, family and network characteristics, children born abroad are more likely to have university aspirations than their peers (12.2 ppt for immigrant boys and 13.7 ppt for immigrant girls, column (3)). With regard to expectations, a similar picture emerges from table C2. Furthermore, the immigrant-non-immigrant differentials in aspirations and expectations seem to grow over time. I find no significant differences in the immigrant-native aspirations-expectations gap presented in columns (3) and (7) in table C3, suggesting that children born abroad are not more likely to have expectations falling short of aspirations than their peers.

Table C1: OLS coefficients from regressions of aspirations in grade 8 and 9, respectively, CILS4EU

	Aspirations grade 8			Aspirations grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Born abroad	−0.000829	0.0120	0.122***	−0.00392	0.0736***	0.174***	0.174***
	(0.025)	(0.026)	(0.034)	(0.026)	(0.026)	(0.041)	(0.040)
Female			0.0952***			0.107***	0.101***
			(0.019)			(0.017)	(0.018)
Born abroad × Female			−0.0807*			−0.0963**	−0.0985**
			(0.045)			(0.047)	(0.047)
Higher educated parents			0.0979***			0.0588***	0.0584***
			(0.016)			(0.014)	(0.014)
Language test score (std)			0.0954***			0.0128	0.0140
			(0.010)			(0.010)	(0.010)
Cognitive test score (std)			0.0391***			0.0116	0.0114
			(0.010)			(0.010)	(0.010)
All friends: female			−0.0109				0.0261
			(0.025)				(0.020)
All friends: foreign-born parents			0.0585*				0.0585*
			(0.035)				(0.032)
All friends: higher educ parents			0.00976				−0.0117
			(0.027)				(0.026)
All friends: university aspirations			−0.0368*				−0.0228
			(0.021)				(0.019)
Grade sum						0.0754***	0.0756***
						(0.005)	(0.005)
Constant	0.667***	0.673***	0.564***	0.630***	0.754***	0.293***	0.290***
	(0.003)	(0.003)	(0.014)	(0.003)	(0.002)	(0.025)	(0.025)
Observations	4364	4075	4075	4354	3381	3381	3381
Adjusted R^2	−0.000	−0.000	0.075	−0.000	0.002	0.164	0.164

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regressions. Standard errors are clustered at the classroom level. All regressions include classroom fixed-effects. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having aspirations for a university degree ("What is the highest level of education you wish to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)").

Table C2: OLS coefficients from regressions of expectations in grade 8 and 9, respectively, CILS4EU

	Expectations grade 8			Expectations grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Born abroad	−0.00181	0.00208	0.0975***	−0.00946	0.0477*	0.143***	0.140***
	(0.023)	(0.025)	(0.037)	(0.026)	(0.028)	(0.036)	(0.036)
Female			0.0559***			0.104***	0.0978***
			(0.020)			(0.017)	(0.018)
Born abroad × Female			−0.0369			−0.0673	−0.0679
			(0.050)			(0.049)	(0.049)
Higher educated parents			0.0953***			0.0995***	0.0985***
			(0.017)			(0.015)	(0.015)
Language test score (std)			0.105***			0.00847	0.00846
			(0.009)			(0.011)	(0.011)
Cognitive test score (std)			0.0585***			0.0104	0.0107
			(0.009)			(0.009)	(0.009)
All friends: female			0.0279				0.0242
			(0.028)				(0.021)
All friends: foreign-born parents			0.0497				0.0372
			(0.040)				(0.041)
All friends: higher educ parents			−0.0273				−0.0578**
			(0.030)				(0.029)
All friends: university aspirations			−0.00893				0.0147
			(0.024)				(0.020)
Grade sum						0.0933***	0.0936***
						(0.005)	(0.005)
Constant	0.522***	0.528***	0.427***	0.562***	0.676***	0.110***	0.105***
	(0.002)	(0.003)	(0.014)	(0.003)	(0.003)	(0.026)	(0.027)
Observations	4364	4075	4075	4353	3377	3377	3377
Adjusted R^2	−0.000	−0.000	0.080	−0.000	0.001	0.203	0.203

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regressions. Standard errors are clustered at the classroom level. All regressions include classroom fixed-effects. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having expectations for a university degree ("What is the highest level of education you think you will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)").

Table C3: OLS coefficients from regressions predicting the aspirations-expectations gap in grade 8 and 9, respectively, CILS4EU

	Aspirations-expectations gap grade 8			Aspirations-expectations gap grade 9			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Born abroad	0.0190	0.0256	0.0413	−0.00115	0.0153	0.0269	0.0289
	(0.020)	(0.022)	(0.035)	(0.015)	(0.021)	(0.029)	(0.029)
Female			0.0298**			0.00845	0.00868
			(0.014)			(0.012)	(0.012)
Born abroad × Female			−0.0485			−0.0461	−0.0473
			(0.044)			(0.039)	(0.039)
Higher educated parents			−0.00817			−0.0402***	−0.0397***
			(0.013)			(0.012)	(0.012)
Language test score (std)			−0.0106			0.000640	0.00154
			(0.008)			(0.008)	(0.008)
Cognitive test score (std)			−0.0147**			−0.000246	−0.000589
			(0.007)			(0.007)	(0.007)
All friends: female			−0.0323				0.00281
			(0.021)				(0.017)
All friends: foreign-born parents			0.0193				0.0146
			(0.035)				(0.028)
All friends: higher educ parents			0.0134				0.0349*
			(0.021)				(0.021)
All friends: university aspirations			−0.0204				−0.0272**
			(0.020)				(0.014)
Grade sum						−0.0190***	−0.0190***
						(0.003)	(0.003)
Constant	0.175***	0.175***	0.175***	0.0903***	0.104***	0.213***	0.214***
	(0.002)	(0.002)	(0.011)	(0.002)	(0.002)	(0.017)	(0.018)
Observations	4364	4075	4075	4349	3377	3377	3377
Adjusted R^2	−0.000	0.000	0.003	−0.000	−0.000	0.018	0.018

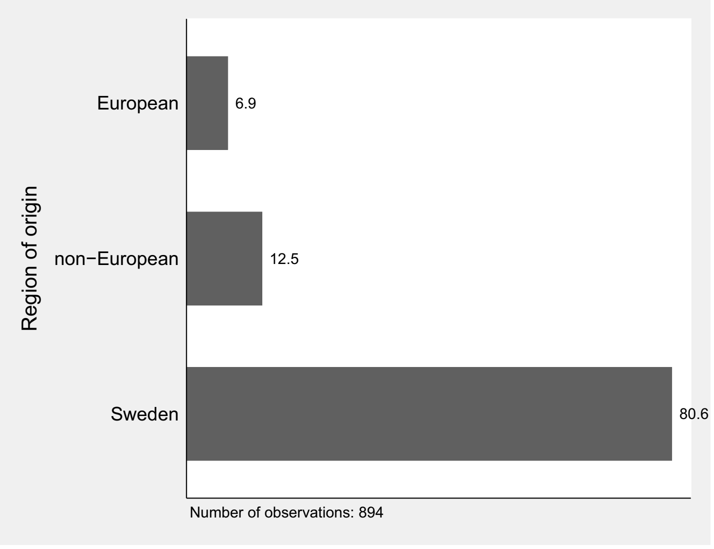
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regressions. Standard errors are clustered at the classroom level. All models include classroom fixed-effects. Variable definitions are found in section 3.7. The dependent variable is a dummy defined as having aspirations for a university degree (having responded "College/university" to the question "What is the highest level of education you wish to get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)" but not expecting to get one (having responded less than "College/university" to the question "What is the highest level of education you think you will actually get? (Don't know, No degree, Compulsory school, Upper secondary school, College/university)" .

D Figures

Figure D.1: Distribution of region of origin, LNU



Chapter 3

The Key Player in Disruptive Behavior: Whom Should We Target to Improve the Classroom Learning Environment?*

1 Introduction

In this paper, I address the question of how disruptive behavior spreads in a classroom. More specifically, I ask: Who is the individual that exerts the greatest negative influence on the classroom learning environment? In a world of competing ends and scarce means, this is a question of potentially great relevance – namely, if aggregate outcomes can be improved by focusing existing resources on a small number of disruptive peers.

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To answer this question, I invoke the key player model from network economics (Calvó-Armengol and Zenou, 2004; Ballester et al., 2006, 2010). Based on a set of behavioral assumptions, this model predicts how much each individual contributes to disruptive behavior in the classroom, not just as a function of their own behavior, but also their location in the network as facilitators or inhibitors of the disruptive behavior of peers. I use the socio-metric information on individuals' localities in the network to investigate the structure of the network and how it affects own disruptive behavior. By combining the key player model with a unique data set on disruptive behavior and student networks among eight graders, I can provide novel evidence on how disruptiveness spreads in the classroom. Moreover, an application of the key player strategy in the school context can yield important insights into how to create effective policy interventions in education, for example how to alter the grouping of students in order to improve the learning environment for everyone.

Although the field of peer effects is well-established within economics, the empirical evidence concerning peer effects in school outcomes is not conclusive, which can, in part, be explained by the econometric problems associated with identifying and estimating causal peer effects (Manski, 1993; Sacerdote, 2011; Angrist, 2014). Previous studies on this topic suffer from a number of inferential obstacles like *selection*, the *reflection problem*, or *common shocks*. In addition, research based on observational data, for example register data on classrooms, often suffers from endogeneity problems. To circumvent these issues, this paper employs a theoretically informed model of peer influence and tests it using the unique classroom network data from Swedish schools. To address the issue of simultaneity, I use two alternative approaches: instrumental variables arising from the network structure and Maximum Likelihood (Drukker, Prucha, and Raciborski, 2013). I overcome the issue of endogenous group formation by using the control function approach where I simultaneously estimate network formation and outcomes (Heckman et al., 2013).

The study draws on recent sociometric data in the longitudinal cohort survey Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU) from more than 100 schools across Sweden (n=4,794 students), collected when participating students were in the eighth grade (aged 14-15). The respondents have been asked to provide the names of their best friends in the classroom. By using network data on students' friendship links and self-reported problem behavior, I am able to identify the most disruptive individual in a peer group (network). I use a composite of different measures for problem behavior indicated by survey self-reports of delinquency (e.g. arguing with teacher(s), getting punished and skipping school).

The empirical analysis encompasses three main steps. First, I estimate the standard model of peer effects, the average peer effect model, using the estimation methods Two-Stage Least Squares (2SLS) and Maximum Likelihood (ML).[1] Borrowing from the literature on identification in social networks (e.g. Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2016)), I use an instrumental variable arising from the network structure to arrive at a causal estimate of peer effects. The idea is to use characteristics of the friends of friends, under the assumption that own friends, but not friends of friends, are actively chosen (Bramoullé et al., 2009). Due to a weak instrument problem, I complement the GS2SLS analysis with ML estimations (Drukker, Prucha, and Raciborski, 2013). This approach deals with the issue of simultaneity by using a specification of the likelihood function that accounts for simultaneity by not allowing the regressors to be correlated with the error terms.

Next, I use the peer effect estimate together with the behavioral model to identify the "key player" in terms of classroom disruptive behavior. I identify the key player in a social network as the individual who once removed generates the largest reduction in aggregate disruptive be-

[1] As a robustness test, I also estimate two alternative models of peer effects: the hybrid and the aggregate model. Results from these estimations are shown in Appendix A.

havior. In the third and final step, I calculate the predicted reduction in aggregate disruptiveness from changing class composition, i.e. when the key player is missing. Following Lindquist and Zenou (2015), I first calculate the change in aggregate disruptiveness by each network. Then, I create dummies for different types of players: the key player, the most active player and a random player. I focus on the individual with the highest self-reported disruptiveness level (most active individual) and the individual who once removed generates the largest reduction in aggregate disruptive behavior (key player). Finally, I regress the change in aggregate disruptiveness on these dummies in each network separately. This procedure allows me to address to what extent the key player strategy outperforms alternative policies such as targeting the most active individual.

The contribution of this paper is threefold, First, I provide a micro-founded behavioral model of the contagion of disruptive behavior in the classroom. Second, I measure the size of network effects in disruptive behavior using field data. Third, I nail down the type of mechanism at work and resort to a key player simulation in order to pick optimal candidates for treatment. To the best of my knowledge, this is the first study that applies the key player strategy to social networks in education.

I find that the key player and the most active individual is the same person in 28 out of 329 networks (approximately 8.5 percent). Interestingly, the typical key player scores well on the language and cognitive tests and is not more likely to be a boy than a girl. I find evidence that removing the key player has a significantly larger effect on aggregate disruptiveness in a network than removing the most disruptive individual, implying that policy aimed at the most noisy individual could be inadequate. Based on these results, I suggest alternative strategies on classroom organization to rectify aggregate disruptive behavior.

The paper unfolds as follows. Previous literature is presented in section 2 followed by a description of the model in section 3. In section 4, I present the data and the definitions. I describe the identification strategy and the identification of structural parameters in section 5. The results from the estimations of the peer effects models and the key player simulation are presented in section 6, followed by a discussion of policy implications in section 7. I conclude the paper in section 8.

2 Related literature

In this section, I give an overview of the related literature and discuss the contribution of this study.

2.1 Peer effects in education

Previous research shows that peers influence adolescent behaviors (see, for example, Sacerdote (2011) for an overview of the literature). According to standard models of peer effects, influence can occur both through the composition of the classroom, e.g. the average level of parental education among peers (the so-called contextual effect), or through a direct interaction with classmates. For example, one student's decision not to disrupt the class can directly influence the behavior of other students in the classroom. In addition, students may respond differently to different categories of peers.

The literature on peer effects in education suggests several plausible models of peer effects: the *bad apple*, *shining star*, *average* and *aggregate model* among others and the behavior mechanisms of these models point to different policy implications. For example, the average model suggests policies that aim at changing the group norm while the bad apple or the shining star models imply individual-based rules targeting students in the extreme parts of the ability distribution. In this paper, I base the analysis on the average model of peer effects. As a robustness test, I compare the average, the aggregate and the hybrid model of peer effects.[2]

[2]In Appendix A, I test the alternative models of disruptive behavior. The results suggest that the average model explains the data best. Liu et al. (2014) also compare the average and the aggregate model but in contrast to this study, they examine the interaction between the variables study effort and sport activity using the National Longitudinal Survey of Adolescent Health (AddHealth) survey. See also Lindquist

This comparison is informative since it tells us whether it is the sum of friends' disruptive behavior or the norm, i.e. the average disruptiveness among friends, that best describes peer effects in disruptive behavior and to what extent policy should be aimed at targeting the most active or the most central individual. Below, I describe the average model in more detail.

According to the average model, or the so-called standard linear-in-means model, the individual outcome may be affected by the mean outcome of the peer group, individual characteristics, the mean characteristics of the peer group and unobservable correlated effects at the group level. Peers can set norms of conduct and exert social pressures for or against misbehavior and this model incorporates a cost for deviating from the social norm; individuals may be penalized if they deviate from the average activity of the reference group (see e.g. Liu et al. (2014) for a discussion on the social conformity effect). If students tend to conform to the social norm, then policy should be aimed at the majority in the classroom to promote desirable behavior.

One of the underlying assumptions of this model is that the peer effect is the same for all members of a given peer group. However, this assumption may be erroneous as the spillover effects may be larger for some categories of students than for others. In addition, the effects of peers may operate non-linearly or through moments other than the mean. A number of papers have recently addressed this issue by trying to estimate different types of heterogeneous peer effect models. Overall, the findings are mixed; while some studies reject the linear-in-means model (see in particular Hoxby and Weingarth (2005)), others provide evidence in favor of the model when compared to individual-based models such as the bad apple or the shining star model (Liu et al., 2014; Tatsi, 2015). Hoxby and Weingarth (2005) find that students seem to benefit from interacting with classmates at the top of the ability distribution while Tatsi (2015) finds support for the linear-in-means model, implying that students tend to conform to the classroom norm.

et al. (2015) for a comparison of alternative models.

2.2 Disruptive classroom behavior

Although prior work on spillovers in eduction is extensive, the literature on student misbehavior and its dynamics remains fairly unexplored. Due to both observed and unobserved heterogeneity across schools and classrooms and the complex nature of social interaction, obtaining credible estimates of peer effects is particularly challenging. The social dynamics of the classroom are complex as defiance of teacher authority can be either overt or covert (McFarland, 2001). Moreover, the rules on classroom interaction vary across schools and classrooms.[3] The same applies to teacher sanctions which may vary in form (formal and informal).

A rather popular method of dealing with the endogeneity issues in studies on peer effects in the school setting is to exploit the year-to-year variation in peer composition in schools in order to identify a causal influence of peers on individual outcome.[4] The recent study of Kristoffersen et al. (2015) makes use of the variation in peer composition in school-cohorts to estimate the influence of peer quality on individual academic achievement. The researchers exploit the entry of disadvantaged children, or so-called "potentially disruptive peers", to identify the peer effect in reading test scores. Three categories of children are of particular interest: children with divorced parents, children with criminal parents and children with a psychiatric diagnosis. They find significant and robust effects on peers' academic achievement in reading when a new potentially disruptive student is enrolled in a school.[5] A related study of Carrell and Hoekstra (2010) investigates the influence of children from troubled families on peers' test scores in maths and reading and in deviant conduct.[6] The authors exploit the variation within families to

[3]Group sizes are also important. See, for example, Lazear (2001), McFarland et al. (2014), Roman (2016) and Frank et al. (2013).

[4]A large strand of the literature (Black et al., 2013; Hoxby, 2000; Gould et al., 2009) uses idiosyncratic variation in peer characteristics across cohorts.

[5]The authors also find heterogeneous effects. The effect seems to be strongest when the new student is a child with a psychiatric diagnosis.

[6]See also Carrell et al. (2016) who show that there are long-run consequences of being exposed to a disruptive peer. The authors apply the same identification strategy as in Carrell and Hoekstra (2010).

arrive at a credible estimate of peers' behavioral externalities. They use children's school records matched with domestic violence cases and find a significant effect of being exposed to a child from a troubled home. The effect is mainly driven by boys and children from low-SES families. According to the authors, the results provide evidence in support of the "bad apple" model of peer effects.

Contrary to prior work based on observational data, I approach the issue of disruptive behavior in the classroom by investigating the architecture of classroom networks. By using a networks approach to this topic, I can identify the transmission channels of teenage group pressure, thus generating new insights into how adolescent behaviors spread in the classroom.

Are boys more susceptible to peer pressure in disruptive behavior than girls? It is possible that teachers reorganize their classrooms in a fashion that disconnects networks of misbehaving students, for example groupings of boys where the peer effect or the group pressure to rebel against the teacher is strong. A long-established strategy is to place boys in the front row or next to girls based on an alternating gender rule. The purpose of a rule as such is to restrain boys from disruptive conduct which suggests that the baseline disruptiveness and/or the peer contagion effect is stronger among boys than girls. Studies like, for example, Hoxby (2000) and Lavy and Schlosser (2007) examine the effect of the gender composition of the classroom on school outcomes. Their findings suggest that both sexes perform better in school in classrooms with a higher proportion of girls.

In this paper, I study the observable characteristics of the key player and examine the notion that boys are more often facilitators of problematic behavior than girls. I assume that the relevant peer group is the direct friendship network: the decision to disrupt depends on the social values of one's friends rather than a random disruptive individual in the classroom.[7]

[7] Presumably, it is not the behavior, in this case the level of disruptiveness *per se*, that influences individual choices but the social values and norms held by one's peers

2.3 The key player

While network measures of centrality have long been used in the sociological literature (see, for example, Wasserman and Faust (1994)), the issue of identifying key players in networks was first introduced by Borgatti (2006, 2003). Previous studies on social networks and behavior have mainly applied the key player strategy to networks of juvenile delinquency (Liu and Lee, 2010) and co-offending networks (Lindquist and Zenou, 2015). In the studies of Ballester et al. (2010) and Ballester and Zenou (2014), the key player is defined as the individual who once removed generates the greatest reduction in aggregate crime.

The idea behind the key player strategy is to aim interventions at key individuals. According to the key player theory, removing the key player can have substantial effects on adolescent behavior because of social multipliers (Zenou, 2016). By lowering the disruptive behavior of central individuals with many social connections, the sum of the disruptiveness among their friends is reduced through both a direct and an indirect effect. The direct effect being the individual's own disruptiveness and the indirect effect being the effect of that individual's behavior on other students in the network (the social multiplier effect).

The literature on social networks in education is relatively scarce (important exceptions include Calvó-Armengol et al. (2009), Bifulco et al. (2011), Patacchini et al. (2017) and Hsieh and Lee (2016)). Apart from the studies of Calvó-Armengol et al. (2009) and Hahn et al. (2015), which investigate the association between an individual's network centrality and her school performance, I am not aware of any other paper that tries to identify the key player in a classroom setting. The scarcity of previous research on social networks in this field is partly due to the lack of detailed network data on schools and classrooms.

This paper picks up where Calvó-Armengol et al. (2009) left off and provides the first illustration of how of the key player strategy could be

(for example unobservable effort). Fruehwirth (2013) and Boucher and Fortin (2016) draw attention to the importance of modeling the proxy and the "true interaction variable" separately.

applied in educational settings.

2.4 Contribution

The first main contribution of this paper is to the literature on peer effects. In contrast to the majority of peer effects studies, which base their empirical analysis on observational data, I use self-reported friendship data in order to solve the methodological problems associated with identifying and estimating peer effects. While it is difficult to construct a research design that convincingly captures the causal effect of peer spillovers, the theoretically informed model of peer influence presented in this paper and the unique network data in CILS4EU enable me to provide credible estimates of peer effects on adolescent misbehavior.

The second contribution is to the literature on social networks in education. To my knowledge, this is the first study that applies the key player strategy to social networks in a school setting. In the spirit of Lindquist and Zenou (2015), I identify the key player in educational networks and discuss optimal targets for treatment.

The third contribution is to the literature on disruptive behavior. It is the first study that explicitly models disruptive behavior in the classroom.

3 Theoretical framework

In this section, I present the theoretical framework of this paper. I describe some network properties and introduce the average model of peer effects. Next, I derive the model equilibrium and thereafter I present the key player strategy.

3.1 Network properties

A friendship network, g, is a set of $N = \{1, ..., n\}$ individuals. $\mathbf{G} = \{g_{ij}\}$ is the associated $n \times n$ adjacency matrix of network g. The relationship between any two actors (i, j) is mapped by their value of $g_{ij} \in \{0, 1\}$

where $g_{ij} = 1$ if i and j are friends and 0 otherwise. I assume that links are reciprocal, i.e. $g_{ij} = g_{ji}$. Furthermore, individuals are not linked to themselves, implying that $g_{ii} = 0$. $\mathbf{G}^* = \{g^*_{ij}\}$ is the row-normalized adjacency matrix of $\mathbf{G}$ where $g^*_{ij} = g_{ij}/g_i$. The denominator, g_i, denotes the total number of friends of individual i, i.e. $g_i = \sum_{j=1}^{n} g_{ij}$. The friends of friends adjacency matrix $\mathbf{G}^2$ is derived by multiplying $\mathbf{G}$ by itself, $\mathbf{G}^3$ is the adjacency matrix cubed and so on. Hence, $\mathbf{G}^k$ holds the number of walks of length k. A *walk* is a sequence of links or edges.

The *degree* of actor i, denoted $\gamma_i(g)$, is defined as the number of friends to whom i is directly linked to, and is equivalent to the number of 1's in row i of g. I define the average degree of a network g as $\gamma(g) = \sum_{i=1}^{n} \gamma_i(g)/n$. Finally, the number of links of an actor is referred to as the *degree centrality.*

3.2 Model

I adopt the network model of peer effects of Calvó-Armengol et al. (2009).[8] The utility function for the average model of disruptiveness is the following:

$$u_i(\mathbf{y}, g) = (a_i + \eta + \epsilon_i)y_i - \frac{1}{2}y_i^2 - \frac{1}{2}\lambda\left(y_i - \sum_{j=1}^{n} g^*_{ij}y_j\right)^2. \quad (1)$$

In the average model, each agent chooses his or her level of disruptiveness, y_i, proxied by problem behavior in order to maximize own utility $u_i(\cdot)$, which is an increasing function of the "gains" of disruptiveness $(a_i + \eta + \epsilon_i)$, the disruptiveness of other students in the network $\mathbf{y} = (y_1, ..., y_n)'$, the social cost or stigma of being punished by the teacher $-\frac{1}{2}y_i^2$, and g which represents the friendship network. The parameter λ captures the strength of social-conformity and $1 > \lambda > 0$. The term ϵ_i represents idiosyncratic shocks and η are network fixed effects which capture the environment at the network level.

[8]In this subsection I closely follow Lindquist and Zenou (2015).

Each individual has his or her own disruptive ability a_i which depends on his or her observable attributes, the average observable characteristics of an individual's friends, and the total number of friends indicated by g_i. Individual disruptive ability is defined as:

$$a_i = \mathbf{x_i}\beta_\mathbf{1} + \frac{1}{g_i}\sum_{j=1}^{n} g_{ij}\mathbf{x_j}'\beta_\mathbf{2}, \tag{2}$$

where $\mathbf{x_i}$ and $\mathbf{x_j}$ are vectors of individual and friend characteristics, respectively. The individual characteristics are captured by β_1 while β_2 represents the contextual effects.

In the average model, individuals are influenced by the social norm. There is a punishment (a cost) for deviating from the social norm which is increasing with the distance from the average activity among one's peers, as indicated by the expression $\left(y_i - \sum_{j=1}^{n} g_{ij}^{*} y_j\right)^2$. The parameter λ, the social conformity coefficient, measures the strength of conformism in a network.

3.3 Model equilibrium

In equilibrium, each agent chooses y_i, her own level of disruptiveness, in order to maximize utility $u_i(\mathbf{y}, g)$. The choices are made simultaneously by all agents. Thus, agent i's best-reply function is:

$$y_i^* = \frac{\lambda \sum_{j=1}^{n} g_{ij}^{*} y_j + a_i + \eta + \epsilon_i}{(1+\lambda)}, \tag{3}$$

where a_i is defined above. Let $\alpha_i = a_i + \eta + \epsilon_i$ for each agent i and α be a vector (non-negative) keeping track of all α_i. Moreover, let $\mu(\mathbf{G}^*)$ be the largest eigenvalue of $\mathbf{G}^*$, the spectral radius. For notational simplicity, let $\phi = \frac{\lambda}{(1+\lambda)}$, the social conformity coefficient in the average network game. Analogously, let $\alpha_i = \frac{a_i+\eta+\epsilon_i}{(1+\lambda)}$ for each agent i and $\boldsymbol{\alpha}$ be a vector (non-negative) keeping track of all α_i.

The key player strategy is generally applied to the aggregate model but the following propositions and definitions apply also to the average network game (by replacing $\mathbf{G}$ with $\mathbf{G}^*$).

Proposition 1 *(Calvó-Armengol et al., 2009; Ballester and Zenou, 2014): Consider a disruptiveness game where the utility function of each agent i is given by* (1) *with $a_i > 0$ for all i defined by* (2). *If $\phi\mu(\mathbf{G}) < 1$, then the game has a unique Nash equilibrium in pure strategies given by:*

$$\mathbf{y}^* = \mathbf{b}_\alpha(g, \phi) = (\mathbf{I} - \phi\mathbf{G})^{-\mathbf{1}}\alpha. \tag{4}$$

In the above equation, $\mathbf{b}_\alpha(g, \phi)$ is a vector whose elements correspond to the Bonacich centralities of all members of the network, $\mathbf{G}$ is the adjacency matrix capturing the friendship network and $\mathbf{I}$ is the identity matrix. Moreover, g, α and ϕ are defined as above. See proof in Calvó-Armengol et al. (2009, p. 1262).

Proposition 1 (Ballester and Zenou, 2014) says that in the Nash equilibrium, each agent's disruptiveness is proportional to her weighted Bonacich centrality. The influence is heterogeneous as a result of the locational differences of individual agents in the network. Both direct and indirect friendship ties matter, but more connected agents are given a larger weight. The Bonacich centrality concept is described further in the following section on the key player strategy.

3.4 The key player strategy

The key player in a social network is defined as the individual who once removed generates the largest reduction in aggregate disruptive behavior. Hence, the planner solves the following problem:

$$\max y^*(g) - y^*(g^{-i})|i = 1, ..., n, \tag{5}$$

where $y^*(g)$ is equal to the aggregate level of disruptiveness in network g and $y^*(g^{-i})$ the aggregate disruptiveness once individual i has been removed. The maximization problem (5), or the so-called key player strategy, involves identifying the individual who contributes most to the aggregate disruptiveness in the network.

The key player strategy is generally applied to the aggregate model. Below, I outline how I define the key player in the average network game. At this point, two assumptions are in order. First, I assume that the adjacency matrix $\mathbf{G}^*$ is fixed. Second, I assume that the individual disruptive ability denoted a_i in (2) is unrelated to $\mathbf{G}^*$.

As a measure of centrality, I use the *Bonacich centrality* (Katz, 1953; Bonacich, 1987). To identify key players in networks, I use the Bonacich centrality measure and a concept called *contextual intercentrality* defined as below.

Definition 1 *(Katz, 1953; Bonacich, 1987): Given a vector* $\mathbf{u} \in \mathbb{R}^n_+$*, and a small enough scalar* $\phi \geq 0$*, the vector of Bonacich centralities of parameter* ϕ *in network* g *is defined as:*

$$\mathbf{b_u}(g, \phi) = (\mathbf{I} - \phi\mathbf{G})^{-1}\mathbf{u} = \sum_{k=0}^{\infty} \phi^{\mathbf{k}}\mathbf{G}^{\mathbf{k}}\mathbf{u}. \tag{6}$$

According to Definition 1 each agent i is given an initial value based on his or her individual location in the network, where more connected agents are assigned higher values. The value is then adjusted by adding the values of agents located k-link away from i (one degree away, then two-degrees away and so on). Each addition is weighed by a factor ϕ^k, which corresponds to the peer effect coefficient. The value is then multiplied by u_i. The elements of the vector $\mathbf{b_u}(g, \phi)$ correspond to the Bonacich centralities of all members of the network.

Definition 2 *For all networks* g *and for all* i*, the contextual intercentrality measure (Ballester and Zenou, 2014) of agent* i *is:*

$$d_i(g, \phi) = B(g, \phi) - B(g^{[-i]}, \phi). \tag{7}$$

Moving on to Definition 2, $B(g, \phi)$ corresponds to the total Bonacich intercentrality in network g while $B(g^{[-i]}, \phi)$ is the total intercentrality once agent i has been removed from the network. An agent i^* is the key player that solves the planner's problem in (5) if and only if i^* is the agent with the highest contextual intercentrality $d_i(g, \phi)$ (see Ballester and Zenou (2014, p. 239)).

If individuals are *ex ante* homogeneous, network location is irrelevant in the average model. Lindquist et al. (2015) provide the first study that includes an application of the key player strategy for the average model.[9] When individuals are identical with respect to their observable characteristics, which individual to target in order to reduce aggregate disruptiveness will not matter unless her locality in the network has the feature of a bridge, i.e. the removal of this agent will give rise to isolated individuals (Liu et al., 2014).

An application of the key player strategy in the average network game is possible in the case outlined in this paper since the friendship networks are incomplete, i.e. individuals are not fully linked to each other. This means that there will be variations in the connectedness and the localities of individual agents as well as individual heterogeneity in disruptiveness which will be captured by the social multiplier. One "calculates" the key player using the estimated parameters in the best reply function and equation (7) (Lindquist et al., 2015).

4 Data and descriptives

In the following section, I describe the data and present some descriptive statistics.

4.1 Sociometric data

The data set I use, Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU, Kalter et al. (2016a)), is a new, longitudinal cohort survey conducted in four countries: England[10], Germany, the Netherlands, and Sweden. The sample is designed to be nationally

[9] Liu et al. (2014) give some examples.
[10] Only England took part in the UK.

representative in each country and was created using a stratified three-stage design, interviewing students in sampled school classes. Schools were stratified according to the proportion of children of migrant background; thus, the sample contains an overweighting of schools with a high number of children with foreign-born parents. Since these schools tend to be located in areas of concentrated economic disadvantage where classroom disruptive behavior is also more widespread, the sample is congenial to my purposes.

CILS4EU data entails several advantages as compared to the data used in previous studies. First, it includes detailed information on the survey participants' friendship links and negative nominations in 249 Swedish classrooms (4,794 students in total). CILS4EU does not only include in-school friendship nominations but also outside-school nominations (not sociometric). Second, the best friend questionnaire included in CILS4EU contains additional information on the characteristics of friends outside of school (see questionnaire items in Appendix D).[11]

The stratified sample allows detailed analyses of the social integration of immigrant children specifically, a group of great interest given the increased importance of immigration in Western countries. Immigrant children and children with an immigrant background lag behind children of native-born in educational performance. Foreign-born students are, for example, less likely to be eligible to attend upper secondary school than their native-born counterparts, but tend to make more ambitious study choices given the attained school grades (see Arai et al. (2000), Jonsson and Rudolphi (2011) and Heath and Brinbaum (2014)).

The first wave was performed in the school year 2010–2011 when participating students were in the eighth grade (ages 14–15). The number of respondents in the main questionnaire in the school year 2010–2011 was 5,025 and the response rate was about 86 percent. I use the Swedish sociometric classroom data (n=4,794) which was collected in the first

[11]To my knowledge, the only comparable data set to CILS4EU in both survey design and size is the AddHealth data set which includes longitudinal sociometric classroom data in the US.

wave of CILS4EU.[12] I define friendship on basis of the question "Who are your best friends in this class?" to which the student could nominate a maximum of five individuals. A link between two students exists if either of them, or both, nominated the other as a "best" friend. Thus, I treat the network as undirected (although an interesting extension in future work may be to allow for directed networks).[13]

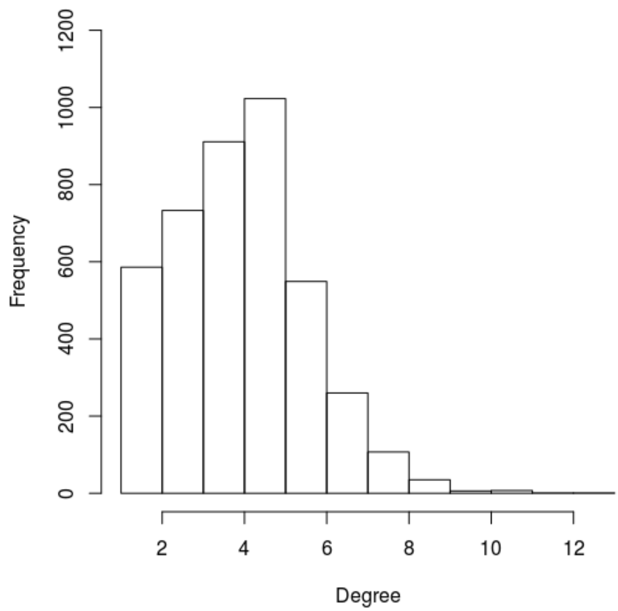
Students who were absent on the day of the network questionnaire or who refused to participate were excluded from the class roster and the set of potential friend nominees. Individuals who did not nominate anyone have been dropped from the friendship network analysis (see Appendix B for more details on data creation procedures). Due to these restrictions, the sample is reduced to 4,219 observations.

Figure 1 plots the distribution of the number of links per individual, the so-called degree centrality. The visible drop at 5 on the x axis is explained by the maximum number of possible nominations; those with a degree greater than 5 have at least one incoming nomination that is not reciprocal.

[12]The advantage of using Swedish data compared to data from the other participating countries in CILS4EU is that there is no formal tracking within the Swedish compulsory school system (grades 1–9). Hence, one would expect there to be less formal sorting of students according to ability than in, for example, Germany with relatively early tracking procedures.

[13]Although it has been argued that a non-response rate of more than about 75 percent could risk the reliability of the nomination measure (see for example Hjalmarsson and Mood (2015) and the references therein), I keep all classrooms in the analysis for efficiency reasons. See Appendix C for robustness checks.

Figure 1: Distribution of degree centrality in the Swedish classroom data, N=4219



4.2 Descriptive statistics

Table 1 shows descriptive statistics for selected variables in the data set. The underlying questionnaire items are described in greater detail in Appendix D. The analysis sample consists of 4,219 individuals and 374 networks. Half of the sample is male and approximately 68 percent have two native-born parents. The sample includes individuals who have nominated others and have themselves been nominated. Students with no friendship links have been dropped.

Table 1: Individual level summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Demographics					
Male	0.486	0.5	0	1	4219
Highest index of occupational status	52.982	20.35	11.74	88.960	4219
Native background	0.677	0.468	0	1	4219
Age	15.029	0.264	13	17	4219
Performance					
Language test scores	18.654	4.949	0	29	4219
Cognitive ability test scores	17.812	4.751	0	27	4219
Delinquent behavior (1=Never, 5=Every day)					
Arguing with teacher	4.435	0.837	1	5	4209
Getting punished	4.666	0.635	1	5	4204
Skipping school	4.637	0.719	1	5	4196
Late to school	3.9	1.037	1	5	4199
Disruptiveness measure	6.362	2.433	4	20	4219

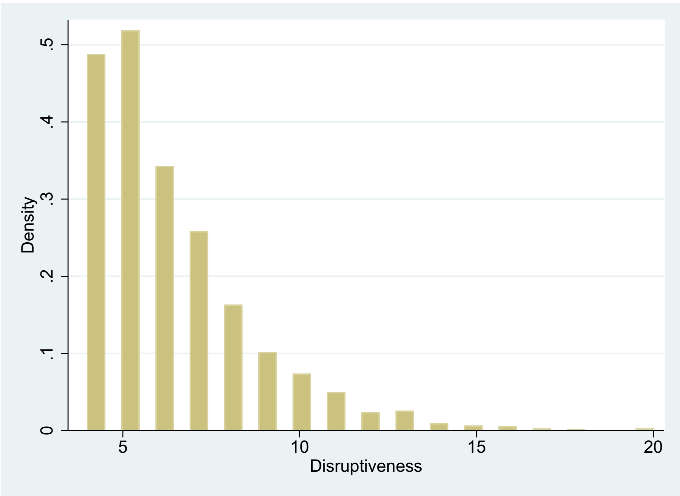
Notes: Summary statistics on demographics and academic outcomes for the analysis sample and delinquent behavior variables for the full sample.

The disruptiveness measure is created using the question: "How often do you... (Every day, Once or several times a week, Once or several times a month, Less often, Never) *(i)* argue with a teacher, *(ii)* get a punishment in school (for example being kept in detention, being sent out of class, writing lines), *(iii)* skip a lesson, and *(iv)* come late to school?". The response options are coded as 1 (Never), 2 (Less often), 3 (Once or several times a month), 4 (Once or several times a week) and

5 (Every day). The imputed disruptiveness measure is thus a summed index of the four delinquency behavior dummies presented in table 1.[14]

The minimum score on the disruptiveness index is 4 and the maximum is 20. Individuals with missing values on all the underlying variables of the imputed disruptiveness measure have been removed (in total 12 students). Figure 2 shows the distribution of disruptiveness. The distribution is skewed to the right and has a mean of 6.4.

Figure 2: Distribution of disruptiveness, N=4219



An important question is what the actual underlying distribution of disruptiveness is as this is going to matter for the treatment. Is a small change in friends' disruptiveness associated with a large or small change in individual disruptiveness? Alternative versions of the disruptiveness measure include the first principal component from a factor analysis and the average of the top four delinquency variables.[15]

Figure 3 depicts the architecture of a classroom network with 27 students. The largest network consists of 28 students and the smallest of 3.[16] The mean network size is roughly 16. The average number of

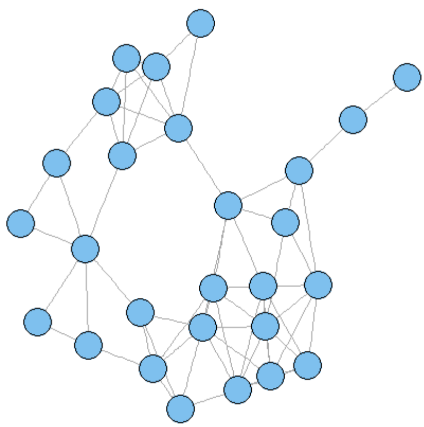
[14]The index is created using the full sample.

[15]I have documented how the effect changes (sign, magnitude and significance) depending on the definition of disruptiveness and the analysis is available upon request.

[16]Networks with less than 3 members have been removed from the key player sim-

links (undirected) is roughly 4. The highest degree is 13 and the lowest is 1. The Bonacich measure ranges from 7.5 to approximately 15.0. The distribution of friendship networks in the sampled classrooms is shown in figure 4.

Figure 3: A classroom network of 27 students (undirected links)



I use a dummy variable to indicate the gender of a student (1=male). The variable HISEI is defined as the highest index of occupational status of parents.[17] Throughout the main analysis of this paper, I define children of immigrants as children with both parents born abroad regardless of own birthplace. The immigrant background variable is based on students' questionnaire answers about their parents' region of birth. The reference category consists of students with at least one native-born par-

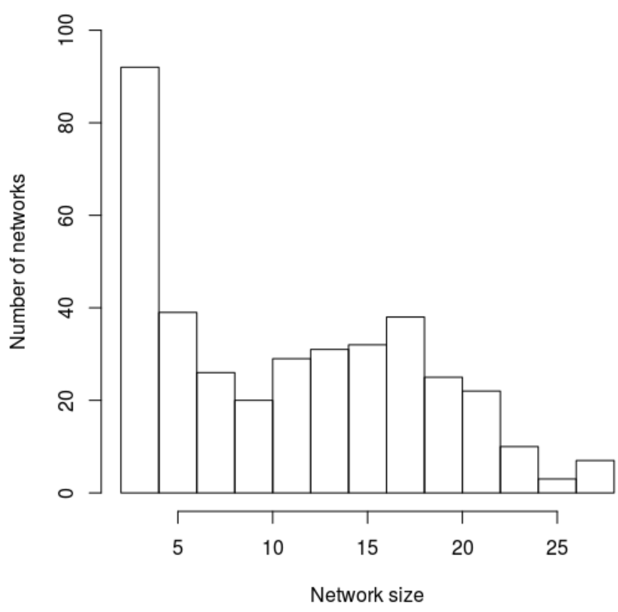
ulation.

[17]ISEI stands for International Socio-Economic Index of Occupational Status. The variable indicates the maximum value of the occupational status of the mother and father. Individuals with missing values on the variable indicating HISEI (272 cases) have been given the sample average. In all estimations in section 6, I include a dummy for missing value on HISEI.

ent.

The CILS4EU data include individual scores on both a cognitive and a language test. The two tests were performed in the first wave of the survey during the school year 2010–2011.[18] The language test is a test of a child's lexicon of Swedish antonyms. The test includes 30 items with 4 alternatives each (for more information, see the technical report by Kruse and Konstanze (2016)). The cognitive test is "language free" and, as such, does not require any particular language skills. It is a 7 minute multiple-choice test of graphical puzzles including 27 items with properties similar to Raven's Progressive Matrices (Raven, 2003). The maximum score on this test is 27 and the minimum is 0.

Figure 4: Distribution of network size, N=374



[18]In the analysis, these variables are treated as exogenous, however, since they are measured at the same time as the outcome variable individual disruptiveness, they could be endogenous. In an ideal setting, these would be constructed with a lag as is common in the network literature.

5 Empirical strategy and identification

In this section, I describe the identification strategy along with the identification of structural parameters.

5.1 Econometric model

The econometric equivalent (written in matrix form) of the best reply function for disruptive behavior in the average model specified in (3) is the following:

$$Y_r = \phi G_r^* Y_r + X_r \beta + G_r^* X_r \gamma + \mu_r + \epsilon_r, \tag{8}$$

where r denotes the network and n_r is the number of observations in each network, Y_r is a $n_r \times 1$ vector of observations of the outcome variable disruptive behavior, X is the $n_r \times k$ matrix of exogenous variables such as age, gender and family characteristics, G^* is the $n_r \times n_r$ row-normalized adjacency matrix that gives the (undirected) connections g_{ij}, $G_r Y_r$ is the $n_r \times 1$ vector of peers' disruptive behavior, μ_r is the network fixed effect, and ϵ_r is the error term. Finally, ϕ, β and γ are the estimated parameters and $\phi = \lambda/(1+\lambda)$.

5.2 Potential threats to identification

Networks are formed endogenously: who our friends are is not at all random but contingent on both our own characteristics and those of our friends. The famous proverbial expression "friends of a feather flock together" describes the tendency of individuals with similar backgrounds and preferences to associate with one another. Moreover, contextual effects, i.e. the mean characteristics of friends (or any reference group), could be correlated with school effects. Thus, in order to identify a credible peer effect, one must first correct for the endogenous sorting of individuals into schools, classrooms and friendship networks. The challenge is to disentangle the effect of the behavior among friends (endogenous effect) from the effect of friends' characteristics (contextual effect) and the influence of the shared environment (correlated effect). Below, I outline how I tackle the potential threats to identification.

The reflection problem, discussed in the seminal paper of Manski (1993), occurs when there is perfect collinearity between the endogenous peer effect and the contextual effect. I avoid the reflection problem since the analysis in this study is based on network data, meaning that the characteristics of direct friends are not the same for all individuals. Thus, given the incomplete structure of the network the contextual effects can be isolated from the peer effect.

The identification of peer effects rests on the assumption that the socio-matrix $\mathbf{G}$ is exogenous (or conditionally exogenous). Peer effect models suffer from two types of biases. For one, there is simultaneity in the outcome variable since individuals choose their disruptiveness level simultaneously; hence, the adjacency matrix $\mathbf{GY}$ has built-in endogeneity.

Second, friendship networks are formed endogenously, i.e. there is an omitted variable bias (cf. Heckman selection bias).[19] The main threat to the identification strategy employed in this paper is potential unobservable heterogeneity at the individual, school or network level. For example, there may exist network-specific factors that are correlated with individual disruptiveness.

I address the issue of simultaneity (Manski, 1993) by using instrumental variables (2SLS/GS2SLS) and Maximum Likelihood (ML) estimation. Different instruments are used in the 2SLS approach in order to take care of potential correlated effects. First, I use characteristics of the friends of friends, under the assumption that own friends, but not friends of friends, are actively chosen (Bramoullé et al., 2009). Peers' characteristics are used as an instrument for average peer outcomes, i.e. the matrix $\mathbf{G^2X}$ is used as an instrument for $\mathbf{Gy}$. Thus, I assume that

[19]The friendship networks could be formed based on, for example, individual disruptiveness. Ideally, one would like to use lagged individual characteristics in peer effect estimations; however, the questions on which the disruptiveness measure is based as well as the cognitive and language ability test scores are only available in the first wave of CILS4EU.

the characteristics of friends of friends do not have a direct influence on individual behavior. The structural parameters in the model can be identified if $\mathbf{I}$, $\mathbf{G}$ and $\mathbf{G^2}$ are linearly independent, i.e. that at least two individuals in the same network have different links, and if the friendship network between individuals is intransitive (everyone is not friends with everyone).

The second instrument (Lee et al., 2010; Liu and Lee, 2010) is defined as the number of friendship ties. Individuals have different numbers of friends and the idea here is that the more friends an individual has, the higher is the aggregate disruptiveness, $\mathbf{JGY}$, in the individual's friendship network. This instrument is only valid in the case of the aggregate model. Following Tatsi (2015), I also use the Best IV as proposed by Lee (2003) and the results are reported in Appendix C. The Best IV performs only marginally better than the "standard" 2SLS.

The ML strategy tackles the problem of simultaneity by modifying the form of the likelihood function in order to control for the autocorrelation between the observations. More specifically, the log Jacobian term in the likelihood function accounts for simultaneity by not allowing the regressors to be correlated with the error terms, thus removing the possible bias in the estimates generated by the simultaneity term (Drukker, Prucha, and Raciborski, 2013). Moreover, the ML approach requires that the errors are distributed normally.

I overcome the issue of endogenous group formation by using the control function approach of Heckman et al. (2013). I estimate a spatial Durbin model (Elhorst, 2010) and a dyadic network formation process (Graham, 2015; Arduini et al., 2015).[20] The root of the omitted variable bias problem is the potential correlation between the errors in the model explaining individual disruptiveness and individual behavior in friendship link formation.[21] The control function approach is described in further detail in section 5.4.

Furthermore, everything that is common at the classroom and net-

[20]See Elhorst (2010) for an overview of different spatial dependence models.

[21]This is discussed in detail in Goldsmith-Pinkham and Imbens (2013).

work level, such as the quality of the teacher, is captured by the network fixed effects (see section 5.3 below). Another potential source of bias is measurement error or incomplete information on friendship links. I use undirected rather than directed links in order to better capture possible pathways of peer influence. In line with Lindquist and Zenou (2015), I perform a number of robustness checks in order to asses the validity of the results (see Appendix C).

5.3 Network fixed effects

In the analyses, I use fixed effects at the network level where the network is defined as subcomponents of the socio-matrix $\mathbf{G}$. A subcomponent of $\mathbf{G}$ consists of all individuals that are weakly connected to each other in a classroom. Thus, the reported direct friends of individual i constitute a subset of i's network. The number of friendship nominations is restricted to 5 classmates. Links are not necessarily reciprocal, hence the degree distribution rages from 1 to 13. Moreover, a network in the analysis sample can consist of up to 28 students.

Common shocks such as, for example, environmental shocks may bias the estimates of peer effects. The fixed effects imply that I only explore variation within networks. Thus, I assume that the relevant interactions take place at the network level. I apply a so-called network-mean transformation by multiplying equation (8) by the matrix $J_r = I_{n_r} - \frac{1}{n_r} l_{n_r} l^{'}_{n_r}$, where I_{n_r} is the identity matrix, l_r is a vector of ones and n_r is the number of individuals in network r. This transformation implies that I subtract the network average from each individual-level variable. Hence, I arrive at the following network-mean transformed average model of peer effects:

$$J_r Y_r = \phi_2 J_r G^*_r Y_r + J_r X_r \beta + J_r G^*_r X_r \gamma + J_r \epsilon_r. \tag{9}$$

5.4 The control function approach

The control function approach consists of two stages: a selection equation and an outcome equation (Heckman et al., 2013; Wooldridge, 2015). Individuals tend to exhibit homophily in covariates such as gender, ethnicity and socio-economic background.[22] The link (or "dyad") formation equation consists of these variables as predictors of friendship ties. In the first step, the binary dependent variable "link" (1=reported friendship link) is regressed on individual-specific observable characteristics and dyad attributes. In order to qualify as a valid instrument for link formation, the exclusion restriction variable(s) should affect the probability of two individuals forming a friendship tie but not the individual decision to disrupt.

I claim that **G** is exogenous, once I correct for possible sorting which is done by including the residuals from the link formation estimation in the outcome equation. Moreover, the links are undirected and the selection correction term is at the individual level as in Graham (2015).[23] The link formation process is modeled as follows:

$$g_{ij} = \alpha_0 + \alpha_d|X_i - X_j| + \alpha_c|X_i - X_j| + \alpha_C C_{ij} + \alpha_f|\varphi_i - \varphi_j|, \tag{10}$$

where C_{ij} represents the link characteristics, $|X_i - X_j|$ the absolute difference in the observed characteristics (either dichotomous or continuous indicated by d or c) of two individuals, and $|\varphi_i - \varphi_j|$ the absolute difference in the unobserved characteristics of two individuals.

The outcome model in the second stage is the average model as described above including the estimated residuals, ν_n, in the first stage:

$$J_rY_r = \phi_2 J_r G_r^* Y_r + J_r X_r \beta + J_r G_r^* X_r \gamma + J_r \epsilon_r + \nu_n. \tag{11}$$

Since the second-stage model includes the residuals from the first stage, the estimated coefficients are plagued with noise from the first

[22]See the seminal work of McPherson et al. (2001) on homophily in social networks.
[23]See Arduini et al. (2015) for a model with directed links.

stage (Hardin, 2002). One way of examining the bias is to use bootstrapping methods. As this procedure is computationally intensive, at this stage I only present the results with robust standard errors and explore how the estimates and standard errors change when the residuals are included in the outcome model.[24]

The selection equation is estimated by OLS and the residuals are added up with respect to each individual. The results are presented in table 2. Recall that the control function is estimated at the dyad level, while the outcome model is estimated at the individual level. For the time being, I assume that the errors are following a normal distribution and that they are independent (although there is room to reconsider this).

The number of possible links is nearly 18 million. The predictors include the absolute difference in scores on the language test, the absolute difference in scores on the cognitive ability test, male dummy (1=both individuals are male), native dummy (1=both individuals are native-born) and the absolute difference in age.[25]

The exclusion restriction in the model is an indicator for living within a 5 minute walking distance from a classmate. The geographical proximity variable affects the probability of two individuals forming a friendship tie but not the individual decision to disrupt and should therefore be a valid instrument for link formation. The indicator variable is excluded from the second stage, i.e. the outcome equation.

Evidence of the non-randomness in link formation is displayed in table 2. Unsurprisingly, geographical proximity seems to be an important predictor of friendship ties. The estimates reflect probabilities and the coefficient for "5 min distance" is non-negligible and significant. Language and cognitive ability test scores and region of origin also seem to

[24] An alternative solution is to follow Murphy and Topel (1985) by adjusting the covariance matrix. Murphy and Topel (1985) provide a consistent estimator of the covariance matrix. See also Del Bello et al. (2015).

[25] Due to the high non-response rate of both students and parents regarding the parents' occupation, I omit the absolute difference in the highest occupational status of the parents as an explanatory variable in the link formation process.

be driving friendship formation. The larger is the absolute difference in test scores of two individuals, the less likely they are to be friends. Homogeneity in terms of region of origin also makes two individuals more likely to form a friendship link.

Table 2: Control function approach: Link formation model

	Link
Constant	0.00048***
	(0.00002)
Language test scores	-0.00002***
	(0.00000)
Cognitive ability test scores	-0.00001***
	(0.00000)
Male	0.00041***
	(0.00001)
Native	0.00056***
	(0.00001)
Age	0.00002
	(0.00002)
5 min distance	0.52904***
	(0.00036)
R^2	0.10928
Adj. R^2	0.10928
Observations	17799961

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Results from OLS regression. The dependent variable is a dummy indicating whether there is a friendship link between two individuals. The explanatory variables include the absolute difference in scores on the language test, the absolute difference in scores on the cognitive ability test, male dummy (1=both individuals are male), native dummy (1=both individuals have at least one native-born parent), the absolute difference in age, and finally, whether or not the two individuals live within a five minute walk from each other.

6 Empirical results

In this section, I estimate the average peer effect model to arrive at an estimate of peer effects in disruptive behavior. The estimates from the regression analysis in section 6.1 are then used in the key player simulation in section 6.3.

6.1 Estimated peer effects

Column (1) in table 3 displays the baseline estimate of the peer effect in disruptive behavior estimated by OLS. The average peer effect estimate is positive and significant ($p<0.01$). Unconditional on individual and friends' characteristics, a one point increase in the average disruptiveness of friends is, on average, associated with a 0.31 point increase in individual disruptiveness (the mean of the dependent variable is 6.36).[26]

Due to simultaneity and omitted variable bias (as discussed in section 5.2), the average peer effect estimate from OLS reported in table 3 is likely biased. In order to address these identification issues, I consider two alternative estimation methods: Generalized Spatial Two-Stage Least Squares (GS2SLS) and Maximum Likelihood (ML).[27] In the next step, I use the GS2SLS and ML estimators for the parameters of a linear cross-sectional spatial-autoregressive model as suggested by Drukker, Prucha, and Raciborski (2013). Both models are estimated using the spreg command in Stata (sppack).[28]

The standard approach in the peer effect literature is to use instrumental variables. Thus, in order to estimate the GS2SLS model I need to find a set of valid instruments. Initially, I only consider the prede-

[26]Note that the social conformity coefficient represented by λ is derived from the following expression: $\phi = \lambda/(1+\lambda) = 0.31$.

[27]See Kelejian and Prucha (1998) and Lee (2003). See also Drukker, Prucha, and Raciborski (2013) and Drukker et al. (2013).

[28]The output from spreg does not include first-stage F-statistics; hence, I try out alternative instruments using the Stata package ivreg2. The first-stage F-statistic of these estimations ranges between 1 and 6 which is much less than the convention or rule of thumb of at least 10. The results from the estimations with the "Best IV" are presented in table C1 in Appendix C.

termined characteristics of friends of friends, such as gender, age and ethnicity. Next, I also include the parents' characteristics (e.g. socioeconomic status). The preferred set of instruments, a combination of predetermined individual characteristics and parental attributes, results in the highest first-stage F-statistic, although it is still weak (around 6). This set of instrumental variables is then used in the estimations using GS2SLS. Note, however, that a weak instrument could potentially do more harm than good by generating inconsistent estimates and incorrect confidence intervals, which is why I extend the analysis with ML estimations.[29]

The regression results for the GS2SLS and ML estimators for the average model are reported in table 3. As the spatial-weighing matrix is row-normalized, the parameter space of ϕ is (-1,1). The average peer effect estimate is 0.169 and it is insignificant in the GS2SLS case with network fixed effects (table 3, column (2)), whereas it is strongly significant when using the ML estimator (column (3)). Thus, in both cases, the peer effect estimate is positive and of moderate size. Importantly, the estimates are almost of equal size. Since the results indicate that GS2SLS is less efficient than the ML, the latter is my preferred model.

Table 3 indicates that in all specifications (columns (1)-(4)), the sign and significance of the individual covariates are consistent. Columns (2) and (3) show the average peer effect conditional on covariates (controls of individual and friends' average characteristics). The individual characteristics consist of language and cognitive test scores, gender, socioeconomic background, region of origin and age.

[29]See Anselin (1988) for a discussion on the finite sample properties of the IV estimator. A drawback of the ML approach is the restrictive assumptions about the distribution of the error terms.

Table 3: Outcome equation (OE) and link formation (LF)

	Baseline (1)	OE (2)	OE (3)	OE and LF (4)
	OLS	GS2SLS	ML	ML
Dependent variable: Disruptiveness				
Constant	4.39***			
	(0.23)			
Language test scores		-0.0185*	-0.0186**	-0.0187**
		(0.0102)	(0.00890)	(0.00890)
Cognitive ability test scores		-0.0370***	-0.0370***	-0.0370***
		(0.00878)	(0.00865)	(0.00865)
Age		0.208	0.208	0.208
		(0.134)	(0.133)	(0.133)
Male		0.0471	0.0474	0.0463
		(0.151)	(0.150)	(0.150)
Native background		0.219**	0.220**	0.220**
		(0.102)	(0.0986)	(0.0986)
Highest index of occupational status		-0.00164	-0.00164	-0.00165
		(0.00186)	(0.00186)	(0.00186)
Missing HISEI		0.417***	0.417***	0.417***
		(0.148)	(0.147)	(0.147)
Friends' average language test scores		-0.0593***	-0.0595***	-0.0594***
		(0.0190)	(0.0156)	(0.0156)
Friends' average cognitive test scores		-0.0382*	-0.0384**	-0.0385**
		(0.0199)	(0.0151)	(0.0151)
Friends' average age		0.0743*	0.0746**	0.0751**
		(0.0443)	(0.0357)	(0.0357)
Proportion male friends		0.0693	0.0696	0.0701
		(0.172)	(0.172)	(0.172)
Proportion native friends		0.118	0.119	0.120
		(0.170)	(0.158)	(0.158)
Friends' average HISEI		1.56e-05	1.46e-05	1.78e-05
		(0.00327)	(0.00327)	(0.00327)
Selectivity bias correction				8.05e-06
				(1.46e-05)
ϕ	0.31***	0.169	0.167***	0.167***
	(0.04)	(0.206)	(0.0182)	(0.0182)
σ^2			4.460***	4.460***
			(0.0974)	(0.0974)
Observations	4,219	4,219	4,219	4,219
Network fixed effects	NO	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Column (1) reports the results from the baseline average peer effect model estimated by OLS. Columns (2) and (3) report the outcome equations. Column (2) shows the results from GS2SLS estimations of the average model with network fixed effects while column (3) shows the ML estimations with network fixed effects. In column (4), the outcome equation is the average model including the estimated errors from the link formation model estimated by ML. The *selectivity bias correction* is reported in column (4). The standard errors are clustered at the network level.

In line with expectations, language and cognitive ability test scores are negatively related to individual disruptiveness. Also as expected, friends' average age is positively related to the outcome variable. The individual and contextual effects give rise to the variations in the individual disruptiveness abilities a_i's, (defined in section 3.2 above) which are used to identify the key player. Since the model includes spatial lags of the dependent variable, the interpretation is less straightforward than in the linear model case. The interpretation of the coefficients for the independent variables is discussed further below.

Next, I turn to the link formation process reported in table 2 in section 5.4. Column (4) in table 3 reports the outcome equation, namely equation (9) including the selection correction term. Neither the magnitude nor the significance of the peer effect changes by including the correction for selection bias. Furthermore, the size of the standard errors remains unchanged. A plausible explanation for this result is that link formation is as good as random after controlling for sorting using individual and friendship characteristics.[30] Overall, the other estimates and their standard errors remain fairly unaffected by including the correction term for selectivity bias which suggests that conditional exogeneity holds and that the peer effect can be interpreted in causal terms. Hence, the peer effect estimate that I will use in the key player analysis is 0.167. The preferred model, the average peer effect model estimated by ML, indicates that individual disruptiveness is positively related to the average disruptiveness of best friends.

6.2 Interpretation of estimates

The interpretation of the estimates in table 3 is less straightforward than in the OLS case. One way of interpreting the coefficients for the independent variables is to calculate the predicted values at different levels of the dependent variable, as suggested by for example Drukker, Prucha, and Raciborski (2013). Due to the built-in simultaneity of the model

[30]See the discussion in Del Bello et al. (2015).

(SARAR), a change in the dependent variable of one individual can alter the predicted values of all other individuals in the sample. Either the units of the exogenous variable are changed sequentially (average total direct impact, ATDI) or simultaneously (average total impact, ATI).

I calculate the predictions using the simultaneous approach. The mean change in the predictions from increasing the individual cognitive ability score by one point is -0.0444. The ATI corresponds to about 2.0 percent of a standard deviation in individual disruptiveness (demeaned).[31] The estimated ATI from a one unit change in the individual language test score is -0.0224 which corresponds to approximately 1.0 percent of a standard deviation in individual disruptiveness.

6.3 Key player simulation

In this section, I proceed by identifying the key player using the concepts presented in section 3.4. The following analysis is based on the average model of peer effects. The estimated peer effect of the average model reported in column (4) in table 3 is positive and statistically significant (0.167, $p<0.01$).

First, I derive the Bonacich measure of each individual using the estimated peer effect of 0.167. I use all the estimated coefficients in the average model reported in table 3 to derive the disruptive ability a_i of each individual in the network. As defined in equation (2), a_i depends on individual observable attributes, the average observable characteristics of an individual's direct friends and the total number of friends. Next, I plug each a_i into the expression (4) and derive the vector of Nash equilibrium disruptiveness levels which corresponds to the Bonacich of each individual (see Definition 1).

The final part of the exercise involves identifying the key player, i.e. the optimal target. This is done by calculating the intercentrality of all

[31] When presented in percentage terms and the denominator is the sample average of individual disruptiveness, the absolute ATI from increasing individual cognitive ability by one point corresponds to a very large number. This is because all variables in the preferred specification have been demeaned at the network level and therefore consist of both positive and negative values (including individual disruptiveness).

individuals in each network (as defined in equation (7)). The key player is the individual with the highest intercentrality. Clearly, the number of key players is the same as the number of networks, which is 374. Networks with less than three members have been removed from the key player analysis which leaves us with a total of 329 networks in the analysis sample. Moreover, the number of most active players is larger than the number of networks since more than one player could have the same level of disruptiveness.

By definition, key players hold important positions in their network and may act as bridges of both desirable and undesirable behavior.[32] The key player is not necessarily the most active individual in the network. In fact, the key player and the most active individual is the same person in only 28 out of 329 networks (about 8.5 percent). Table 4 shows the observable characteristics of the key player and the most active player. Column (1) reports the results from a logistic regression of a dummy variable, indicating whether an individual is the key player or not, on a selected set of observable characteristics such as gender and parents' immigration status. Column (2) displays the corresponding regression results for the most active player.

According to the results in table 4, the log of odds of being the key player is positively related to language test scores ($p<0.01$) and cognitive ability test scores ($p<0.01$). In other words, the higher the test scores, the more likely it is that an individual is the key player.

The odds ratio of 1.141 indicates that boys are 1.141 times more likely to be the key player but the estimate is insignificant. Thus, I do not find any evidence in support of the notion that the key player is more likely to be a boy than a girl; given the same language and cognitive ability test scores, HISEI, age and parents' immigration status, boys are not more likely to be the key player than girls. This is, however, not the case for the most active player. Boys are 1.271 times more likely to be the most disruptive individual in the network ($p<0.05$). Moreover, having at least one native-born parent is negatively related to being the

[32]Bridges have high betweenness centrality.

key player and positively related to being the most active player (both insignificant, however). The log of odds of being the most active player is negatively related to cognitive ability test scores (p<0.10).

Table 4: Observable characteristics of the key player vs. the most active or a random player

	(1) Key player	(2) Most active player	(3) Random player
Language test scores	1.302***	0.988	1.020
	(0.027)	(0.014)	(0.015)
Cognitive ability test scores	1.135***	0.977*	0.980
	(0.022)	(0.013)	(0.013)
Male	1.144	1.271**	0.875
	(0.141)	(0.148)	(0.102)
Highest index of occupational status	0.998	0.997	1.000
	(0.003)	(0.003)	(0.003)
Native background	0.879	1.161	0.969
	(0.151)	(0.158)	(0.132)
Age	1.099	1.156	1.099
	(0.343)	(0.244)	(0.243)
HISEI missing	0.700	1.019	1.251
	(0.190)	(0.240)	(0.274)
Observations	4129	4129	4129
Pseudo R^2	0.184	0.006	0.002

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results from logistic regressions. Column (1) reports the results from a logistic regression of a dummy variable, indicating whether an individual is the key player or not, on a selected set of observable characteristics. Columns (2) and (3) display the corresponding regression results for the most active player and a random player, respectively.

Next, following the analysis employed in Lindquist and Zenou (2015), I investigate the percentage reduction in disruptiveness from removing the key player, calculated as the intercentrality of the key player times 100 divided by the total Bonacich of that network.[33] I run an OLS

[33]It would have been interesting to look at the actual behavioral changes within networks before and after a student has left a class (some students are missing in wave 2 since they have either changed classes or schools) and to compare the predictions of the key player model to actual outcomes from changing class composition. Due to the small number of missing students in each school year, such an exercise will not be possible in this study.

regression of this value on a constant and the independent variable network size. The results of these regressions are shown in table 5. I do the same for the most active player and a random player.

Table 5: Predicted reductions from removing the key player, the most active player or a random player without any baseline

	(1) Key player	(2) Most active player	(3) Random player
Network size (demeaned)	-1.218***	-1.142***	-1.148***
	(0.0416)	(0.0404)	(0.0418)
Constant	13.17***	11.88***	11.95***
	(0.272)	(0.264)	(0.273)
Observations	329	329	329
R-squared	0.724	0.710	0.698

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Results from OLS regressions of the percentage reduction in disruptiveness from removing either the key player, the most active player or a random player, calculated as the intercentrality of that player times 100 divided by the total Bonacich of that network, regressed on a constant and the independent variable network size.

Table 5 reports the predicted reductions without any baseline. The average reduction in disruptiveness for the average network (size=16) from removing the key player is roughly 13.2 percent as compared to removing the most active player, which is about 11.9 percent.[34]

In table 6, the baseline is the most active player or a random player. This approach produces estimates of the performance of the key player strategy relative to other policies such as targeting the most disruptive individual. In the first column of table 6, the dependent variable is the difference in the percentage reduction in disruptiveness from removing the key player as compared to removing a random player. In column (2), the dependent variable is the reduction relative to the most active player. Networks where the key player and the most active individual or a random player is the same person have been removed from the analysis in table 6, which is why the sample sizes are different in columns (1) and (2).

[34]The sample size is the same in all three models since the key player and the most active or random player are allowed to be the same individual.

Table 6: Predicted reductions from removing the key player (KP) when he or she is not the most active player (MA) or a random player (RP) in the network

	(1) Difference KP and RP	(2) Difference KP and MA
Network size (demeaned)	-0.0973***	-0.0973***
	(0.0120)	(0.0138)
Constant	1.412***	1.440***
	(0.0780)	(0.0881)
Observations	295	301
R-squared	0.183	0.144

Notes: Results from OLS regressions. The dependent variable in column (1) is the difference in the average reduction in aggregate disruptiveness from removing the key player as compared to removing a random player. The dependent variable in column (2) is the difference in the average reduction in aggregate disruptiveness from removing the key player as compared to removing the most active player.

The intercept gives an indication of how much the key player strategy outperforms the other two policies. The key player strategy outperforms the other strategies to a significant extent, although the difference is small: the average reduction in disruptiveness for the average network (size=13.1) from removing the key player is 1.41 percent higher than removing a random player and 1.44 percent higher (size=12.9) than removing the most active player. The estimate of network size is, as one would expect, negative in both cases.[35] Table 6 shows the relationship between the average predicted reduction and network size. A one point increase in the number of network members is, on average, associated with a 9.7 percentage point decrease in the difference in the average reduction in aggregate disruptiveness.

In summary, the effect of removing the key player is significantly larger than the effect of removing the most active player; thus, removing the most active player is not necessarily the most effective way of lowering aggregate disruptiveness in the network. The difference in the

[35] The number of networks in both columns (1) and (2) is less than 374 since the networks in which the key player and a randomly chosen player coincide are removed from the analysis. The same applies to the case when the key player is also the most active player in the network. Also, as previously mentioned, networks with less than three members are excluded from the key player analysis.

predicted percentage reduction in disruptiveness is relatively small, however. Furthermore, the predicted reduction is negatively related to network size which is a mechanical property: removing the key player (or actually any player) in a smaller network will have a larger effect than in a bigger network.

7 Discussion

A deeper understanding of how and when peer effects influence adolescent behavior could help both researchers and policy makers create effective policy interventions in education (e.g. how to optimally organize teaching and classrooms) and adolescent risk behavior (e.g. how to reduce delinquent behavior). Should policy be aimed at changing the context (teachers, resources etc.) or the composition of students? Should teachers target the most active individual, i.e. the one making the most noise, or perhaps the most popular individual – such as the key player?

Different classroom situations can bring about different behaviors, as noted by McFarland (2001): "changing either the student or the classroom would change the decision to rebel" (p. 617). Disruption could be rectified through organizational changes of the classroom, for example by altering the formats of instruction or the grouping of students.[36] That said, changing classroom size (teacher/student ratio) or introducing remedial classes could be costly as compared to altering the groupings of students. The implementation of a policy that changes the configuration of classroom networks of students resistant to learning can prove to be less expensive than other policies and the potential gains could therefore be substantial.

The optimal target for treatment hinges on the underlying behavioral mechanism of disruptive conduct. I find that the average model fits the data best, suggesting group-based policies should be more effective than

[36] Educators can alter the grouping of students either by mixing, matching or random assignment.

policies aimed at specific individuals. Thus, in order to reduce aggregate disruptiveness, the social norm – the behavior of the majority in each network– needs to be changed.

I also find that the key player and the most active individual is the same person in 28 out of 329 networks (approximately 8.5 percent). I find evidence that removing the key player has a significantly larger effect on aggregate disruptiveness in a network than removing the most disruptive individual, implying that policy aimed at the most noisy individual could be inadequate.

Improving the behavior of the worst-behaved (most active) students clearly has a positive effect on other students in the classroom because of the social multiplier. Although in this case, the performance of the two strategies involving either removing the key player or the most active player is relatively small (on average a 1.44 percent difference in the aggregate disruptiveness reduction). Targeting the most active individuals is likely less demanding than aiming policy at key players. In practice, it could be difficult to target key players since they are not as easily identified (compared to the most noisy individuals). An alternative strategy is to "reshuffle" classrooms every semester or school year, thereby potentially changing the classroom norm. A drawback of this approach is that positive spillovers from advantaged to disadvantaged peers could be lost by randomly reorganizing classrooms.

A related question is whether to mix or match students according to specific observable characteristics such as grades. The seminal paper of Lazear (2001) derives optimal class size from a model of educational production that incorporates the disruptive behavior of students in the classroom. Lazear (2001) finds that the effect of classroom size is larger for disruptive than for obedient children. From a cost-benefit point of view, reducing the class size by a small number of students may not be of any importance for individual behavior when the class sizes are relatively large.[37] In Sweden, students often have the same classmates all through

[37]In fact, evidence is inconclusive about the effect of class size on student performance. See the discussion in e.g. Hanushek (2002).

the last years of compulsory school; hence, classroom networks are fairly stable. This leaves room for a policy on classroom composition.

Are some classroom environments more likely to facilitate or inhibit aggregate disruptiveness? The question opens up new avenues of research on classroom composition and learning environment. The rules on classroom interaction vary across schools and classrooms. Future research could investigate the relationship between the structure of classrooms and specific adolescent undesirable (or desirable?) behaviors. Do classrooms where individuals sort around the most disruptive student stand out in some observable way, for example with respect to density? If so, what makes students in these types of classrooms more susceptible to disruptive conduct? Are the externalities from bad apples larger in dense classrooms? One possibility is to use popularity ranking in the classroom or negative nominations and examine teacher characteristics more closely (available in CILS4EU). The next step is to also examine the effect of disruptiveness on individual achievement such as school grades and later educational outcomes.

Finally, this study has a number of limitations that should be mentioned. First, since students who were absent on the day of the network questionnaire or who refused to participate were excluded from the class roster and the set of potential friend nominees, there is a risk that I underestimate the effect of friends' disruptiveness and the effect of removing the key player (unless these individuals are isolated). As shown in table C1 in Appendix C.2, the cases dropped from the analysis sample due to non-response are more likely to have higher scores on the disruptive measure while lower scores on the language and cognitive ability tests, implying that the analysis sample is positively selected on these characteristics.

Second, a disadvantage of the CILS4EU data set is that it is based on individuals' self-reports of problem behavior. Ideally, one would like to have data on disruptive behavior collected through classroom observations over time.[38] Furthermore, an important question concerns the

[38]The sociological study of McFarland (2001) is based on classroom observations

nature and level of measurement error in the self-reported variables. Is it systematic or random, i.e. do disruptive students tend to misreport their behavior to a larger extent than others? This and related issues could be further investigated using the teacher questionnaire in CILS4EU.

8 Concluding remarks

This paper set out to investigate the peer effect in disruptive behavior using the architecture of the networks in the classroom and to move towards a policy-relevant application of the key player strategy. I find that being the individual that exerts the greatest negative influence on the classroom learning environment is positively related to test scores in cognitive ability and language proficiency. Moreover, the key player is not more likely to be a boy than a girl. I also find evidence that removing the key player has a significantly larger effect on aggregate disruptiveness in a network than removing the most disruptive individual, implying that policy aimed at the most active and potentially socially isolated individual could be inadequate.

The findings of this study have implications for educational policy on optimal classroom composition. The impact of a policy aimed at key players may prove to be more effective in reducing aggregate disruptiveness and improving the learning environment for all students in a classroom. I suggest a reshuffling policy where students are reassigned to classrooms regularly during the school year along with remedial classes for the most disruptive students.

of two schools and 36 classrooms followed during two school semesters.

A Model specification

In order to test the robustness of the average peer effect model specification, I also estimate the *hybrid* model and the *aggregate* model of peer effects. There are applications of the key player strategy (see, for example, Lindquist et al. (2015)) that employ a hybrid model of peer effects where both adjacency matrices are included in the same model estimation. A potential issue here is that the two matrices could be collinear, i.e. one is a linear combination of the other. To circumvent this problem, Tatsi (2015) transforms the adjacency matrices. However, even if one of the matrices comes out as more important than the other, it is still impossible to rule out collinearity. Hence, in this section, I test the models separately.

The aggregate model suggests that it is the peers' sum disruptive behavior that matters for individual disruptiveness. Furthermore, this effect may be multiplied by the number of students engaging in disruptive behavior. For example, one student's decision not to disrupt the class can directly influence the behavior of other students in the classroom. This mechanism is the so-called social multiplier. The model predicts that the more friends an individual has, the higher is the sum of friends' activity and the higher is individual activity. If it is the complementarities of friends' behavior that affect individual outcome, i.e. if students are more influenced by high-status peers rather than, for example, the most active individual, then the aggregate model should be more relevant in explaining peer effects in disruptive conduct. Next, I present the aggregate model and derive the model equilibrium. In this section, I closely follow Lindquist et al. (2015).

In the aggregate model, each agent chooses his or her level of disruptiveness, y_i, proxied by problem behavior in order to maximize own utility $u_i(\cdot)$, which is an increasing function of the "gains" of disruptiveness $(a_i + \eta + \epsilon_i)$, the disruptiveness of other students in network $\mathbf{y} = (y_1, ..., y_n)'$, the social cost or stigma of being punished by the teacher $-\frac{1}{2}y_i^2$, and g which captures the friendship network:

$$u_i(\mathbf{y}, g) = (a_i + \eta + \epsilon_i)y_i - \frac{1}{2}y_i^2 + \phi \sum_{j=1}^{n} g_{ij} y_i y_j. \tag{12}$$

In the above expression, the parameter ϕ captures the strength of the complementarities (the social multiplier coefficient) and $\phi \geq 0$. Each individual has his or her own disruptive ability a_i, defined formally in section 3.2, which depends on his or her observable attributes, the average observable characteristics of his or her friends, and the total number of friends indicated by g_i. The term ϵ_i represents idiosyncratic shocks and η are network fixed effects which capture the environment at the network level.

The difference between equation (12) and (1) is the last term. In contrast to the average model, an increase in the total disruptiveness of one's reference group increases individual marginal disruptiveness in the aggregate model, represented by the expression $\sum_{j=1}^{n} g_{ij} y_i y_j$.

In equilibrium, each agent i chooses y_i, her own level of disruptiveness, in order to maximize utility $u_i(\mathbf{y}, g)$. The choices are made simultaneously by all agents. Thus, agent i's best-reply function in the aggregate model is:

$$y_i^* = \phi_1 \sum_{j=1}^{n} g_{ij} y_j + a_i + \eta + \epsilon_i, \tag{13}$$

where $a_i + \eta + \epsilon_i$ are defined as above.

Definition 3 *For all networks g and for all i, the contextual intercentrality measure (Ballester and Zenou, 2014) of agent i is:*

$$\begin{aligned} d_i(g,\phi) &= B(g,\phi) - B(g^{[-i]},\phi) \\ &= \mathbf{\Gamma'_n M}\alpha - \mathbf{\Gamma'_n M}\alpha^{[\mathbf{i}]} - \mathbf{\Gamma'_n M^{[i]}}\alpha^{[\mathbf{i}]} \\ &= B(g,\phi) - B(g^{[i]},\phi) + \frac{b_{\alpha[i],i}(g,\phi)\sum_{j=1}^{n} m_{ji}(g,\phi)}{m_{ii}(g,\phi)}. \end{aligned} \tag{14}$$

Moving on to Definition 3, $B(g,\phi)$ corresponds to the total Bonacich intercentrality in network g while $B(g^{[-i]},\phi)$ is the total intercentrality once agent i has been removed from the network. $B(g,\phi) = \mathbf{\Gamma'_n M}\alpha^{[\mathbf{i}]}$ where $\mathbf{\Gamma_n}$ is a vector whose elements are equal to one and $\mathbf{M}$ is a matrix equal to the expression $(\mathbf{I} - \phi\mathbf{G})^{-1}$. $\boldsymbol{\alpha}$ is a vector keeping track of all α_i and is defined as above. $\boldsymbol{\alpha}^{[i]}$ is a $(n \times 1)$ column vector where all elements exclude α_i except for entry i which stores the initial α_i. $\mathbf{M^{[i]}}$ is a matrix whose elements are equal to $m_{jk}^{[i]} = \frac{m_{ji}m_{ik}}{m_{ii}}$. Finally, $B(g^{[i]},\phi) = \mathbf{\Gamma'_n M}\boldsymbol{\alpha}^{[i]}$ and $\frac{b_{\alpha[i],i}(g,\phi)\sum_{j=1}^{n} m_{ji}(g,\phi)}{m_{ii}(g,\phi)} = \mathbf{\Gamma'_n M^{[i]}}\boldsymbol{\alpha}^{[i]}$. The first term of the expression in the last row of equation (14) corresponds to the contextual change effect while the second term denotes the network structure effect.

The econometric equivalent (written in matrix form) of the best reply function for disruptive behavior in the aggregate model specified in equation (13) is the following:

$$Y_r = \phi_1 G_r Y_r + X_r\beta + G_r^* X_r\gamma + \mu_r + \epsilon_r, \tag{15}$$

where the parameters are defined as in section 5.1. The corresponding aggregate model of peer effects with network fixed effects becomes:

$$J_r Y_r = \phi_1 J_r G_r Y_r + J_r X_r\beta + J_r G_r^* X_r\gamma + J_r\epsilon_r. \tag{16}$$

Finally, the aggregate model including the first-stage residuals is the following:

$$J_rY_r = \phi_1 J_r G_r Y_r + J_r X_r \beta + J_r G_r^* X_r \gamma + J_r \epsilon_r + \nu_n. \qquad (17)$$

Table A1 shows the results from the regressions for the average, the aggregate and the hybrid model of peer effects estimated by standard OLS. Columns (1) and (2) report the results from the average and the aggregate models of peer effects in disruptiveness, respectively. The baseline model, the raw hybrid model of peer effects which incorporates both effects of peer spillovers, is shown in column (3). If both effects are not included, there is a potential upward or downward bias (Liu et al., 2014).

Unconditional on individual and friends' characteristics, a one point increase in the average disruptiveness of friends is, on average, associated with a 0.31 point increase in individual disruptiveness (the mean of the dependent variable is 6.36). The estimate in the aggregate model is shown in column (2). A one point increase in the aggregate disruptiveness of friends is associated with a 0.02 point increase in individual disruptiveness, on average ($p<0.01$). In sum, both effects are positive and significant in the separate models but when they are both included in the hybrid model, the estimate for the aggregate peer effect vanishes and loses significance (see column (3)) while the average peer effect estimate remains unchanged (0.31, $p<0.01$)

Next, I add fixed effects at the network level (table A1, column (5)). Once I control for possible sorting and common environmental factors, the average peer effect estimate changes signs and loses significance (-0.10, $p<0.10$). A plausible explanation for this result is that too much variation has been lost by introducing the network fixed effect.

The purpose of this exercise is to try to identify the transmission mechanism. The question is whether it is operating among direct friends, the friendship network (friends of friends) or at the classroom level. The network fixed effect should take care of any extreme cases at the network level. However, if the causal peer effect operates through a channel other than the friendship level, for instance a factor at the classroom level, not controlling for sorting into networks is going to result in a biased peer effect estimate. On the other hand, by introducing a classroom fixed effect, the network may capture part of this variation rather than the peer effect estimate at the friendship level. In that case, the estimated coefficient could switch sign and still be biased because the effect is carried over to the network level. All in all, the results from the different specifications in table A1, columns (1)–(3), suggest that the average model explains the data best.[39]

Due to simultaneity and omitted variables, the peer effect estimates from the OLS regressions reported in table A1 are likely biased. Therefore, I estimate the models by 2SLS and ML. Moving on to table A2, the average peer effect estimate is 0.169 and insignificant in the GS2SLS case with network fixed effects (column (2)), whereas strongly significant when using the ML estimator. Thus, in both cases, the peer effect estimate is positive and of moderate size. Column (3) reports the ML results for the aggregate model and the peer effect is highly significant and positive, 0.054 ($p<0.01$). The aggregate model GS2SLS results are found in column (4). The peer effect estimate equals 0.125 and is significant ($p<0.01$) but the instrument is invalid.

The two final candidates are the average model and the aggregate model estimated using ML. As a robustness test, I compare the Log Likelihood of the average and the aggregate model and they turn out to be almost equal (-9156 versus -9159). The preferred specification is the average model of peer effects since it produces a significant and non-negligible peer effect estimate and is the model that explains the data best as suggested by the results in tables A1 and A2.

[39]However, the results should be interpreted with caution. As previously mentioned, a potential issue here is collinearity between the two adjacency matrices.

Table A1: Alternative models of peer effects estimated by OLS

	Average model	Aggregate model	Hybrid model	Average model	
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Disruptiveness					
Constant	4.39***	5.92***	4.38***	3.54	
	(0.23)	(0.12)	(0.23)	(4.39)	
Average peer effect	0.31***		0.31***	0.30***	-0.10*
	(0.04)		(0.04)	(0.04)	(0.06)
Aggregate peer effect		0.02***	0.00		
		(0.00)	(0.00)		
Language test scores				-0.03***	-0.02**
				(0.01)	(0.01)
Cognitive ability test scores				-0.04***	-0.04***
				(0.01)	(0.01)
Male				0.24**	0.17
				(0.10)	(0.11)
Highest index of occupational status				-0.00	-0.00
				(0.00)	(0.00)
Native				0.18*	0.18
				(0.10)	(0.12)
Age				0.15	0.17
				(0.16)	(0.15)
Missing values: HISEI				0.41**	0.49**
				(0.18)	(0.20)
Friends' average language test scores				0.01	0.02
				(0.02)	(0.02)
Friends average cognitive test scores				-0.00	-0.04
				(0.02)	(0.02)
Proportion male friends				-0.21	-0.04
				(0.13)	(0.15)
Friends' average HISEI				0.00	-0.01*
				(0.00)	(0.00)
Proportion native friends				-0.07	0.09
				(0.15)	(0.23)
Friends' average age				-0.02	-0.12
				(0.27)	(0.35)
Network fixed effects	NO	NO	NO	NO	YES
Observations	4219	4219	4219	4219	4219
Adj. R^2	0.04	0.01	0.04	0.05	0.14

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Columns (1)–(3) report the baseline estimates for the average model, the aggregate model and the hybrid model of peer effects. Columns (4) and (5) present the results from OLS estimations of the average model including covariates. In column (5), network fixed effects are included. The standard errors are clustered at the network level in all models.

Table A2: The average and the aggregate model of peer effects in disruptive behavior estimated by ML and GS2SLS

	Average model		**Aggregate model**	
	ML	G2SLS	ML	G2SLS
	(1)	(2)	(3)	(4)
Dependent variable: Disruptiveness				
Language test scores	-0.0186**	-0.0185*	-0.0190**	-0.0142
	(0.00890)	(0.0102)	(0.00891)	(0.00942)
Cognitive ability test scores	-0.0370***	-0.0370***	-0.0368***	-0.0348***
	(0.00865)	(0.00878)	(0.00866)	(0.00874)
Age	0.208	0.208	0.206	0.193
	(0.133)	(0.134)	(0.133)	(0.134)
Male	0.0474	0.0471	0.0486	0.0306
	(0.150)	(0.151)	(0.150)	(0.150)
Native background	0.220**	0.219**	0.234**	0.224**
	(0.0986)	(0.102)	(0.0986)	(0.0987)
Highest index of occupational status	-0.00164	-0.00164	-0.00161	-0.00173
	(0.00186)	(0.00186)	(0.00186)	(0.00186)
Missing HISEI	0.417***	0.417***	0.423***	0.407***
	(0.147)	(0.148)	(0.147)	(0.147)
Friends' average language test scores	-0.0595***	-0.0593***	-0.0603***	-0.0496***
	(0.0156)	(0.0190)	(0.0156)	(0.0170)
Friends' average cognitive test scores	-0.0384**	-0.0382*	-0.0400***	-0.0283*
	(0.0151)	(0.0199)	(0.0151)	(0.0169)
Friends' average age	0.0746**	0.0743*	0.0762**	0.0503
	(0.0357)	(0.0443)	(0.0357)	(0.0394)
Proportion male friends	0.0696	0.0693	0.0728	0.0581
	(0.172)	(0.172)	(0.172)	(0.172)
Proportion native friends	0.119	0.118	0.130	0.0774
	(0.158)	(0.170)	(0.159)	(0.162)
Friends' average HISEI	1.46e-05	1.56e-05	0.000216	0.000563
	(0.00327)	(0.00327)	(0.00327)	(0.00328)
ϕ	0.167***	0.169	0.0540***	0.125***
	(0.0182)	(0.206)	(0.00606)	(0.0465)
σ^2	4.460***		4.468***	
	(0.0974)		(0.0976)	
Log-likelihood	-9156.496		-9159.382	
Observations	4,219	4,219	4,219	4,219
Network fixed effects	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Columns (1) and (2) report the average model of peer effects estimated by ML and GS2SLS while columns (3) and (4) report the aggregate model estimated by ML and GS2SLS. All models include network fixed effects. The standard errors are clustered at the network level.

B Data creation notes

CILS4EU is a multileveled survey containing rich information on the family, teacher, school and classroom. It includes five sub-questionnaires directed at students, parents and teachers, entitled "Parents", "Teachers", "Youth classmates", "Youth friends" and "Youth main". The last three are directed towards students. The network data in this paper is created using the "Youth main" and the "Youth classmates" questionnaires. The number of respondents in the main questionnaire in the school year 2010–2011 was 5,025.

The analysis is based on the full data set including 249 classrooms, although sample restrictions could be considered in order to increase the proportion of participants per classroom (see an important discussion in Hjalmarsson and Mood (2015) on CILS4EU classroom data). Table B1 below shows the number of classrooms if the sample is conditioned with respect to the degree of participation.

Table B1: Share of participants and sample restrictions. *Source:* Kruse and Konstanze (2016), Children of Immigrants Longitudinal Survey in Four European Countries. Sociometric Fieldwork Report. Wave 1 – 2010/2011, v1.2.0.

	ENG N(classes)	**GER** N(classes)	**NET** N(classes)	**SWE** N(classes)	**TOTAL** N(classes)
>60 percent	202	243	220	250	915
>75 percent	191	201	211	235	838
>90 percent	153	97	158	172	580

The analysis sample is constructed in the following way. The full sample in the "Youth classmates" file consists of 4,794 individuals (249 classrooms and 129 schools). As a first step, I drop all individuals who have not nominated anyone in the "Youth classmates" questionnaire (311 individuals). Based on the reduced sample, I then create an edgelist file including all pairs of friendships. Table B2 shows the classroom characteristics of the full sample.

Next, I prepare the vertex file with all individual background variables including classid, schoolid, male age, disruptiveness, native, and

Table B2: Classroom characteristics, full sample

Variable	Mean	Std. Dev.	Min.	Max.	N
Classroom size	20.353	4.287	6	31	4794

HISEI. In the following step, I match the vertex file with a datafile with records of the students' language and cognitive ability test scores (4,804 observations). Individuals that performed the language and cognitive ability tests but did not take part in the main questionnaire were excluded (221 individuals in total). Individuals with missing values on HISEI (272 cases) have been given the sample average. In all regressions that include the HISEI variable, I add a dummy for missing values on HISEI. I match the vertex file with the achievement file which leaves me with a total of 4,792 distinct cases. Next, I merge the vertex file with the edgelist. Since there are more distinct observations of "friends" (5,149 cases) than of "egos" (4,468 cases), I need to remove cases where egos are missing among the friends. Thus, I remove the observations from the edgelist file that contain an island among all the edges. In this step, 806 individuals are excluded due to matching issues. The analysis sample consists of about 72 percent of the total number of sampled students by CILS4EU. Table B3 reports the classroom characteristics of the analysis sample.

Table B3: Classroom characteristics, analysis sample

Variable	Mean	Std. Dev.	Min.	Max.	N
Classroom size	18.298	4.445	3	28	4219

The matrix analyses are done in Stata, Mata (sppack) and R. I use Stata to construct the vertex file and the edgelist file which are then exported to R (gplot). In R, I create the network data for the key player simulation. Due to implementation and data memory issues, the second stage estimations in the control function approach are done in Mata. Robustness checks are performed in Stata and Mata (sppack).

C Robustness checks

C.1 Instruments and exclusion restriction

I perform a number of robustness checks in order to asses the validity of the instruments and the exclusion restriction in the control function approach. For the aggregate model, I complement the friends of friends characteristics instrument with alternative instruments, including variation in the number of friendship links (Lee et al., 2010; Liu and Lee, 2010). Individuals have different numbers of friends and the idea here is that the more friends one has, the higher is the aggregate disruptiveness in one's friendship network. The instrument turns out to be very weak and is therefore considered invalid in this particular setting (the results are available upon request).[40] Table C1 shows the results from two alternative 2SLS estimations. Column (1) shows the results from rearranging the order of the matrices when deriving the instruments in R while column (2) displays the results from the Best IV approach (Lee, 2003). The two alternative methods fail to produce higher first-stage F-stats than the standard 2SLS estimation.

With regard to the exclusion restriction, tables C2 and C3 report the correlation between individuals' characteristics and the average characteristics of their friends in the classroom conditional and unconditional on their 5 minute distance neighborhood cluster. The size distribution of these neighborhood clusters is presented in figure C.1. The number of observations is smaller than in the main analysis (3,253 versus 4,219) since individuals have reported friends who are not found in the network analysis sample. Either they opted out or were absent during the day of the survey. The results found in table C3 indicate that several estimates are noticeably reduced once I condition on the 5 minute distance network variable.

[40] The standard practice is to instrument $\mathbf{G}$ with $\mathbf{G}^2$, i.e. the characteristics of friends of friends. However, other instruments are also theoretically motivated (for example $\mathbf{G}^3$ and/or $\mathbf{G}^4$ and/or $\mathbf{G}^3$). Moreover, one could consider parents' characteristics such as marital status, paid job, religion, age, nationality and ISCO 2008.

Table C1: Alternative 2SLS specifications: GJGX versus JGGX estimated using the Best IV approach

	GJGX	**JGGX**
	(1)	(2)
Constant	0.00	0.00
	(0.04)	(0.03)
Language test scores	-0.03***	-0.03***
	(0.01)	(0.01)
Cognitive ability test scores	-0.04***	-0.04***
	(0.01)	(0.01)
Male	0.24***	0.24***
	(0.08)	(0.08)
Highest index of occupational status	-0.00	-0.00
	(0.00)	(0.00)
Native	0.20*	0.20*
	(0.10)	(0.10)
Age	0.11	0.10
	(0.16)	(0.17)
HISEI missing	0.45***	0.45***
	(0.16)	(0.16)
Average language friends	0.02	0.02
	(0.03)	(0.03)
Average cognitive friends	-0.00	-0.01
	(0.04)	(0.04)
Proportion male friends	-0.19	-0.18
	(0.17)	(0.18)
Average HISEI friends	-0.01	-0.01
	(0.00)	(0.00)
Proportion native friends	0.00	0.02
	(0.24)	(0.25)
Average age friends	-0.19	-0.20
	(0.33)	(0.33)
Average HISEI missing	-0.10	-0.09
	(0.37)	(0.37)
Local average peer effect	0.34	0.28
	(0.55)	(0.61)
R^2	-0.05	-0.03
Adj. R^2	-0.06	-0.04
Observations	4219	4219
Wald test	5.962	6.057

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Column (1) reports the estimates from 2SLS regression with the adjacency matrix placed in the “reversed” order. Column (2) shows the results from the Best IV approach. Both columns (1) and (2) include network fixed effects.

Figure C.1: Size distribution of neighborhood networks

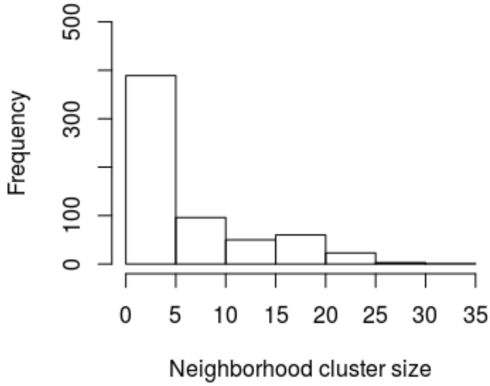


Table C2: Correlation between an individual's characteristics and the average characteristics of his or her self-reported friends in the classroom *unconditional* on the five minute distance neighborhood cluster

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	9.11***	10.59***	0.25***	0.19***	13.73***
	(0.49)	(0.50)	(0.02)	(0.01)	(0.50)
Language test scores	0.51***				
	(0.03)				
Cognitive ability test scores		0.40***			
		(0.03)			
Male			0.49***		
			(0.03)		
Native				0.72***	
				(0.02)	
Age					0.09**
					(0.03)
R^2	0.11	0.06	0.10	0.00	0.29
Adj. R^2	0.11	0.06	0.10	0.00	0.29
Observations	3253	3253	3253	3253	3253

Standard errors in parentheses
$^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: Results from OLS regressions.

Table C3: Correlation between an individual's characteristics and the average characteristics of his or her friends in the classroom *conditional* on the five minute distance neighborhood cluster

	Model 1	Model 2	Model 3	Model 4	Model 5
Language test scores	0.47***				
	(0.03)				
Cognitive ability test scores		0.39***			
		(0.03)			
Male			0.49***		
			(0.03)		
Native				0.70***	
				(0.02)	
Age					0.07**
					(0.03)
Observations	3253	3253	3253	3253	3253
Adj. R^2	0.14	0.08	0.10	0.30	0.02

Standard errors in parentheses
$^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: Results from OLS regressions.

C.2 Individual non-response

In order to estimate the network model, all isolated individuals (students with no friendship nominations) must be dropped as by construction the adjacency matrix cannot include missing values. As described in the data creation section B, I drop all individuals who have not nominated anyone in the "Youth classmates" questionnaire (311 individuals). None of these "isolated" individuals filled in the main questionnaire hence I am unable to explore their observable characteristics.

To get an indication of the degree of non-random selection due to individual non-response I investigate the characteristics of those excluded from the network analysis, in total 806 individuals. I perform this test on the individuals that are not matched with the edgelist file (those who did not take the language and cognitive ability tests are not included since they have already been dropped). It is not unlikely that these 573 individuals stand out in some way (non-random selection). Being absent at the time of the survey could be an indication of school shirking which is likely correlated with individual disruptiveness. I explore their observable characteristics in the descriptives table C1 below.

The cases dropped from the analysis sample are more likely male and have an immigrant background. They also have higher scores on the disruptive measure while lower ones on the language and cognitive ability tests implying that the analysis sample is positively selected on these characteristics. With regard to the test scores, the means are significantly different from each other. The dropped individuals also have, on average, statistically higher self-reported disruptiveness levels. The direction of the bias of the estimated effect depends on the network localities of the excluded individuals (high or low degree nodes?). The mean number of observations per classroom in the analysis sample is roughly 18 (see table B3).

Table C1: Observable characteristics, dropped individuals and the analysis sample

Variable	Mean	Std. Dev.	Min.	Max.	N
PANEL A: Dropped individuals					
Language test scores	15.515	5.829	0	30	573
Cognitive ability test scores	15.439	5.726	0	27	573
Age	15.122	0.387	14	17	573
Male	0.571	0.495	0	1	573
Disruptiveness	7.201	3.104	4	20	573
Native background	0.546	0.498	0	1	573
Highest index of occupational status	49.139	20.277	14.21	88.960	573
PANEL B: Analysis sample					
Language test scores	18.654	4.949	0	29	4219
Cognitive ability test scores	17.812	4.751	0	27	4219
Age	15.029	0.264	13	17	4219
Male	0.486	0.5	0	1	4219
Disruptiveness	6.364	2.433	4	20	4219
Native background	0.677	0.468	0	1	4219
Highest index of occupational status	52.982	20.35	11.74	88.960	4219

D Questionnaire items

This section presents a selection of the questionnaire items that were used in the Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU, Kalter et al. (2016a); Kruse and Konstanze (2016)).

The "Youth classmates" questionnaire in wave 1:

- (Q1) Who are your best friends in this class? (Here you may write down no more than five numbers.)
- (Q9) Which of your classmates live within a 5 min walk from your home?
- (Q10) Who do your parents know?

The "Youth main" questionnaire in wave 1:

- (Q20) How often do you... (Every day, Once or several times a week, Once or several times a month, Less often, Never)
  - ... argue with a teacher?
  - ... get a punishment in school (for example being kept in detention, being sent out of class, writing lines)?
  - ... skip a lesson?
  - ... come late to school?
- (Q81) Have you done the following things in past 3 months? Your answers will be kept secret. (Yes, No)
  - Deliberately damaged things that were not yours?
  - Stolen something from a shop/from someone else?
  - Carried a knife or weapon?
  - Been very drunk?
- (Q93) How often do you... (Every day, Once or several times a week, Once or several times a month, Less often, Never)
  - ... drink alcohol?
  - ... smoke cigarettes?
  - ... use drugs (for example, hash, paddos, ecstasy pills)?

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