Differences in social capital and the inequality of educational outcomes

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Abstract: This dissertation assesses if and how cultural properties that augment social ties, commonly denoted as social capital, are related to differences in the inequality of educational outcomes (IEO). Cultural properties of social aggregates (and several other factors) influence the likelihood of social ties and thus constitute a social context moderating IEO. The main hypothesis is that collective social capital will make experiences of status groups more similar by mitigating differences in cultural capital and thus will also reduce IEO. This hypothesis is challenged by analyzing the effects of three different contextual levels where collective social capital can become relevant: countries (paper 1), schools (paper 2) and school class networks (paper 3). The first article (*Collective social capital. Does it make a difference for the inequality of educational outcomes?*) deals with the context effects of the average level of generalized trust and membership in voluntary associations in different countries by using data from the World Values Survey (WVS), European Values Study (EVS) and PISA. The second article (*Do school-level differences in social capital shape IEO? School-level context effects of connectedness of students and parental school volunteering.*) tests this hypothesis on the school level by analyzing the effect of ties of students and their parents' school volunteering by using the same data sources. The third article (*Network resources, resource deficits and the consequences of homophily on educational outcomes. Evidence from school class networks in 4 European countries.*) adds to the debated topics by developing a resource theory, analyzing resource deficits in 4 European countries. Additionally, it tests for effects of higher socio-economic status homophily in school classes on the outcomes of students by application of estimates derived from ERG models. This analysis is based on micro-data on students' social ties collected by the Children of Immigrants Longitudinal Survey (CILS4EU).

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Contents

0 Intro

0.1 Introduction

Since the early days, theory and research of inequality of educational outcomes (IEO) has been accompanied by thoughts and research on social capital. For education is in essence communication, it seems to be self-understood that it is also about interaction and social ties. While there is high research activity on e.g. the effects of specific ties and networks on individual educational outcomes, fewer works try to consider these micro-sociological findings in a wider framework of societal contexts and considerations about the resulting distributions and inequality of educational outcomes.

This dissertation researches different societal contexts that influence educational outcomes by altering social ties or networks and thus can be hypothesized to moderate IEO. The central research questions inciting this dissertation were: Does social capital on (different) aggregate levels matter for educational outcomes of individuals? How do those effects influence IEO?

Both question have high societal relevance and try to merge two (theoretical and empirical) themes of research: The question which contextual factors are relevant for educational outcomes and the question what role social networks play in achieving educational goals.

The main theme of this dissertation is to challenge the hypothesis, that aggregates with denser social ties, or cultural properties that stimulate such, will also make the experiences of different members of status groups more similar, reduce the differences in cultural capital (and other properties) and thus mitigate the inequality of educational outcomes. The dissertation contributes to this topic by analyzing the effects of three different contextual levels where social capital can become relevant: countries (paper 1), schools (paper 2) and school class networks (paper 3).

To provide a common context for the three papers that make up this dissertation, we want to show the theoretical considerations and findings that form the basis of this work. First, we present a short summary of theories on the inequality of educational outcomes and its relations to societal contexts (0.2). Second, we give an overview of theories on individual, collective and aggregate social capital and the moderation of IEO (0.3). Finally we give an short summarizing overview over the papers. A conclusion on the whole dissertation is drawn in chapter 4.

0.2 Inequality of educational outcomes

0.2.1 Processes involved in IEO

Early research on the inequality of educational outcomes (IEO) has shown that the status of parents (defined by occupation or education) is a strong predictor for the educational success of their children (Blau & Duncan, 1967; Sewell & Hauser, 1975). Throughout this dissertation we will use the term inequality of educational outcomes (IEO) in this specific sense.[1]

Despite the drastic educational expansion that mirrored the increasing demand for educated workers in consequence of innovation and sectoral changes, in most industrial countries the initial differences in cultural capital of students that enter school is perpetuated across the educational career. In consequence, substantial inequality of education based on status has remained (Breen, 2010; Haim & Shavit, 2013; Ishida, Müller, & Ridge, 1995; Rijken, 1999; Shavit & Blossfeld, 1993). With other traditional sources like status classes loosing relevance (Breen, 2010), IEO became even more important and has turned into the key factor of the stratification of modern societies beyond economic wealth and other traditional sources.

The main drivers of IEO are the differences in experiences and situations. Apart from genetic variation[2], IEO can be tracked back to differences in social experiences, that are especially related to family, since parents and siblings have the earliest possible interaction, have the most time and often affectual enforced opportunities to exert influence. Early learning processes of children can be very different and constitute very different social worlds. Parents vary strongly in capacities[3], in parenting styles (Spera, 2005), in how much time they devote to their children and which regular activities they incite. Other possible agents of (co-)socialization

[1] Other definitions may reference to distributions, we reserve it for the differences in educational outcomes by socio-economic status (SES) groups of families and the underlying different chances to achieve specific educational outcomes.

[2] While it can not be ruled out that effects of SES may be partly due to genetic variation across groups due to inaccessibility of data and research on dominant genes relevant for success in the educational systems, this aspect has to be excluded from our analysis.

[3] For example, parents are different in the number of words they use and in other knowledge they possess and thus the adequacy of explanations they give to their children in reaction to their curiosity on reality.

of students also mirror properties of their parents. Either because they were deliberately selected by their parents or they show similarities to their parents due to other social processes[4]. Therefore, complementary (early childhood) experiences with other members of society are again more similar to the experiences with their parents.

The family a child is born into is the key factor in terms of acquiring live-long repertoires of action, knowledge and other cognitive (and non-cognitive) capacities. In consequence, children differ in predominant habits and character traits, capacities and knowledge. They enter schools or preschools very differently adjusted to the demands of the education system (Bourdieu, 1983; Bourdieu & Passeron, 1971).

Similar to resulting differences in cultural capital, preferences have been shown to be another important and genuine factor that influences the trajectory of an educational biography. Alike to cultural capital they are transferred to children by adoption of repetitive presented behavioral patterns of parents. This includes education-related preferences and aspirations (Sewell & Shah, 1968) and preferences for a desired status position, like e.g. status maintenance (Breen, 2006; Breen & Goldthorpe, 1997). It also includes dispositions like time preferences and risk aversions (e.g. a preference for stability in life time income, Breen, van de Werfhorst, & Jæger, 2014). Preferences are also the main drivers of future-related goals and thus actions. Intentions and goals of parents and children can match the aims of the educational system more or less.

Beyond influences on the cognitive development of their children, being born into a specific SES is consequential in various other ways. For example material resources as economic capital (e.g. mediated by school and study fees) and property (e.g. mediated by effects on and consequences of the expected lifetime income), or other access rights to goods and services (e.g. remedial teaching) define very different conditions and requirements that are alike consequential for decisions and outcomes of education (Bourdieu, 1983). For example, being born into a family with specific SES is also decisive for the social contexts (e.g. neighborhoods) one lives in, or whether the access to the specific segments of the labor market is more or less likely.

All in all, both main consequences of SES background of families result in different cultural capital (Bourdieu, 1983; Bourdieu & Passeron, 1971) and differences in opportunity structures (Boudon, 1974). Both influence education-related decisions that can reinforce prior differences between status groups. Educational outcomes

[4] For example, inhabitants of certain geographic regions show similarities due to previous sorting processes. Tie partners might get to know each other by similarities in leisure activities which are, mediated by preferences, also systematically related to SES.

are far from being the passive results of available resources but actors creatively form expectations and decide between different available options. The most relevant is the recurring decision on how much time to invest on education – in terms of school exercises as well as educational years. There is a broad tradition to model education-related decisions by assuming rational actors, that optimize their expected utility (Becker, 1975). While the possible sources of utility, for heuristic or other reasons, have often been oversimplified by researchers in tradition of economics of education, the utility functions, however, can be adjusted by wider conceptions (Finkel, 2008). More elaborate models of educational decisions conclude that the underlying information processes make them – like almost always in all other aspects of social reality – generally limited, bounded, incomplete and insecure (March & Simon, 1958).

All aspects taken together, educational processes show a dynamic interdependence or sequential causation by differences in cultural capital, preferences, economic situation and decisions. For example, preferences will be shaped by social, cultural and economic capital and also are decisive for future cultural capital and social capital. And there exist path dependencies and feedback loops like Mathew effects: Social actors that have more cultural capital might be able to augment it over-proportionally, e.g. if previous learning results reduce the effort of learning (Bourdieu & Passeron, 1971).

0.2.2 Societal contexts to IEO

While all aforementioned processes are decisive for IEO, those processes happen in social contexts that shape educational processes on the individual level. Social contexts have been defined as attributes of reality that affect every member of a certain unit altogether, while not necessarily in the same way. Cross-country differences in the strength of status-based IEO has directed the focus of research to such contextual conditions like e.g. properties of the educational system (e.g. Hillmert, 2007; Schlicht, Stadelmann-Steffen, and Freitag, 2010), the labor market, welfare states (e.g. Breen, Luijkx, Müller, and Pollak, 2010) and forms of political regimes.

Of course, the most prominently researched contexts were the national specifics of education systems which differ in entry time and minimum years in mandatory education, decisions on curricula, rules for sorting and tracking and allowance to subsequent education. For example, highly tracked or streamed education systems separate students from different backgrounds early and thus increase initial

differences in cultural capital (van de Werfhorst, 2018).
In short such systematic and institutional settings determine the strength of the link between individual experiences in a specific social world and educational outcomes. For example, compulsory education does set limits to the dissimilarity of experiences, because in principle for the length of the school day students are influenced in the same informational environment.[5] Another extremely relevant example are institutions of compensation of performance differences (e.g. early child development and care, remedial teaching) and the criteria for selection and allocation of children to schooling.
Various other societal contexts (e.g. labor markets and neighborhoods) shape the link between education-related experiences and outcomes and thus can either increase or mitigate the IEO. Tax funded welfare systems redistribute economic resources and contribute to reducing wealth differences and influence the differentials that shape education-related decisions. They reduce educational risks and impact education-related financial support and grants. Because, as earlier mentioned, educational decisions anticipate future occupational careers and job chances, the latter are also highly relevant for educational outcomes.
While extensively researched, due to complex patterns of confoundedness and interaction, the effects of such contexts, however, are far from easy to understand and research results in our opinion are subject to severe problems that can result from confusion of sources by misspecification and under control in analyses of higher aggregates (see p. 32).
However one can generalize common aspects of all these settings and interventions and learn a lesson from it. Decisions of the education system directly define what happens to students from families of different status and cultural background and how strong this difference in experiences out of school will result in different experiences and outcomes inside of school.
Other social contexts beyond the education system can also influence the strength of differences in experiences of students and their families and thus in which states students enter the schools. All societal macro context that equalize the general experience outside of families will similarly reduce IEO. While most of the previous works on contexts of education put their focus on institutional settings of the education system, comparatively much less research has been conducted on non-institutional contexts. This dissertation thesis tries to contribute to this gap by researching cultural contexts and especially social capital on aggregate levels.

[5] Thus the length of the school day (ignoring differences in school types) can be a parameter related to the equality of educational outcomes.

0.3 IEO and social capital

0.3.1 Theories on individual social capital and IEO

In the previous consideration of influences of educational outcomes we deliberately did not include the consequences of differences in social ties. Since they are the main topic we are interested in, this section is dedicated especially to their influence on educational outcomes.

Bourdieu (1983) and Coleman (1988) popularized the idea that social relations have an instrumental value that allows for treating and labeling them as *social capital*. Several authors developed this idea before and merged it into this special term (Hanifan, 1916; N. Lin, 1982; a more complete historical overview is e.g. given by Halpern, 2005).The idea behind this concept is straightforward: *individual* social ties (defined by repeated and more or less institutionalized interaction) enhance the chances of achieving social mediated goals and constitute a social resource. Like other adaptions of the original term of economic "capital" (Bourdieu, 1983), the notion social capital implicitly postulates that an imaginary state of the world, desired by a member of society becomes more likely by controlling this "capital". Even early sociologist were perfectly clear about this instrumental value of social ties. For example Weber (1978, p.34) stated that "social relationships which are valued as a potential source of present or future disposal are, however, also objects of economic provision".

The social resource theory of Lin et al. (N. Lin, 1982; N. Lin, Cook, & Burt, 2001) related this potential in a very productive way to status attainment and inequality. Beyond the clarification of these theoretic links, the main contribution in our opinion lies in the stimulating questions and hypotheses on which kind of ties are the most effective for acquiring social goals. All three papers of this dissertation draw heavily on the thoughts developed in the tradition of these authors and especially their reasoning on inequality (N. Lin, 1999, 2000).

With N. Lin (2001) we can summarize the sources of the utility of social ties: Social ties define the communication position of members of society and thus influence their information intake. Where social ties exist, one can influence the actions of others. Ties reduce the costs of using others' economic and cultural resources. And tie partners can be used as credential: By taking the existence of ties between already trusted social participants and a stranger as a signal, the previous trust can be expanded on strangers. All those aspects of social ties are more or less directly relevant for the educational processes that we have sketched so far. Most theories on social capital and educational outcomes are information transfer theories. They put the focus on educational resources that are shared between and accumulated by social ties. For example, Coleman and Bourdieu regarded the accumulation of "human capital" (Coleman, 1988) or "cultural capital" (Bourdieu, 1983) as being dependent on the social ties to family and community. We agree with this prioritization and focus this mechanism in all three papers. Social capital allows, however, also for other properties but knowledge that turn out beneficial in the educational system. Social ties do not only determine what people know or not know, but they also allow for transfer of values, emotions and other states of mind and mindsets that are related to educational motivation and thus effort.

0.3.2 Social capital of aggregates

We will research two different kinds of aggregates of social capital, that we want to conceptually differentiate: Collective Social Capital and Aggregate Social Capital. Both can constitute societal contexts, but they correspond to different social processes in the real world.

Collective social capital, on the one hand, relates to properties of aggregates. The main idea behind was the fact that patterns of perceptions and actions, which are shaped by cultural institutions, can increase or decrease the likelihood of ties. In consequence, members of societies or groups that are connected denser or more intense gain benefits and can solve tasks more easily. This can be formalized by the following formulation that underlies most conceptions of collective social capital (e.g. Coleman, 1990; Krishna, 2002; Putnam, 1992, 2000): A property y of aggregate X (e.g. a group, township or geographical region) is collective social capital, when, first, y increases the likelihood of tie formation and thus social ties in X and, second, those ties have beneficial consequences to the members of X.

The scope of what kinds of aggregates are perceived to have collective social capital has widened with the popularization of the concept. From the collective social capital of groups (Coleman, 1990) to those of geographic regions (Putnam, 1992) and countries (Krishna, 2002; Putnam, 2000). Although generated by individuals, collective social capital is a property and a resource of the group and is beneficial to all – which makes it a collective good (Ostrom, 1992).

There is a variety of things said being collective social capital: patterns of spending leisure time and especially membership in associations (Putnam, 2000), trustfulness and collective identities[6], to cite just a few. Previous research on collective social capital has not always differentiated relational patterns from contexts of actions that facilitate or hamper them. For clarity, we define collective social capital to be the conditions of aggregates or their members that indirectly promote the creation of social ties between individuals and not the state or distribution of those ties in its own.

On the other hand, we use the term *aggregate social capital* for describing emergent properties of networks that evolve from individual ties.[7]

Both forms, collective social capital and aggregate social capital, can also be used as proxies for networks of individual ties. Theories why collective social capital or aggregate social capital should cause an state of the world, always have to use references to social networks and specific social ties.

Paper 1 in our view researches a collective social capital (generalized trust) and an aggregate social capital (the state of memberships which are a representation of a tie), while paper 2 researches two aggregate social capitals: connectedness of students in schools and parental involvement in school. Paper 3 researches the aggregate social capital in school classes based on directly measured social networks. Both can be related to IEO. If collective or aggregate social capital should influence IEO, as seen before, this properties must have the tendency to somehow make experiences of different social status classes more alike.

Since it has often been confused, we state the simple: When everyone gets more of whatever and this increases the individual levels of education-related outcomes, this does not necessarily mean, that inequality changes. If we look at the distributional aspects of education, we can ask whether the same inflow for two groups changes the inequality. If the increase of a property of a social context influences all members of a society the same, this will be neutral to (our term of) IEO without further assumptions. Effects of collective social capital on IEO in our definition always have to result from status group-specific differences - either because the effect of collective social capital on the group is different and results in different increases of social ties or because the effect (size and direction) of the same increase of additional social ties on educational outcomes is different. In all three papers we

[6] There is also an ongoing debate on *collective identities* like e.g. attachment to geographic origin or similarities. The questionable assumption here is, that people who identify themselves with communities of imagined similarities (Anderson, 1983) do interact more easily and frequently with members of those.

[7] Lazarsfeld and Menze (1969) distinguished several properties of higher level aggregates that have been derived from the individual properties. In their terminology aggregate social capital would be a *structural* property of a higher level cluster, since the type of individual level property it is derived from is in their terminology *relational*.

make special assumptions on decreasing returns of cultural capital or social capital and the resulting saturation processes. Without such processes one should not expect a context to have an effect on IEO.

Besides minor differences, the papers are connected by common assumptions that result in our central hypothesis: Conditions in sub-societies that promote social relations, at least in the absence of closure or segregation, will increase the likelihood that experiences of status groups are more similar and thus will reduce differences in e.g. cultural capital and also IEO.

0.4 Overview over the papers

All papers of this dissertation at the same time research social ties, networks and aggregate properties of it. They merge the aforementioned themes of educational research by analyzing the effects of three different contextual levels where collective social capital can become relevant: countries (paper 1), schools (paper 2) and school class networks (paper 3).

To achieve conceptual clarity and allow for comparison, all three papers share the same research questions and a common corpus of theoretical assumptions, that has been developed with every additional publication. All papers use educational performance as the main dependent variable – math test scores in paper 1 and 2 and math grades in paper 3. The main interest lies on IEO, which, in accordance with previous research (e.g. Schütz, Ursprung, and Wößmann, 2008), is conceptualized as the linear relationship between the familial SES and those measures of educational performance[8]. While all papers rely on assumptions on networks and the distribution of ties, only paper 3 assesses social networks and also segregation directly.

[8] We also did several robustness checks for reading and science scores.

Paper 1: Collective social capital. Does it make a difference for the inequality of educational outcomes?[1]

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Abstract: This paper assesses how several cultural properties that augment social ties (commonly denoted as social capital) might help to explain cross-country differences in the inequality of educational outcomes (IEO). After theoretic considerations we address this question by computing estimates of the country level of generalized trust and membership in voluntary associations based on the World Values Survey (WVS) and use these to assess their contextual effect on the educational performance of students tested in 50 different countries in PISA 2012. While we find country-level generalized trust being remarkably correlated with the performance of students, we had to reject our hypothesis that collective social capital reduces IEO. Our data gives support for effects of opposite direction: A higher level of trust seems to be associated with more educational inequality. Our second social capital indicator, membership in voluntary associations, mirrors the previous result with weaker effects, but we have to reject the hypothesis, that association membership is related to IEO.
Keywords: Inequality of educational outcomes (IEO), (collective) social capital, generalized trust, membership in voluntary associations, context effects of culture, PISA

1.1 Introduction

Country comparison reveals significant differences in the degree to which educational outcomes of students are influenced by the origin status of their families. While the last years have seen significant progress in explaining these country differences in the inequality of educational outcomes (IEO)[2] by different social contexts, e.g. specifics of the education system (Schlicht et al., 2010) or labor market, there is still high uncertainty about the role of cultural contexts. This article tries to shed light on the question whether IEO is decreased in countries with cultural properties that increase the likelihood of interaction. If IEO was lower in countries where people are more sociable and more densely connected to each other, there could exist a complementary and not widely recognized means to attenuate educational inequality.

We first review and extend a general theoretic conception of the hypothesized causal influence of social capital on IEO (section 1.2). Then we present previous research on two variants of collective social capital: the country levels of generalized trust and participation in voluntary associations (section 1.3). After describing

[2] While several concepts of educational inequality have been labelled IEO (e.g. the overall dispersion of outcomes) we reserve the term for differences in the conditional outcomes for members of groups defined by individual properties.

our operationalization and used data sets (section 1.4), we put our hypotheses to a test and estimate the effect of Collective Social Capital on societal IEO by a cross-country hierarchical analysis based on PISA, World Values Survey, European Values Study and European Social Survey (section 1.5).

1.2 Theory: Collective social capital and inequality of educational outcomes

To simplify analysis individual educational outcomes can be treated as mere function of the different availability of education-related resources.[3] Following the simple resource theory of Bourdieu (1983), the most important factor for educational success is cultural capital. Slightly different from the way Bourdieu uses the term cultural capital we here use it to denote all results of experiences and processes beneficial to outcomes in school: Cognitive and non-cognitive capacities, acquired traits and preferences (e.g. educational aspirations), knowledge and information on relevant societal processes, e.g. knowledge of the options in the education system and likely outcomes of educational decisions. Typically, parent-child relations are the most important source of cultural capital, while this transfer to children is moderated by the relation quality (Liu, Bellens, Van Den Noortgate, Gielen, & van Damme, 2014; von Otter & Stenberg, 2014) and time spent between parents and children (Cordero-Coma & Esping-Andersen, 2018).

The cultural capital accessible to students is also moderated by the familial economic capital – which allows for acquiring goods and services that augment cultural capital (e.g. books, technical learning infrastructure, entrance to cultural performances, remedial teaching) – and alike important: their social capital. The idea behind any notion of social capital is straightforward: *Individual or familial ties* (defined by repeated and more or less institutionalized interaction) enhance the chances of achieving social mediated goals and thus can be conceptualized as social resource (Hanifan, 1916; N. Lin, 1982; Bourdieu, 1983; Coleman, 1988; more complete historical overview e.g. by Halpern, 2005). The specific utility of social ties stems either from altered communication positions, the opportunity to moderate others' actions, the reduction of costs for using the resources of others or simplifying the building of trust by transferring reputation (N. Lin et al., 2001).[4]

[3] We heuristically ignore genetic similarities between parents and children and other confounders of the status transmission process mediated by cultural capital.

[4] Portes (1998), in contrast, considers, that these individual benefits can also have negative effects to society: The "exclusion of outsiders, excess claims on group members, restrictions on

Applied to education we presuppose[5] that the social ties of a family are related to the cultural capital resulting in higher educational outcomes:

Students from a family with more social ties gain access to additional cultural capital and thus perform better. (P1)[6]

This presupposition also has strong empirical evidence regarding various types of social capital (Dika & Singh, 2002)

Nonetheless, this simple hypothesis ('ties increase cultural capital') may be too simplistic, since the individual effects of social capital also depend on the composition of the network and especially the *resources available within this network*. The educational benefits arising e.g. from a friendship of the parents will depend on the education-related resources accessible (e.g. whether the friend has a certain "skill") and whether the type of relation allows for transfer (e.g. this friend spends time with the child allowing to learn this "skill" by some kind of deliberate or unintentional performance).

Students perform the better the more cultural capital is accessible through the ties of their family. (P2)

Finally the impact of social capital on performance could be different because the effect of an increase of cultural capital might depend on the amount of cultural capital available *within* the family.[7]

Thus students from families scarce in education-related resources might profit more from social capital (that functions as substitute for initial cultural capital) than families with higher educational background. One acquaintance of a low cultural capital family who has a higher educational background might make the difference by e.g. helping out with school-related knowledge, explaining homework, informing parents about risks and chances of higher education or by becoming a role model that turns the balance for choosing a track into higher education while in another family with high cultural capital the same acquaintance might have no or only little effect on the educational outcomes.

individual freedoms, and downward leveling norms." (p.15) Also note, that social contacts are costly in terms of resources and time (both decreasing the marginal utility of additional ties and limiting its maximum accumulation).

[5] We denote presuppositions – theoretically justified but not empirically tested assumptions – by P and hypotheses that are tested by H.

[6] This is meant probabilistic. In addition, there might be a trade-off between time spent with social ties and formal learning. And there might exist social ties that are malicious to the acquirement of cultural capital.

[7] We regard this theoretic assumption being plausible although von Otter and Stenberg (2014) come to different conclusions. They however survey only parental-school involvement and don not control for the cultural capital accessible in this network.

The increase in performance due to cultural capital accumulated in social ties is higher for students with low cultural capital. (P3)

While individual resources in principal determine educational outcomes this happens in *social contexts* that alter the accumulation of resources available to the students and modify the relation between resources and outcomes (and in reality often influences both at different points in time). An exemplary social context is the *structure of the education system* which strongly influences the relations between resources acquired outside of school and the resulting outcome inequality in terms of acquired skills and education certificates by setting e.g. rules of tracking (Burger, 2016; Chiu, Chow, & Joh, 2017; Hanushek & Wößmann, 2006; Schütz et al., 2008), streaming (Chiu et al., 2017) and allowance to subsequent education, the average class size (Wößmann & West, 2006), compensatory practices (e.g. remedial teaching), rules for and share of private schools and also by structural decisions like school entry times and hours of the school day (Figlio, Holden, & Ozek, 2018) – and hence how much of the day pupils spend in similar informational contexts).[8]

Abstracting from the concept of individual social relations as resource several authors conceptualized *social capital* also *as social context*. Guided by the idea that certain specifics of social groups might facilitate the realization of social contacts for their members, e.g. Coleman (1990) used the term social capital to define differences in trust inside of ethnic or religious groups as their specific social capital. The canonical study of Putnam (1992) stimulated an ongoing debate by stating the idea that social problems can be solved better in (geographic defined) aggregates whose members form denser social networks (relations being higher in number, frequency and intensity).[9]

While we share the skepticism of Bjørnskov and Sønderskov (2013) about defining entities by its function, we use the term collective social capital (CSC) as heuristic term denoting properties of aggregates that at average lead to denser networks in a society.[10]

[8] Labor market conditions are another example of a social context moderating the conditional educational outcomes by influencing (path-dependent) anticipatory educational decisions and thus can eventually change IEO given a conditional distribution of educational resources.

[9] Putnam defines the term social capital to denote "features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit" (Putnam, 1995, p. 67) and thus "improve the efficiency of society" (Putnam, 1992, p. 167)

[10] To be specific: The notion that X is a collective social capital is identical with claiming, first, that certain behavioral patterns of the aggregate's members lead to denser social networks and, second, that these result in certain beneficial outcomes for the members of the aggregate compared to those of aggregates not having this property. Whether certain properties of society members constitute a *collective* social capital is an open empirical question and will

Continuing the previous arguments we expect collective social capital of a country to be a context that influences individual educational outcomes by increasing the chances for ties and subsequent additional cultural capital from an enlarged individual network (P1): *The educational performance of students is c.p. higher in countries with higher collective social capital.* (H1)

In result of this overall boost of cultural capital through better circulation of information the amount of collective social capital might also equalize educational outcomes through homogenization of the distribution of cultural capital. Like other social contexts CSC will reduce IEO if it helps to make experiences of students previous to schooling and at the time of the day not spent in school more alike (and thus the levels of cultural capital they acquire)[11]: *In societies with higher levels of CSC the inequality of educational outcomes will be smaller. (H2)*

As previously stated this can be expected because students from families with less cultural capital should have higher educational returns from additional cultural capital in consequence of (compensatory) social ties (see P3). However, this higher utility of additional ties for low cultural capital groups might be outweighed by a lower availability of cultural capital inside their network (P2). For example, if societal members with low educational background would interact not at all with members of high educational background, Collective Social Capital would augment only relations inside of each group resulting in far lesser gains in education-related resources for groups with lower educational background. Thus social closure between status groups might prevent the transmission of cultural capital to groups with less cultural capital – even in countries where CSC is higher. The relation between CSC and IEO should therefore depend on how much it helps to establish social ties that *bridge* status groups – e.g. by positively changing the perception of out-groups (Reeskens, 2012).[12]

Because the likelihood of such bridging ties is dependent on the behavior of the members of different status group, we can hypothesize that – opposite to the common conception of a context effect of collective social capital (defined e.g. as a mean of a society affecting all its members) – there might exist different context effects from average cultural properties of members of higher (or lower status) groups:

also depend on group-specific differences in the distribution of this properties, networks and education-related resources besides social networks.

[11] Note that IEO is a conditional distribution and thus is never directly influenced by the absolute amount of *any* resource but only by its distribution across groups who are compared by their educational outcomes.

[12] Note that there is also the possibility that CSC results in social ties that are disproportionate distributed along status groups and thus will influence the effects of IEO.

The different distribution of CSC by education-groups moderates the cultural capital transfer between them and thus the effect on IEO. (H3)

Dependent on e.g. cultural borders between status-groups or status-homophily (M. McPherson, Smith-Lovin, & Cook, 2001) in tie formation resulting in social closure, the effect of CSC will vary and the specific distribution underlying CSC will result in different likelihoods for ties between high and low status groups to form and – thus different IEO. In order to address this, we will consider the distribution of CSC when looking at the possible effects of collective social capital.

The cultural capital transfer-thesis stated here in our opinion is the most important path of effects of CSC on IEO while in theory – depending on the actual cultural aspect constituting a CSC – there have been discussed others. For example generalized trust can not only help to form ties but also increase the ease of enforcing educational norms.[13]

After the presented theoretical considerations on the relation between CSC and IEO, the next chapter will give an overview of two cultural properties that were defined as collective social capital: generalized trust and membership in voluntary associations.

1.3 The influence of generalized trust and membership in voluntary associations on IEO: Conceptions, research, causal issues

After having defined collective social capital (CSC) to be properties of geographic regions which can be believed to enhance the social connectedness of their members and establishing a theory that relates those properties to inequality of educational outcomes (IEO) we discuss and research two specific cultural properties: the level of generalized trust (GT) and the degree of people being a member in a voluntary association (VA). While there exist several other societal properties that have been suggested to be CSC [14] we chose GT and VA because they are traditionally well researched cultural contexts and for the availability of their measurements in many countries at different points in time. Both can be expected to increase the overall connectedness of society members (which makes them CSC *by definition*) and thus,

[13] See the explanation of Coleman (1988) on norm-enforcement through inter-generational closure. In short, he hereby denotes relations of parents subsequent to friendship of their children.

[14] For example van Oorschot, Arts, and Gelissen (2006) analyze the relevance of meeting friends and family for institutional trust and civism (which they define to be an index of trustworthiness and interest in politics).

deploying the previous assumptions, reduce IEO.
Before we concentrate on these possible effects of societal levels of GT and VA on education in detail we shortly review some research on patterns of variation and especially possible causes of both variants of CSC. As previously stated our interest is on the path linking GT (indirect by reduction of perceived transaction costs, Fukuyama, 2001b) and VA (direct by increasing networks) to changes in the societal distribution of cultural capital and thus IEO. However since there are various other "social mechanisms" (Hedstrom, 2005) involved that might interfere this relation, we will not only report research on the effects of GT and VA on IEO but also the societal structure possibly causing them as well as IEO.

1.3.1 Generalized Trust

Individuals significantly differ in how much they trust others, which has attracted the attention of social research. The reason for the genuine popularity of this research on trustfulness stems from the hypothesized benefits to society. For example Coleman (1988) assumed that a person in a group of higher average trust will have less interaction costs [15], making it by subsequent consequences of augmenting social ties a beneficial cultural context. A necessary causal bridging hypothesis at the micro-level is that answers to trust questions are actually correlated with subsequent trusting actions for which Capra, Lanier, and Meer (2008) found support.
Trustfulness has been differentiated by the proximity to people that are trusted ("scope of trust" or "radius of trust" Fukuyama, 2001a). Apart from the more particular trust into members of ingroups one either identifies with or is more likely to interact with (e.g. trust into neighbors, co-workers, store members, church members), the term generalized trust (GT) denotes a believe that most of not personally known strangers are trustworthy and benevolent. For several decades survey participants stemming from different societies were typically asked whether they agree, that "most people can be trusted or one can not be careful enough" (e.g. WVS, ESS, EVS) and if people in general try to be "fair" (ESS) or "helpful" (ESS). A number of positive social consequences have been theorized and researched being positively influenced by GT: Following the argument of Arrow (1972, p. 357) that

[15] This reduction of transaction costs is plausible, because we can expect that trustful people will value the utility of interaction and cooperation higher, because they c.p. anticipate lower costs and possibly higher benefits. This potentially makes it easier, to get into contact and communicate with them.

"every commercial transaction has within itself an element of trust" there has been a high interest of research in the consequences on economic wealth (e.g. Knack and Keefer, 1997; Tortosa Ausina and Peiró-Palomino, 2012), growth (e.g. Algan and Cahuc, 2013; Knack, 2002; Krishna, 2002; Zak and Knack, 2001) and human development (e.g. Özcan and Bjørnskov, 2011). Other examples of possible benefits are higher levels of cooperation (e.g. Sønderskov, 2011), political participation (e.g. Bäck and Christensen, 2016), better societal conflict resolution (e.g. Justwan and Fisher, 2016), more favorable health outcomes (e.g. Carl and Billari, 2014; van der Veld and Saris, 2011) and higher individual well-being and happiness (e.g. Bartolini, Bilancini, and Pugno, 2008; Carl and Billari, 2014; van der Veld and Saris, 2011).

We here follow the question whether GT might reduce IEO. As discussed above, we expect GT to make interactions between random society members more likely and thus increase social ties and educational resources. Effects on IEO will occur only if the increase of educational resources from additional ties for students from higher status families is outweighed by the effects for students from lower status families.

Research indicates that those having higher educational degrees are more trustful (Frederiksen, Larsen, & Lolle, 2016) than those having lower education and one could conclude that this will increase their social ties, widen the gap in educational resources compared with lower status families and thus results in *higher* IEO. On the other hand we expect higher returns for GT for students from families of lower status because of their higher returns to educational resources. Beyond that a higher level of GT can be expected to especially decrease status barriers, because additional ties to others include people from other status and cultural background that one would not be connected to without having this basic trust. The higher GT of higher educated has also been shown to be accompanied by a wider scope of trust (Frederiksen et al., 2016), e.g. having higher trust in people from other nationalities[16]. As status barriers are related to social closure actions of higher status groups, GT can be especially expected to reduce these barriers and thus transfer educational resources from higher to lower status students and reduce IEO. Given that the social mechanisms work into the opposite direction, the total effect cannot be inferred theoretically but has to be determined empirically.

To prepare this analysis we complete our report of research on GT with several other facts of relevance. First, comparing levels, causes and effects of aggregated GT between countries and drawing conclusions about its causal relations has been

[16] This can be explained not only by being more cosmopolitan but also by having more such interactions.

subject to several validity concerns. There is an ongoing debate on measurement variance, especially if survey participants in different countries really understand the same thing when they are asked to report their perceptions about the trustworthiness of people not known to them. Such could be induced by a different association of who is meant by "most others" or in short: measurement of different scopes (Delhey, Newton, & Welzel, 2011) and especially discrepancies in imagination of an unknown person as a citizen of the same country, religion, cultural background or a foreigner from another country, religion, culture (Torpe & Lolle, 2011). Since participants of ESS and WVS are asked several questions that are supposed to measure the same construct of GT, this allows for application of single (CFA) and multi-group confirmatory factor analysis (MGCFA) this problem has been assessed in parts. Freitag and Bauer (2013) find scalar invariance allowing for comparison of means across most of the countries of their analysis, while Reeskens and Hooghe (2007) find at least metric equivalence for the three items-scale.

Since the influential hypothesis of Putnam (2000) that collective social capital is declining in the US, research replicated this global trend for GT with various sources. Fairbrother (2014) shows controlling for economic wealth and inequality that from 1981-2008 there has been an overall trend for decline in GT in 97 countries. However there is strong variation between and opposite trends in certain countries of the world (e.g. Paxton, 1999).

In anticipating our considerations on possible confounders, we also give a short review of the research on causation of GT.

First of all, there is good reason to believe in some kind of biological heredity of GT. Based on a survey of 1012 twins in the Netherlands Van Lange, Vinkhuyzen, and Posthuma (2014) estimate that genetic factors explain about 5 percent of the variation of GT. Freitag and Bauer (2016) find that particular trust (in friends) and GT (in strangers) both depend on a subset of the traits of the five-factor-model (FFM; especially agreeableness, openness and conscientiousness). It is also shown to be positively correlated with intelligence (Carl, 2014), while Carter and Weber (2010) relate it to the additional cognitive capacity to detect lies.

However, besides this biological factors the findings suggest that the by far biggest part of variation can be explained by social experiences. In consequence a vast number of projects has been devoted to find societal determinants of building GT and by identifying specific individual experiences inside of macro-level processes that lead to or destroy GT: On the individual level GT has been shown to be strongly influenced by early events in life (Kuwabara, Vogt, Watabe, & Komiya, 2014) and in spite of strong influence of drastic events for many people being at a quite stable level (Baumert, Halmburger, Rothmund, & Schemer, 2017). Most people seem to get more trustful when they get older and married persons are also more trustful than those being not married (Valdivieso & Villena-Roldán, 2014). In terms of e.g. gender experiences there are mixed results ranging from men being more trustful to no differences or results that such differences depend on (e.g. labor force) equality between men an women (Mewes, 2014). Several negative experiences in the life course like economic stress (Lindstrom & Rosvall, 2016), changed financial conditions and decline in personal health have been shown to erode GT (Sturgis, Patulny, & Allum, 2009).

Individual levels of trust are also cultural inherited in inter-generational relations (Uslaner, 2008) and conserved under changed conditions. Based on the analysis of migration episodes into 130 different countries Helliwell, Wang, and Xu (2014) estimate that the trust level of migrants can be explained to about one third by the level of trust of there origin countries.

Beyond focusing on individual conditions, several social context seem to be important for shaping the GT of individuals: A common theoretical and empirical concept is that trust develops in trustworthy environments – be it individuals one interacts with, neighborhoods or government institutions. The average level of corruption is related to individual level trust in people of another nationality. Charron and Rothstein (2016) hypothesize that in reality education changes the capacity to evaluate the trustworthiness of an environment and thus is moderating the relation between government and GT.

Growing up in denser social communities has also been researched for being a building block of GT (Lo Iacono, 2018). Several studies show that higher levels of GT is associated with properties of welfare states (van Oorschot & Finsveen, 2009; Wallace & Pichler, 2007). Relations to inequality are mixed: While Bjørnskov (2007) finds a negative correlation with economic inequality, Olivera (2015) and Hastings (2018) were not able to reproduce this. Hu (2017) finds that those who perceive society to have run short of inequality as well as those finding the level of inequality drastically to high show lower values of GT. Rapp (2016) relates trust to societal conflicts by showing that lower trust in societies is associated with higher opinion polarization. While Bjørnskov (2007) reported the level of ethnic diversity being related to less social trust others have shown this relation to be moderated by attitudes and other societal factors (Dinesen, 2011; Kesler & Bloemraad, 2010). Participation in voluntary organizations seems also to help building trust in (personally known or unknown) others. Concerning the US in the year 2000 Glanville, Paxton, and Wang (2016) estimate that two third of this effect is due to

the higher network diversity resulting from participation.
All in all research allows treating GT as a acquired latent trait of individuals that is, however, also strongly shaped by broader cultural patterns and societal contexts. In terms of causation the current state of research shows a puzzling pattern of covariation with other variables which suggests a broad rang of up today not very well understood causative factors at the macro-, meso- and microlevel that results in characteristically variations across countries (Algan & Cahuc, 2013).

1.3.2 Participation in voluntary associations

Another form of well-researched collective social capital is the (average) participation in voluntary associations (VA), that is theoretically and empirical shown to not only being increased by but also to increase generalized trust (GT).[17] While in consequence their might exist mediations of effects of VA and GT on IEO, the share of people or average time spent being engaged in voluntary associations, taking into account the previous considerations, can be regarded being related to the density of social ties (Paxton, 2007). This, however, is only true if there exist no functional structures that are analogous (in terms of network extensiveness and segregation) and cannot be controlled for, e.g. private meetings of families being similar of ties.[18] While the societal effect of the level of participation in associations might strongly vary by type of association, specific topic, membership criteria (*Can everyone join or are there exclusive requirements for participation?*) and social composition (*Who is actually associated?*), associations can be expected to increase the average number of ties (making it CSC)[19]. Second, associations have the potential to bridge status boundaries. Both tendencies will, given the previous assumptions, have effects on IEO. In short the overall effect on IEO is dependent on the absolute level of participation in associations, status-specific differences in participation and

[17] People with higher levels of generalized trust participate more often in civic organizations and by participating additional increase their level of trust (Botzen, 2015).

[18] To understand this imagine two different villages. In village A people participate the whole weekend in meetings of public associations. In village B families meet befriended families for the whole weekend. Whether interaction and exchange is higher or lower will depend on factors like segregation of ties and the intensity of social relations in both ways of spending leisure time. When it comes to testing for the overall effect by comparison of countries with different levels of VA, such tests will only be valid when making the in our opinion plausible assumption that the functional equivalents (e.g. private meetings) do not fully compensate for the lower participation in voluntary associations, which we assume to have more extensive social networks.

[19] The in our opinion sound assumption that participation in voluntary associations actually results in a higher volume of acquaintances has been shown e.g. for Spain (Lubbers, Molina, & Valenzuela-García, 2019).

dropout-rates (Wiertz, 2016) as well as the segregation and openness or social closure of the according associations. By using the Social Capital Community Benchmark Survey 2000 Glanville (2016) shows that participation in voluntary associations in the United States is at average accompanied by a more diverse social network in terms of socio-economic positions and ethnicity.
In this paper we are not able to control directly for this possible national differences and just have to leave this considerations to future research. This said, countries with higher level VA are expected to show lower levels of IEO.

1.4 Data, Operationalization and measurement issues

Our data analysis included various data sets of 50 countries and an evaluated time-span between 1985 and 2015. Micro-data from the Programme for International Student Assessment (PISA) was used for a model of the relation of socio-demographic background variables and educational performance of 15 year old students in the participating countries. This data set was augmented by context data on social capital from the World Values Survey (WVS)[20], the European Social Survey (ESS)[21] and the European Values Study (EVS)[22].

1.4.1 Country sample selection and missingness strategy

Since we were interested in model-based inference we treated the surveyed properties of countries in principle being (erroneous) measurements that are caused by a common causal mechanism. Because cross-country analysis in general suffers from few cases on the country level our selection strategy was guided by maximizing the possible statistical power by keeping as many countries as possible for the question at hand. For our main analysis we decided to use a sample consisting of 50 countries that participated in the years 2006-2015 consisting of round 1.5 million surveyed students (Supplement table 6.3.1, p.108).
We excluded item-specific non-response on level one and also for the sources of the

[20] Inglehart et al. (2014a, 2014b, 2014c, 2014d, 2014e, 2014f)
[21] ESS Round 1 (2002), ESS Round 2 (2004), ESS Round 3 (2006), ESS Round 4 (2008), ESS Round 5 (2010), ESS Round 6 (2012)
[22] EVS (2011a, 2011b, 2011c, 2016)

context data by listwise deletion.[23]

For modeling time effects we had to make a compromise between the number of available countries and time points. Country set 2 included 34 countries participating 2000-2012 with all in all 1.3 million students (Supplement table 6.3.2, p.110). Country set 3 included 38 countries with 1.2 million participants in PISA waves 2003-2012 (supplement, Table 6.3.3, p.111).

1.4.2 Educational inequality

Alike to Schütz et al. (2008) we conceptualize IEO as c.p. linear relationship between the familial socio-economic status and the PISA test of math performance.[24] The maximum socio-economic status of the parents which was operationalized by the International Socio-economic Index (ISEI, Ganzeboom, De Graaf, and Treiman, 1992) derived from students answers on the job of their parents.[25] The mean math scores estimate based on the plausible values (6.2) was 470.1. Over the used waves the computed standard deviation was at average 102 points difference in math performance scores. For estimation of multivariate relations we also used separate models for each PV and pooled the results according to the standard combination of imputed models (Rubin, 1987). The resulting coefficient for ISEI was treated as a measure of the degree of dependence of educational performance on the status background. Further we examined moderation by country-level contexts.

[23] Since our context analysis compares implicitly means of effects across countries this induces an unclear bias. In consequence, the sample might systematically deviate from the population of the sampling frame while the aggregated contexts measures are also biased due to different missingness patterns of the WVS, ESS, WVS samples. Nonetheless, we withdrew from multiple imputation because we were not able to develop an adequately justified missingness model.

[24] We also did several robustness checks for reading and science scores.

[25] In theory there potentially arise several problems in terms of validity (e.g. problems due to the introduction of a random error due to imprecise knowledge or differences in perceiving or comprehending social desirability that might be dependent on the previous educational biography of the students or cross-country measurement variance). However, because there has been shown that self-reports of students are highly correlated with parents' reports (e.g. for Germany Maaz, Hausen, McElvany, and Baumert, 2006 and Sebastian, Moon, and Cunningham, 2017) we use the ISEI scores as status indicator.

1.4.3 Measurements of country-level collective social capital

We operationalized CSC by aggregation of micro-level variables out of a pooled data set from WVS[26], EVS[27] and ESS[28]. Since Puntscher, Hauser, Walde, and Tappeiner (2016) warn of the consequences of confounding levels when applying the still common technique of factorizing on the individual level and aggregating individual factor scores afterwards, we decided to use no factors but single-item questions.[29]

For both social capital measures a design-weighted mean was computed for every combination of country and year – resulting in the share of people having the according property. These and all other country-level context variables including controls were computed for the time period students were able to experience them. For this purpose missing values were first imputed for country-time-combinations by interpolating between valid measurements and eventually extrapolating for previous or subsequent years by fixing the last valid value. Finally, this resulted in a table of real and imputed values for every year and country. This yearly contextual mean values – smoothed linearly by interpolation – were averaged for all years a specific student had lived in this country-year context. This resulted in one specific value for each student and context variable that corresponded an average of the context for the values of 15 years before the time of the according PISA survey (Supplement table 6.5, p.115 ff.).

1. *Generalized trust.* For reasons of availability across all measured waves of the surveys we chose the "trust or can't be careful enough"-version of the question although Lundmark, Gilljam, and Dahlberg (2016) find by comparison of differences in wording and scale points that shorter, not fully balanced versions of the question have higher validity.
   We transformed the answers from different waves from either binary (WVS, EVS) or Likert-scales (ESS) into a quasi-metric scale of approval (varying from 0 to 1 and in case of being undecided recoded to 0.5). These weighted values

[26] The world values survey (WVS) was conducted in different countries at different times ranging from 1981-1984 (W1), 1990-1994 (W2), 1995-1999 (W3), 2000-2004 (W4), 2005-2009 (W5) and 2010-2014 (W6).

[27] The European values survey (EVS) was conducted in different countries at different times ranging from 1981-1984 (W1), 1990-1993 (W2), 1999-2001 (W3), 2008-2009 (W4).

[28] The European Social Study (ESS) was conducted in the years 2002 (W1), 2004 (W2), 2006 (W3), 2008 (W4), 2010 (W5), 2012 (W6), 2014 (W7) an 2016 (W8).

[29] A more elaborate analysis of our analysis would require the usage of multi-group confirmatory factor analysis.

were averaged for every country[30] having at least 100 valid values resulting in an estimate of the percentage being trustful in strangers (Supplement figure 6.4, p.119).
The resulting data estimates that the country with the lowest level of trust is Columbia for which the average live time value of PISA 2015 students is about 0.1, while the highest trusting country was Sweden in which PISA 2000 students lived in a context where trust was about 0.63.

2. *Membership in Voluntary Associations.* Intending to get a rough estimate of national differences in participation we combined data from WVS and EVS on the average membership in associations[31]. While there were given detailed categories of associations[32] the comparability and category changes across waves made us use all waves that asked for participation exhaustively, also asking for an 'other' residual category. Although we theoretically are interested in active participation in associations there were several inconsistencies in the data. Questions on voluntary work for different associations are available only for WVS1990-1994 and EVS starting from 1990. Besides that they were conditioned on unpaid work while there is no question on paid work. Since the distinction between active and inactive membership was also not available across all waves of EVS/WVS we had to use the proxy estimate of membership as second best alternative which we believe to be correlated with active participation in this association. [33] As for generalized trust, we computed average values for the participation in associations by usage of a recoded indicator variable whether a participant was member of at least one association. This resulted in the share of people that were member of at least one association in the according time and country. These raw measures of the national average share of members in association – while having a somehow consistent level over the whole time period – was quite noisy in terms of differences in measurement from wave to wave. This indicates in part

[30] We decided to excluded means for countries that had only 100 or less responses in this year.
[31] We did include ESS, since questions related to participation in associations are non-exhaustive and conditioned on political associations that "improve things" or prevent them from "going wrong"(EVS, 2006, 2012, 2013a, 2013b; EVS / GESIS, 2013).
[32] The categories of associations include social welfare, religious group or church, cultural associations (related to arts, music or educational), trade unions, political parties and groups, local community, environment, professional, youth, sports and recreation, women's rights, peace, animal rights, consumer interest and self-help groups (Inglehart et al., 2014a, 2014b, 2014c, 2014d, 2014e, 2014f).
[33] The estimates of average national active participation, however, might be biased if there is a different ratio of inactive to active members.

real changes and measurement problems (Supplement figure 6.5 p.120). This measurement error, however, in part will be mitigated for we also averaged over the years the students lived in the specific societal context of average membership in associations. In consequence we generated a rough measure of the national level of participation in association that contextualized the educational career of the students in PISA.

3. *Variants conditioned on education and distribution across the population.* For both measures the education-group-specific distribution varies in the ESS sample and was taken into account for the analyses of the effect of collective social capital. We computed variants of the life-context averages for levels of different educational background. Measures conditioned on high education included the values of tertiary educated. The measures conditioned on low education included the values of those only having secondary education or lower.

1.4.4 Control of confounders

1. *Preliminary consideration on controls for context effects.* Unobserved variables are a serious problem to all survey-based social analysis and can only be addressed by identification and recognition of such sources. This problem for comparative analysis of contextual effects is doubled because social outcomes are explained by aggregates in relatively few countries varying in various social relevant aspects. Thus there is a high danger of estimation bias by under-specifying models and not observing variables confounded with the dependent and the independent variable.[34]

   While it is a common principle that confoundedness has to be controlled for and the according variation captured at the corresponding level, context analysis with a combination of micro-macro and macro-micro-relations from different data sources adds some complications that are schematically depicted in Figure 1.1. Uppercase symbols denote country-level and lowercase letters micro-level entities. Our focus lies on the macro-micro relation of path 1 where contextual generalized trust or participation in voluntary associations

[34] This is especially problematic for the analysis of effects of cultural properties of countries, because these only moderately change over time. Therefore it is impossible, to apply common strategies to isolate effects, like e.g. explaining changes in outcomes by changes in explaining variables.

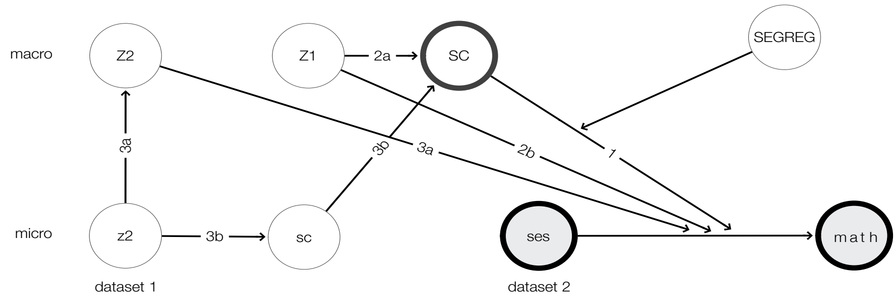

Figure 1.1: Possible confoundedness of country-level measurements of CSC

(SC) moderates the micro-level dependence of educational outcomes of students on the parental socio-economic status of their parents (short: ieo). Confounders in cross-country analysis are obviously all variables measured at the macro-level that are related by a macro-macro link (path 2a) to SC and by a macro-micro link (path 2b) to ieo. The commonly applied method of aggregating variables from different sources (here: WVS, ESS, EVS) and merging them as macro-context variable to other micro-level surveys (here: PISA) results in additional problems of confoundedness. Since the individual-level generalized trust and participation in voluntary associations (sc) as previously presented must be theoretically expected to depend on various micro-level variables of which we depict only one denoting it z2, SC will also systematically correlated with z2 and its country-level composition Z2 (paths 3b). When the country-level composition z2 or a measure derived by aggregation of z2 (Z2) must theoretically expected to influence also ieo, all variables in a structural relation like z2 will be confounders for the relation SC to ses and math (via paths 3a and 3b) – in result making causal reasoning of context effects really puzzling. Since sc and SC are sampled from a different population than ieo z2 cannot be controlled for in a micro-level model (for ieo). The only solution for this confoundedness[35] is to include aggregated variables describing the composition of z2 by macro-level controls Z2 to the micro-level model which is limited by the low statistical power (Cohen, 1988) of view cases on the macro-level (country).[36]

[35] This problem is not specific to our question but potentially occurs in *any* micro-model that uses context variables derived from other sources that are still commonly used in the analysis of effects of education systems, macro-economic conditions, as well as political and welfare regimes.

[36] Another possibility would exist if the populations of context data source and primary data source are so similar that controls for z2 added into a micro-level model could be a proxy for Z2. That is obviously not the case for the populations of 15-year old students and the total population in the country.

2. *Used control variables.* As previously explained *individual-level confounders* of the macro-micro relation of context variables would have to somehow "cause" them – either by causal influencing it directly (micro-macro-link) or by intermediary relations (e.g. micro-micro-macro-link). There are obviously many moderators of ieo at the micro-level (properties and experiences of students that mitigate the relevance of socio-economic status (SES) such as e.g. having additional cultural capital beyond family). However, those could be confounders of our question only if their individual value would also change the country-level value of SC. While it is unconvincing and ignorable that an individual student property should influence a country-level property there is another role of micro-level controls in context analysis. By improving the model for the relevant micro-level relation (ieo), disturbances from other micro-level influences can be excluded. If the included population (PISA students in schools) is correlated with national level properties it might function as proxy. But even if a variable does not contribute to controlling confounders on higher levels, the reduction of the micro-level residuals also helps to increase the precision of the estimates of variance components of higher levels by reducing random cluster homogeneity.
   Following the previous argument we only sparsely "controlled away" micro-level variance and tried to avoid mediators of ISEI (like familial wealth indicators). Since our focus lies on the influence of parental socio-economic status on the educational outcomes of students, indifferent to the social mechanisms this relation is realized by, we are in danger of drawing from this variance when including correlated variables.
   On the individual level, we tried to separate the effects of SES of those of *migration* (recognizing other compositional differences related to migration) by inclusion of two dummy variables for *migration experiences in second generation* (either father or mother migrated) *or first generation (student migrated).* We also included the variable *gender* that should be unrelated to the SES-dependence of math but explains a considerable part of the variation in math performance and thus should increase estimation precision. We decidedly did not include several other routinely included micro-level variables for other reasons (e.g. age because school entry time is a likely mediator of SES-specific outcome differences.)
   We also included some controls at the *school level* although our focus lies on the explanation by macro-level variables. First of all we controlled for the school being in a *town smaller than 30.000 inhabitants* (from PISA's

school questionnaires, PSQ) for this regional variation might be the source of differences in both IEO and CSC. We controlled for the *size of the school* (school questionnaire) since differences in the average size of schools might change the realization of collective social capital as well as being related to IEO. Other sources known to be related to IEO were included for being possibly influential to or proxies for variables that might influence collective social capital: *Private schooling* (PSQ), and the *student-teacher-ratio* (PSQ) at the specific school.

In consequence of the previous considerations of potential confoundedness of CSC and IEO we also included several *country-level controls* that we had to introduce sequentially in different models because of the limitation of the maximum number of higher level variables that can be included into still identifiable models. Since the economic wealth of a country could be related to GT (by funding of infrastructure for building and maintaining trust or opportunities for public meeting) and VA (by public funding of clubs and associations) and also can provide resources that (dependent on the concrete usage) change IEO, we controlled for the *logarithmized GDP per capita* (measured in current international PPP)[37] (Figure 6.7). For the same reasons we also controlled for the resources directed into the education system for an average student for which we used the proportion of educational expenditure per student as share of GDP per capita[38] as a more concrete measure of the potential means to reduce IEO. We additionally controlled for the inequality in the income-distribution by inclusion of the *Gini-Coefficient*[39] to account for possible influences on CSC as well as the national variation in the availability of this resources across status groups related to IEO (Thorbecke & Charumilind, 2002).[40] Educational systems differ also in the *yearly hours students spend at school*, which is an indicator of the time spent in the same informational environment. Because our main argument is related to cultural capital differences that result from differences in experiences out of school,

[37] Unesco Institute of Statistics (UIS). Indicator: `DEMO_DS/NY_GDP_PCAP_PP_CD`. Downloaded from http://data.uis.unesco.org/ on 2017/08/29. The reasoning behind computing the logarithm was the expectation of decreasing returns which also mitigates the existence of extreme upward outliers like Qatar.

[38] Unesco Institute of Statistics (UIS). Indicators: `EDULIT_DS/XGDP_FSGOV+XGDP_02_FSGOV+XGDP_1_FSGOV+XGDP_2T3_FSGOV`. Downloaded from http://data.uis.unesco.org/ on 2018/9/15.

[39] World Bank, Development Research Group. Indicator: `SI.POV.GINI`. Downloaded from: https://data.worldbank.org/indicator/SI.POV.GINI on 2018/10/18

[40] While health differences of students might account for math differences we did not control for differences in the health system by including the spending in the health sector since we expected the health issues of the 15 year old students to be a minor source of variations.

the time spent in school is related to IEO. Because it might also be a source of higher national CSC, we controlled for the average hours as reported by the OECD in school.[41] Finally we controlled for the *official age of entrance to primary education*[42] (Figure 6.9) since this will not only have an influence on IEO by changing the times students were in the school context and thus had more similar experiences of children than in their families but might also be related to the generation of CSC. As previous explained for SC-context variables, we computed for every student a value that specifies the average over the years she spent in the contexts of this macro indicator. Only entrance age was linked to the year the students entered school instead.

1.5 Analysis

To answer the question whether and how inequality of educational outcomes (IEO) is related to collective social capital (CSC), we computed several hierarchical three-level models that try to explain the educational outcomes of pupils in schools in countries for the waves of PISA and different performance measures. Here we primarily focus and discuss the models related to the math scores for the PISA 2012 survey. [43]

The students' results in the performance test are a consequence of all personal traits and previous experiences including the country-specific different CSC context on which the focus of this paper lies. Homogeneity of the test scores on higher level is due to all similarities in experiences and uncontrolled composition. For example school-level homogeneity is not only result of implementations of education but also due to prior institutional performance selection and composition differences of schools, which also mirror regional or neighborhood-differences. Alike, country-level homogeneity is influenced by compositional differences not controlled for. Although we not intend to analyze and explain the school-level homogeneity, we include it for decreasing disturbances in the identification of genuine country effects.

For a preliminary assessment of the overall variation of performance scores across 15485 schools and 50 countries we decompose the variance in math performance into parts on the according levels by computing an empty model for math performance.

[41] Because of availability in only 33 countries we computed a separate subsets of model for this control variable'

[42] Unesco Institute of Statistics (UIS). Indicator: EDULIT_DS/299905. Downloaded from http://data.uis.unesco.org/ on 2019/01/13.

[43] The results of additional models and variants using different controls are available in the supplement to this article (Section 6.7, p.128).

This contains only the variance components of the random country- and school-level intercepts and is used as baseline model (Table 1.1, Model 1).[44] The mean math score over all countries, giving each country the same relevance and correcting for deviations from random sampling of school and student inside this countries[45], is estimated to be 460.8 ($\hat{se} = 0$). The intra-class correlations[46] shows that about 30 percent of the total variation in math scores is on the school level, while 26 percent of the variation can be attributed to sources associated with the country level.

Model 2 adds the highest parental occupation-based status background (ISEI) while controlling for the students' gender and being migrant (1st gen immigrant) or being a child of a migrant (2nd gen immigrant).[47] Concerning all variables being tested significant, the model indicates a salient status-based inequality of educational outcomes[48]. One can, however biased for ignoring heredity, estimate that if a child of least favorable status background would have been born into the most favorable status background[49] this c.p. would result in a noticeable math score increase of about 55 points. Model 3 introduces two school-level controls.[50] Students in small town schools perform at average -18.3 score points less, while students in private schools – due to selection or schooling – perform 18.7 points higher. Comparison of Models 2 and 3 depicts that the IEO is not drastically changed by the inclusion of our school-level controls.

By computation of the same models for the PISA surveys 2000 to 2012 we can see that this dependence of educational test scores on the family status moderately declined for the countries in country set 2 (see 6.3.2) (Supplement figures 6.11 - 6.12, p.126).

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[44] The asterisks in all subsequent models follow the usual conventions:
$* := p < 0.05, ** := p < 0.01, *** := p < 0.001$

[45] For the applied weighting techniques see Supplement, section 6.1, p.106.

[46] See e.g. Hox, 2002

[47] Female students of this country sample are estimated to perform at average -14.9 points lower than male students in math tests, second generation immigrants at the average perform -12.2 points weaker and students that had own migration episodes -17.8 points worse compared to native students. The introduction of this properties did not drastically change the variance proportions of the different levels.

[48] Note that we previously operationalized IEO as covariation of parental occupational status and math scores.

[49] Note that the difference from the highest to lowest occupational status ISEI_{max} scores varies between 11 and 89 $ISEI$ scores.

[50] We also did an more detailed analysis of our initial set of controls (section 2) of school level controls (Supplement table 6.6, p.6.6). For missingness of school-level variables we had to decide on a trade-off between under-control bias from missing school level variables and bias from non-randomness in the social missingness process leading to non-reply on school-level. For not dropping too many schools we had to exclude school size, which at least can be expected being imperfectly correlated with small town schools and the student-teacher-ratio, that turned out to be insignificant in the full control model with less cases (Supplement table 6.6, p.128).

After having established a suited individual- and school-level reference model, we can test our assumptions. In hypothesis 1 we assumed that a higher country level of social capital is associated with at average higher educational outcomes.
Model 4 thus introduces the country-level generalized trust (GT) and based on the test of the coefficient we have to reject the opposite assumption that there exists no association. According to this idealized model one can estimate that if 10 percent of the population in a country would believe that strangers can be trusted, this (at mean over all countries) would be associated with an about 24 points higher math performance of the students in this country.
Because of the high risk of macro-level confounders we controlled several variables that influence IEO as well as GT. Given the small number of cases on the country level and different availability of variables for those countries, we computed separate models entering this variables only one at a time and compared the estimated effect of GT prior and after (Supplement tables 6.8-6.10, p.130ff.). While logarithmized Gross Domestic Product (GDP), the economic inequality as measured by Gini and average educational expenditure, but not the estimates for average teaching hours and entrance age on the country level were tested to be significant when entered without GT, this was only the case for average teaching hours when entered together with GT.[51] Controlling for teaching hours[52] reduces the estimated coefficient of GT only moderately, e.g. resulting in a reduction of the estimated difference of math scores of two countries, one with a 10 percent more trustful population than the other, by only 0.95 PISA score points. Based on our simple control strategy we can conclude that there is a salient covariation of higher levels of trust and better math result, which is compatible with H1.
To test hypothesis 2, that CSC might reduce inequality, as a reference model, we first allowed for country level variation of the effect of parental occupation background on math scores by introducing random slopes (Table 1.2, Model 5) and used this model as reference. We find the commonly reported pronounced country-level differences in how strong the performance of students depends on the parental status.[53]. Model 6 introduces a cross-level interaction to test the hypothesis

[51] While it was not possible to infer the exact reason, we can not neglect, that this is an artifact introduced by the outliers India, Chile and Mexico that that the OECD reports to have more than 800 yearly teaching hours. For the graphs of the covariation structure see Supplement, Figure 6.10, p.125.

[52] The marginal effect of teaching hours is actually estimated to be negative which seems counter-intuitive and to point to confoundedness. The reason is not fully understandable based on our analyses, however, it might be caused by correlations of the country level composition of school types and special needs classes.

[53] The variance component of the slope for the parental background has to be interpreted in the scale of the coefficient for the parental ISEI. E.g. two standard deviations of the

that country-level GT moderates the dependence of math scores on parental status. Based on our model we have to reject the view, that there exist no such association. The effect, however, is opposite to what we hypothesized. The model estimates that if the share of trustful people in a country is e.g. not 10 but 20 percent, this would be associated with an additional math score difference between students from lowest and highest status background (that in this model is estimated to be at average 36 scores higher) by additional 8.9 scores in the math test. Opposite to H2, countries with higher GT are also associated with higher IEO. We further estimate the same moderation effect, but conditioned on the trustfulness of those having tertiary education (Model 7) or those who acquired an educational certificate below secondary education (Model 8). Both moderation effects are estimated being even higher compared to the CSC of the whole population. Students from families of higher status seem to profit even more, if especially the lowest and the highest educated of a country are more trustful. While the underlying social mechanism has to be analyzed more deeply, we can take this as hint that while H3 is relevant, the mechanisms behind are more complex.

We analyze the same set of models also for associational membership (Table 1.3): From model 10 we can analogous estimate that if in a country 10 percent more of the citizens are being members of voluntary associations, this is associated with an at average 6 points higher math performance.[54] Finally, Model 12 tests for the interaction of associational membership and the influence of parental status background which however turns to be insignificant. There is no evidence that the share of people being in associations is associated to the inequality of educational outcomes.

1.6 Conclusion

We presented a theory that hypothesized a causal relation between collective social capital or aggregate social capital on country-level and inequality of educational outcomes. We put this theory to a first test by combining PISA and an aggregate dataset from different large-scale surveys.

Our analysis shows that country-level trust in strangers as well as the share of members in associations is associated with higher math scores of students in this

between-country differences in the coefficient for parental background can be estimated to lie around
$0.7 \pm 2 \cdot \sqrt{\tau^2_{country,var(isei_{max})}} = 0.7 \pm 0.2$.

[54] The same estimate controlling for average teaching hours was 3.7.

countries. Students perform better in countries whose inhabitants are more trusting and that show a higher share of association members.

However, we found no evidence for our main hypothesis of an decreasing effect of those examples of collective social capital on the inequality of educational outcomes. In fact, the cross-level interaction between the parental status and generalized trust was opposite to our expectations, suggesting that countries with higher levels of trust show *higher* levels of IEO. The cross-level interaction for the share of members in associations was insignificant.

The author is aware of the limits of this basic analysis that neither can rule out reverse causation nor the confoundedness of the analyzed associations with other country-level properties. We gave a detailed overview of the problems that arise for all similar studies that merge aggregate variables derived from other large-scale data sources to a micro-level dataset like PISA.

We hope that our preliminary sketch incents future research that in our opinion should include more precise controls and should also consider and test for differences in status segregation.

Table 1.1: 3L MLM: Covariation of math test scores with parental occupational status and country average of *generalized trust* (1)

	Math Performance			
	(1)	(2)	(3)	(4)
Intercept	460.972 ***	437.677 ***	441.891 ***	354.036 ***
	(7.588)	(7.021)	(7.14)	(15.111)
(Parental) ISEI		0.698 ***	0.683 ***	0.683 ***
		(0.053)	(0.054)	(0.054)
Generalized trust				240.066 ***
				(34.266)
– School level Controls –				
Small Town			-18.311 ***	-18.334 ***
			(2.724)	(2.722)
Private School			18.677 ***	18.645 ***
			(4.039)	(4.04)
– Indiv. Level Controls –				
Female		-14.924 ***	-14.948 ***	-14.947 ***
		(1.016)	(1.019)	(1.019)
1st Gen Immigrant		-17.79 *	-18.193 *	-18.198 *
		(7.576)	(7.444)	(7.443)
2nd Gen Immigrant		-12.249 **	-12.697 **	-12.703 **
		(4.625)	(4.681)	(4.681)
– Variance Components –				
$\tau^2_{country}$	2812.072	2553.458	2483.978	1467.854
	(449.395)	(434.478)	(418.489)	(362.537)
τ^2_{school}	3230.714	2695.919	2556.096	2556.219
	(285.837)	(244.646)	(257.33)	(257.343)
σ^2	4827.041	4624.404	4624.584	4624.572
	(238.566)	(213.611)	(213.943)	(213.942)
– Intra Class Corr. –				
$\rho_{country}$	0.259	0.259	0.257	0.17
ρ_{school}	0.297	0.273	0.264	0.296
ρ_{σ}	0.444	0.468	0.479	0.535
n students	363623	363623	363623	363623
n schools	15104	15104	15104	15104
n countries	50	50	50	50
Largest FMI	0.005	0.011	0.055	0.055

Table 1.2: 3L MLM: Covariation of math test scores, parental occupational status and country average of *generalized trust* (2): Models for *education groups*

	Math Performance			
	(5)	(6)	(7)	(8)
Intercept	440.521 ***	365.993 ***	357.283 ***	374.534 ***
	(7.106)	(15.467)	(16.524)	(16.893)
(Parental) ISEI	0.696 ***	0.429 ***	0.373 ***	0.442 ***
	(0.04)	(0.083)	(0.085)	(0.081)
Generalized trust...				
...Total Population		203.652 ***		
		(35.808)		
...only high educated			194.999 ***	
			(32.2)	
...only low educated				195.071 ***
				(43.161)
ISEI*Gen. trust		0.729 **		
		(0.232)		
ISEI*Gen. trust HiEdu			0.755 ***	
			(0.2)	
ISEI*Gen. trust LoEdu				0.749 **
				(0.253)
–Variance Components–				
$\tau^2_{country}$	2219.531	1489.036	1467.957	1605.511
	(426.063)	(343.793)	(317.053)	(371.553)
$\tau^2_{country,var(ISEI)}$	0.073	0.064	0.062	0.064
	(0.012)	(0.013)	(0.013)	(0.014)
$\tau^2_{country,cov(ISEI,\_cons)}$	1.441	-1.178	-1.473	-0.922
	(2.124)	(2.043)	(1.968)	(2.107)
τ^2_{school}	2582.897	2583.03	2582.902	2583.068
	(271.42)	(271.413)	(271.388)	(271.42)
σ^2	4595.077	4595.065	4595.078	4595.061
	(216.87)	(216.868)	(216.868)	(216.868)
– Controls –				
School:SmllTn,PrvtSchl				
Female	-15.08 ***	-15.08 ***	-15.08 ***	-15.08 ***
	(1.022)	(1.022)	(1.022)	(1.022)
1st Gen Immigrant	-17.905 *	-17.907 *	-17.909 *	-17.906 *
	(7.276)	(7.275)	(7.275)	(7.275)
2nd Gen Immigrant	-12.274 **	-12.275 **	-12.275 **	-12.274 **
	(4.639)	(4.638)	(4.638)	(4.638)
n students	363623	363623	363623	363623
n schools	15104	15104	15104	15104
n countries	50	50	50	50
Largest FMI	0.053	0.053	0.053	0.053

Table 1.3: 3L MLM: Covariation of math test scores with parental occupational status and country-level *percentage share of associaton members*

	Math Performance			
	(9)	(10)	(11)	(12)
Intercept	445.032 ***	413.952 ***	443.786 ***	417.953 ***
	(6.768)	(15.714)	(6.739)	(13.6)
(Parental) ISEI	0.673 ***	0.673 ***	0.684 ***	0.604 ***
	(0.055)	(0.055)	(0.041)	(0.089)
Association Member		58.58 *		48.695 *
		(26.539)		(23.449)
ISEI*Assoc.Memb				0.149
				(0.169)
–Variance Components–				
$\tau^2_{country}$	2369.219	2176.403	2082.214	1949.097
	(410.416)	(465.434)	(404.561)	(416.386)
$\tau^2_{country,var(isei\_max)}$			0.075	0.073
			(0.012)	(0.013)
$\tau^2_{country,cov(ISEI\_max,\_cons)}$			1.611	1.201
			(2.17)	(2.274)
τ^2_{school}	2539.878	2539.939	2568.349	2568.423
	(263.647)	(263.646)	(278.447)	(278.451)
σ^2	4592.782	4592.776	4562.644	4562.637
	(220.621)	(220.622)	(223.334)	(223.334)
– Controls –				
School:SmllTn,PrvtSchl				
Female	-15.067 ***	-15.067 ***	-15.204 ***	-15.204 ***
	(1.022)	(1.022)	(1.024)	(1.024)
1st Gen Immigrant	-23.425 ***	-23.427 ***	-23.115 ***	-23.116 ***
	(5.904)	(5.903)	(5.623)	(5.623)
2nd Gen Immigrant	-15.803 ***	-15.804 ***	-15.379 ***	-15.38 ***
	(4.225)	(4.225)	(4.153)	(4.154)
n students	350406	350406	350406	350406
n schools	14778	14778	14778	14778
n countries	48	48	48	48
Largest FMI	0.043	0.043	0.035	0.035

Paper 2: Do school-level differences in social capital shape IEO? School-level context effects of connectedness of students and parental school volunteering. [1]

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Abstract: We present a theoretical overview of the relation between individual- and school-level social capital and the educational outcomes as well as educational inequality. We try to answer four basic questions: Do better social connected students perform better? Is it beneficial to students when their parents are involved in school? Is it additionally beneficial to go to a school where all others are also better connected and more parents are involved? How is average connectedness and participation of parents in school activities related to the inequality of educational outcomes? Based on 50 countries surveyed in PISA 2012 we confront this theory by analyzing two variables: the reports of students on their own connectedness at school and the volunteering of their parents in school. Our results indicate that social capital matters at the individual as well as at the school level.
Keywords: Inequality of educational outcomes (IEO), social capital, collective social capital, parental school involvement, peer effects, social networks

2.1 Introduction

Educational outcomes and the inequality in terms of the socio-economic status of families are complex social processes, that are even harder to understand because they happen in social contexts. This article tries to shed light on a rather basic question: Does higher social capital on the school level (in terms of better connected students and higher parental involvement) help to mitigate inequality of educational outcomes?

First, we present more general considerations on the effects of individual and school-level social capital on educational outcomes which we apply to two kinds of social capital: connectedness of students and parental school involvement (2.2.1). After hypothesizing about possible consequences for educational inequality (2.2.4), we consider problems of identification and giving an overview over the data and variables used in our research(2.3). Due to the different topics and aspects involved, we report research at the end of the parts to which it contributes. We test our theory by using an estimate for individual school contacts of students and parental school involvement based on PISA data including 50 countries (2.4). Finally, we summarize our findings and put them into a larger context (2.5).

2.2 Theory

We first present theoretic considerations that explain effects of individual social capital and school-level social capital on the educational outcomes and inequality of education.

2.2.1 Effects of social capital on educational outcomes

Following basic resource theories and especially Bourdieu (1983), it can be assumed that educational outcomes are mainly shaped by differences in educational input resources (e.g. cultural capital and economic capital)[2] that are distributed unequally across families. Adolescent citizens have very different biographical experiences that are systematically related to status of their origin family[3] and result in differences in knowledge and skills, the availability of learning related goods and services, but also future-related preferences, expectations of life careers and academic self-concepts that shape motivations and learning behavior. In consequence, students are differently adjusted to the requirements of successful in-school learning. Amount and relevance of these differences are influenced by schooling, e.g. by implementing different curricula or other institutional settings in school (e.g. compensatory practices like remedial teaching).

Beyond what is (and can) be done by teachers, there are additional social interactions in or related to school, namely the ties between students and the relations of parents to other students or teachers. Social interaction is accompanied by automatic or deliberate exchanges of information and goods making them a resource or social capital (N. Lin et al., 2001)[4] that can become influential in a number of ways. The most obvious effect of ties on educational outcomes involves the transfer of cultural capital, namely knowledge and capacities. Additionally, social ties give access to *other education-related goods and services* (e.g. the borrowing

[2] While our arguments are focused mainly on cultural capital differences, economic resources can be a strong source of inequality when it comes to the affordance of early childhood care, access to private schools, availability of professional remedial teaching.

[3] Of course the transfer of cultural capital from parents to children requires the actual interaction between them and thus the parent-child-relations and family structure are both moderators of the relation between parental cultural capital and the outcomes of their children (Miller, 2014; von Otter & Stenberg, 2014). The analysis of Liu et al. (2014) implicitly shows that there exist cross-cultural differences regarding this relation.

[4] The term social capital conceptualizes ties as potential, as increased *opportunity* to acquire resources or achieve goals. In short we can imagine the individual social capital consisting of n possible contact partners denoted as j. Defining p_j to be the likelihood of interaction with partner j, R_j defining the resources of interaction pattern j and ϕ_j the likelihood of access to or transmission of R_j from j than the the utility from the ego-network of i is $U_i = \sum_{i=1}^{n}(p_i \cdot R_i \cdot \phi)$

of books, leisure activities with effects on education or the access to computers, which has been especially relevant to early adopters of the digital revolution). Finally, social ties affect educational outcomes in a number of other ways, e.g. by transmission of norms, by influencing preferences, aspirations (Buchmann & Dalton, 2002) and the self-concept (framing or reference group effects) or by giving emotional support.

Since social capital increases the availability of education-related resources, it increases individual educational outcomes. (H1)[5]

Besides effects of tie patterns of individuals, educational outcomes might also be linked to structural properties of networks in school which are an aggregate property of schools. Schools vary in how well students (and especially those of the same-age cohort) are affiliated with each other (e.g. average number of student ties related to possible ties, the density of ties in a school class). Such differences in school-level social capital form a social context that can be expected to impact the effect of schooling (net of individual ties and other school differences like different teaching quality) by changing in-school as well as out-of-school learning conditions and the availability of resources.

Another path linking school-level social capital to educational outcomes is *norm enforcement*: For example, Coleman (1988) stated the hypothesis that intergenerational closure [6] helps parents to achieve educational goals by coordination of standards and sanctions, which would increase the educational success of their children. Finally, as the tie density on the school level can also be an indicator of quality of relations and school climate, it might be associated with other beneficial effects. For example, denser networks at schools might at average prevent bullying (Springer, Cuevas Jaramillo, Ortiz Gómez, Case, & Wilkinson, 2016)), while a cohesion of most but not all might be a risk factor for bullying. Despite those other paths we hypothesize:

Schools with denser social networks are characterized by more communication and thus higher exchange and distribution of cultural capital and higher norm enforcement and in consequence better learning outcomes. (H2) [7]

[5] For example, the information available by a tie also depends on the position in a more extensive network. Dependent on what we experience and who we are related to, we have different information and are in a different social world, filtering certain aspects of social reality, perceiving others.

[6] Coleman (1988) reports that students friendship relations are often accompanied by the parents also getting into contact and befriending with each other and calls this tie pattern (parents interacting with the parents of the friends of their children) intergenerational closure.

[7] Note that heuristically we concentrate our argument on the number of social ties, while in reality quality of ties (frequency, emotional intensity) will also matter and moderate effects of ties.

While the simple theory presented so far predicts only positive effects of social capital, we nonetheless acknowledge that there might also exist adverse effects that could outweigh benefits. First, the previous argument of better distribution of information and faster adoption of behavioral patterns and preferences in denser schools might also hold for norms and behavioral patterns that are unfavorable for educational outcomes, e.g. deviant or risky behavior and crime (McMillan, Felmlee, & Osgood, 2018). The general argument by Portes (1998) that social capital could result in the "exclusion of outsiders, excess claims on group members, restrictions on individual freedoms, and downward leveling norms" can be applied also to social capital that is based on relations in school. This is also outlined by Van Rossem, Vermande, Völker, and Baerveldt (2013). Comparing the networks of 60 first-grade classes in Dutch elementary schools they found students in denser classes (controlling for various individual- and class-level characteristics) to have higher academic performance. Higher density, however, can also come at the price of "clique-like structures" that appear to lower academic performance and can foster behavioral problems. For example, as already mentioned, bullying can occur in classes of a majority of densely integrated students which decrease educational chances of the minority of "outsiders". Furthermore, one can expect another trade-off of social capital: As social contacts are costly in terms of resources and time, marginal utility of additional peer ties should be decreasing and there should exist a limit to its maximum accumulation.[8] Nonetheless, we only hypothesize and empirical test *positive* effects of social ties.

We subsequently deal with two specific kinds of social capital, social connectedness and parental school involvement. An instance for the first are all processes of knowledge or motivational transfers that are beneficial for educational outcomes. The latter are all kinds of educational outcomes that are mediated by interactions between parents and teachers on the one hand or parents and students on the other hand that also can transfer knowledge and motivation – be it by enabling parents to better assist their children in learning or better adaption of teachers to students needs by additional feedback. We apply both presented hypotheses to both types of social capital and report the previous state of research on the topic.

[8] We ignore the possibility of practices of students from higher status families that deliberate (or unknown to the actors) aim at the limitation of own ties to exclude others and thus increase the own relative position in grading.

2.2.2 Social connectedness and educational outcomes

Relations to other students can become a social capital associated with increased educational outcomes. If e.g. student A failed to understand her teacher's instructions, some friend B due to prior experiences (or cognitive capacities) might instantaneously help out or mobilize available complementary cultural capital (e.g. ask her mother). In any case A would profit from B's resources by having a tie to her. As previously summarized, one can think of many mechanism by which ties to peers might influence educational outcomes. Because they are not separable in our analysis, we subsume them altogether under the term education-related resources and hypothesize:

Students with more peer contacts have more access to education-related resources and thus achieve higher educational outcomes. (H1a) [9]

Beyond individual benefits from social capital, we postulate collective benefits from a higher average density of ties on the school level, which acts as an enabling opportunity structure for transfer of cultural capital.[10] A higher connectedness of students increases the educational resources that can be accessed by an additional tie to a random student in the school, because whether an interaction partner e.g. has a specific knowledge is dependent on previous communication with and co-learning from other students. Thus, the density of the networks on the school level should be of relevance for the amount of education-related resources that are available.[11]

Ties and their quality to students are also of relevance to some other mechanisms, that are not related to resources. For example, the school climate may be shaped by the degree of the students' interconnectedness. And the ties of students might be related to the teaching quality by influencing the communications in school. The previous argument on norm enforcement is also not limited to parents or teachers but we can hypothesize that denser relations of students are also a precondition for the enforcement of school norms that form a beneficial learning environment or school climate:

Since denser peer-relations at the school-level result in higher circulation of educational resources and better enforcement of beneficial norms, educational

[9] Note that we state general hypothesis by numbers and their applications to peer ties and parental school involvement by adding the letters a and b.

[10] Alike Halpern (2005) summarizes, here with reference to relations of teachers, that "social capital becomes a lubricant of knowledge transfer and development, and it pays considerable educational dividends."

[11] This means that ties result in a higher circulation of cultural capital, which possibly flourishes, but at least not diminishes by sharing it. In consequence, every student in school has c.p. a higher likelihood of profiting from the ties to the same peers.

outcomes will be higher in schools with more social capital (having higher density and quality of relations) (H2a).

Previous research on both hypotheses (educational effects of individual ties and school-level density), depending on used methods and populations, reveals mixed results. Using the National Longitudinal Study (NELS) 1988-1992 that relies on answers from American students Morgan and Sørensen (1999) find evidence that students having more friends show a higher mathematics performance and they also report a higher additional effect from higher school-level density. Zimmer and Toma (2000) who analyze a pooled data set of 13 to 14 year old students from 5 countries via a fixed-effects approach, not appreciating multi-level characteristics, find peers to have positive effects on educational outcomes which are stronger for students with lower ability. Van Rossem et al. (2013) compare 1036 children in Dutch elementary schools and conclude that a higher indegree in a playmate-network is significantly associated with better academic performance (measured by ratings of teachers), although this effect was not very strong.

However, there are also works indicating no or opposite effects. Dijkstra, Veenstra, and Peschar (2004) analyze multilevel models on a small data set of 1400 students in classes from 25 schools in the Netherlands and find no evidence that those who have friends at the same school are performing better in math or languages and observe only a minor reduction of behavioral problems. Boucher, Bramoullé, Djebbari, and Fortin (2010), who exploit the variation in group size and control for selection, estimate that secondary education students in Quebec perform at average better when their peers have higher average test scores.

Several other authors research the more specific hypothesis that the composition of individual ego-networks (e.g. in terms of parental socio-economic status, cultural capital or academic performance) moderates educational outcomes, e.g. by taking into account the test scores, familial resources or status of peer ties.

2.2.3 Parental school volunteering and educational outcomes

While theory and hypothesis presented so far were related to the connectedness of students, we now focus on parent-to-teacher ties or, in short: parental school involvement.[12] First, we expect the engagement of parents to increase their

[12] While this term is used widely for all kinds of relations of parents, we use the term in the specific sense of having ties to school and research it for parental volunteering at school. For example, Sebastian et al. (2017) distinguish and empirically research three different dimensions of parental school involvement: parent-initiated involvement, teacher-initiated involvement and parental volunteering.

awareness of the learning goals of the school and thus allow them to better give or organize complementary support (like helping with homework, remedial teaching). Second, parents could use ties into school, to better adjust school to the needs of the children. Since such attempts to improve school are biased by the view they developed in interaction with their own children, they likely result in outcomes that favor especially their own children. Both aspects taken together, we can hypothesize:

Since school involvement of parents increases the education-related resources for their children, parental school involvement of the own parents increases the educational outcomes of students. (H1b) [13]

Apart from the benefits students gain from the involvement of their own parents, there appear to be conceptually different effects that influence students when a larger number of parents gets involved. First, in schools where parents are more involved and engaged their education-related resources might be transferred to other students beyond their own children. Ways in which relevant knowledge could be transferred from parents to other children in school are e.g. visits in class and the enrichment of curricula by the experiences and knowledge of parents, taking responsibility for other students or co-parenting and by organizing or participating in community activities such as celebrations. Second, parental school involvement allows for coordination of parents. When trying to understand the comparable good educational results in catholic schools, Coleman (1987) attributed this in part to their higher levels of social capital and especially personal relations between parents of students enabling enhanced enforcement of school-related norms which he labeled as intergenerational closure. Some authors have also considered possible negative consequences of norm-enforcing communities, e.g. the "loss of autonomy and redundant information" (Portes & Landolt, 1996) and thus question Coleman's hypothesis on the relevance of intergenerational closure. Other possible beneficial effects of parental involvement discussed in literature include effects of increased self-efficacy of teachers (Hoover-Dempsey, Bassler, & Brissie, 1987).

Schools with more parental school involvement, having more relations of parents to other students or the teachers, are characterized by a higher transfer of educational resources from parents to children and higher norm enforcement and, in consequence, better learning outcomes. (H2b)

[13] Because we do not analyze parent-teacher relations, we excluded several mechanisms, that hold especial for communications between parents and teachers: For example, parents might give valuable feedback on their children and their behavior that can be used by teachers to fulfill the goals of school. And communication with teachers might allow parents to selectively motivate or sanction behavior that is desired by the school.

While many studies deal with parental school involvement, they are mostly related to communication between teachers and parents. Previous empirical results have plausibilized an association between parental school involvement and better individual educational achievements. Based on the National Longitudinal Survey of Youth (NLSY) 1992 and 1994 Parcel and Dufur (2001) find parental involvement in school activities to be associated with modest positive effects on the math scores. (Yan & Lin, 2005) using 4 waves of the National Education Longitudinal Study cohort 1988 find an significant effect of prior parental participation in parent-teacher organizations and attendance of school programs on the math scores in grade 12, but only for Caucasian-whites, not for parents of other ethnicity. However, the meaning of this association has been taken into question. As for all deliberate actions and volunteering, those who are involved in school can be expected to be a self-selected subpopulation. McNeal Jr (2012) discusses the "reactive hypothesis" that suggests that parents whose children have academic or behavioral difficulties might also increase their engagement in school which would result in an underestimation of such effects. Strier and Katz (2016) additionally find those who participate in school to have higher generalized trust than those not participating.

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2.2.4 Consequences for inequality of educational outcomes

Differences in experiences of students result in the well-researched preservation of status privileges by moderation of educational outcomes. For differences, e.g. in cultural capital prior to entering school and paralleling the school career, higher equality of educational outcomes can be achieved only if students with less familial educational resources are successful in catching-up processes. Learning new concepts in school, however, always demands prior knowledge and skills. Ignoring non-linearities of learning, those requisites have to be acquired by less favored students in less time while learning other concepts that are also new to students already having this requisites.

Inequality of educational outcomes (IEO) due to social background has been shown to depend on several societal context factors that influence these catching-up processes. Most prominent are the specific arrangements of different education systems like the rules of sorting, tracking (Chiu et al., 2017; Hanushek & Wößmann,

2006), streaming and allowance to subsequent education[14], compensatory practices (or remedial teaching) and the duration of the average school day (and hence how much of the day pupils spend in similar informational contexts). Unsurprisingly, also properties of schools have been shown to matter for IEO, while most previous studies found moderate to lower effects of reduction under advantageous conditions (e.g. Agasisti and Longobardi, 2016).
Drawing from the previous theory on the relation between social capital and educational outcomes we can similarly infer that social capital can influence IEO under the precondition that it changes differences in educational resources or makes experiences of different status groups more alike.
N. Lin (2000) explains that personal ties can affect the outcomes of different groups either because they have an different amount of social capital ("capital deficit" of one group) or because the same amount of social capital has different effects on them ("return deficit"). There exists a relatively consistent research on the *resource deficit* showing that adults of lower social status have less ties which in addition gives less access to resources. While results on students are still being disputed, e.g. Hjalmarsson and Mood (2015) find poorer youths to have fewer friends and being in higher risk to be isolated.
Besides, there is also reason to believe that for families from different social status social capital results in *different consequences of social capital.* First, we can assume that students with low educational resources (e.g. those having no ties that can help with school or to role-models that foster their educational aspirations and motivations) might profit more from additional cultural capital which is irrelevant for a student that has already a high level of cultural capital.[15] Beyond that, we can postulate that the inequality in the distribution of skills across the population will contribute further to this process. There will exist skills that most (adult) interaction partners have and others that can be learned only from few interaction partners. Thus for higher levels of cultural capital there should exist a lower likelihood of augmenting it by social interaction (experiencing and acquiring these

[14] Education systems define what happens to students from families with different cultural background and how different experiences *out of school* will result in different experiences and outcomes *inside* of school. E.g. in highly tracked or streamed education systems students from different backgrounds are early separated and initial differences in cultural capital are increased by different levels of learning.

[15] Besides that, there might exist ceiling effects for students with high cultural capital. Either because there are disproportionalities in the relation between available cultural capital and learning results (e.g. because it requires increased effort or intelligence to make use of remaining cultural capital embedded in social ties) or because grading procedures at school inherently truncate the outcome differences for the highest performers because additional cultural capital can not have any influence beyond having the maximum grade.

skills and knowledge otherwise not available to the students) with a random tie. Both social processes should result for students that have higher cultural capital – which is related to social status of parents – in decreasing returns for cultural resources accessible through additional social ties.[16]

On the other hand, effects of this mechanism might be "overruled" by group-specific differences in abilities to utilize the resources embedded in social ties: For example for students from families that are better equipped with educational resources, new concepts could be understood or linked to previous knowledge more easily.

Especially for parental school involvement one could expect that members of different status groups have different means to shape school policies according to their *perceived interests of there children.*[17]

While in consequence we cannot infer unambiguously the total effect of more ties (be them peer ties or parental involvement), we nonetheless make a heuristic decision by stating the following hypothesis:

Students from lower status-families have higher educational returns to social capital – in part because additional cultural capital increases their educational outcomes stronger and in part because they have a higher likelihood that a random social tie will be able to increase their cultural capital. (H3)

Finally we have to consider the consequences of higher density in terms of peer and parental school involvement. Are there reasons to believe that the beneficial consequences stated in Hypothesis 2a and 2b will effect students from different status backgrounds differently? As we saw in terms of educational outcomes, students from lower status background have at average more to gain from additional direct ties to students of higher status background. In consequence – assuming random tie formation between students – denser networks result in a higher circulation of educational resources and a higher likelihood that they are distributed from those having them to those in need of[18] and thus higher density should be more beneficial to students from lower status families. However, whether a higher density at the school level will in fact increase the educational outcomes of students from lower

[16] The assumptions are quite plausible, but there might be additional complicating limitations to acquiring cultural capital. It could be possible that usage of available cultural capital/information requires prior knowledge and thus less accessible to children from families with lower cultural capital.

[17] "In many schools across the OECD parents have become agents in deciding educational policies. Increased school autonomy and participation of parents allow for decisions on the start of the school day, extracurricular activities, institutional facilities. Political negotiations might favor different groups. There is no reason, that status groups are represented equally in school politics."

[18] Since cultural capital can be transmitted through paths with intermediate nodes (students), this is different from the previous hypothesis on effect of individual ties.

status background more than those from higher status background will depend on the actual tie patterns between students from different status background.
In reality, the tie formation is patterned by social attributes and deviates from randomness resulting in school-level segregation by familial status or correlated with it: segregation by performance. Even in schools with on average more ties between students, students of lower status families will not have higher chances to catch up when the tie patterns at the same time are strongly segregated by social status – be it because of essential patterns or homophilous preferences of students. Additionally, a high average density can stem from high connectedness of high status background students and a minimum connectedness of low status students.[19]
Although we do not directly measure and analyze segregation, we nonetheless expect a higher average density of ties to reduce IEO. To understand this, consider a situation where most students in a school are more comfortable with (and thus choose preferential ties to) students from the same status background. Under the condition that there is a limit in tie opportunities to students of the same status background (especially because other tie preferences will also be relevant[20]), a higher number of school-level ties will increase the likelihood for ties between different status background – even given homophilious preferences or school-level segregation stemming from other sources (e.g. residential segregation).[21]
The argument so far relates to peer relations, but can also be adjusted to parental school involvement: For the same reasons, denser parental school networks might help to redistribute resources to lower status students – even when parents from lower status backgrounds engage less likely.
Higher density of peer relations (a) and parental school involvement (b) on the school level reduces IEO. (H4a/b)

2.3 Data set and operationalization

For our analysis we used data from the student- and school-questionnaires of PISA 2012 which is outstanding in terms of size and quality and cross-country comparability of performance tests. Thus we were able to infer from 14929 different schools in OECD countries. Educational outcomes were measured through several

[19] Furthermore, as already mentioned, density can also go hand in hand with bullying.
[20] Homophilious preferences are never total determinations of tie decisions because other preferences and dislikes interact on the tie formation.
[21] In reality, the causation sequence could be reverse. However, while school density could also be a consequence of lower segregation, this will not change the argument on IEO and our subsequent analysis.

performance tests of which we used the overall math scores. Status background was operationalized by the highest occupational status of the parents (ISEI). IEO was conceptualized as the linear relation between this parental occupational status and math performance.

Because the social capital indicators available in PISA are quite limited we used students' perceptions of their integration and parental reports on their involvement. We regard the students perceptions of their integration into school to be a proxy for the actual relations at school. Students were asked if they, thinking of their own school, feel "liked by other students", are "making friends easy" or "feel as outsiders", "strange or awkward" or "lonely".[22] (Supplement section 7.4, 137). While these items will idiosyncratically deviate (being possibly confounded with other social psychological dispositions[23] of the students) we postulate that they also (imperfectly) mirror the actual number of contacts students have and the quality of these relations – allowing for treating them as proxies for their social network[24]: Since a perception of being liked, having friends, feeling not lonely, awkward and an outsider at school will at average depend on the factual ties of students, we simply averaged over the (non-missing) items. We used the resulting value that could vary between 0 and 1 as index of social integration. If at least two items were missing, the index value of the person was also treated as missing value.[25] This rather rough measure of peer social capital does not allow to infer on relations of individual students and alike the properties of students' interaction partners (e.g. having partners with higher cultural capital or social status) cannot be directly measured.

We used a second indicator for social capital based on *parental school involvement* that was based on an indicator variable being 0 if parents did not participate and 1 if they were engaged in one way – be it in extra-curricular activities, appearing as a guest speaker, assisting teachers in school, volunteering at school canteen or participating in local school government (Supplement section 7.4, p.138). While

[22] We agreed to not include several other possible related items that are a result of perceived high quality of relations, but require other conditions' sine qua non: Either they were related to schooling quality and a positive perceived school effectiveness (feeling happy at school, feeling satisfied at school) or to identification with school (feeling happy at school, feeling belonging to school) while in reality students might be part of well-connected but school-critical (sub-)cultures.

[23] Such psychological dispositions are also mediators of parental status.

[24] The combination of items was previously used by Jungbauer-Gans (2004) with the PISA 2000 data set while they perceived them to measure the feeling of belongingness.

[25] The resulting percentage of item-non-response ranged for computed 10 quantiles of parental ISEI between 34.3 and 36.4 percent and there was no sign of a systematic pattern, while of those students who had no value for ISEI, the percentage having also a missing value in school integration was 45.9 percent.

some of those answers depend on opportunity structures at school, the mere existence of such structures will also be associated with higher parental school involvement.

For both individual-level indicators we also computed weighted *average school means* and treated these as a contextual property of the schools.

We sparsely control for several individual level variables that could confound the relation between social capital and educational outcomes: Gender and (first and second generation) immigration status can be expected to influence both social capital and math score. To control for specifics of schools, our models included indicator variables for schools in small towns and private schools, but not the school size and student-teacher ratio[26]

2.4 Analysis

We analyze data of 15 year old students who participated in the PISA survey 2012. The estimates for the country population from this data set are particular biased estimates, because special needs students are excluded from PISA. However, after listwise deletion of missing cases we are able to analyze 236718 students in 14929 schools from 50 different countries. Before following our main analysis of social capital effects on the school level, we show some basic covariation patterns. A descriptive analysis of the data suggests that there are considerable differences across schools in terms of how well math performance differences can be explained by a linear relation to the occupational status background of parents inside of schools (Supplement figure 7.1, p.139). When it comes to perceived social integration of students across countries there exist salient differences. Students in Macedonia are the least integrated, followed by the ones in Thailand and Hong Kong while students in Israel, Germany, Spain and Australia perceive themselves as best integrated.

Figure 2.2 shows the distribution of our measure of the student social contact conditioned on the maximum ISEI level of their parents.[27] The higher the social status of their parents, the more often students report items associated with being

[26] For missingness of school-level variables we had to decide on the trade-off between under-control bias from missing school-level variables and bias from non-randomness in the social missingness process leading to non-reply on school-level. For not dropping too many cases we had to exclude school size, which at least can be expected being imperfectly correlated with small town schools and the student-teacher-ratio, that turned out to be insignificant in the full control model (Supplement table 6.7, p.129).

[27] This simple (descriptive) statistic was computed using the final student weights and comparison with the unweighted variant revealed that better integrated students were over-represented in the sample.

better connected in school. Students from lower status families have a salient social "resource deficit" N. Lin (2000), which gives a first hint that social capital might mediate the effect of status background on educational outcomes.

Our analysis strategy was to first control parsimoniously for individual effects,

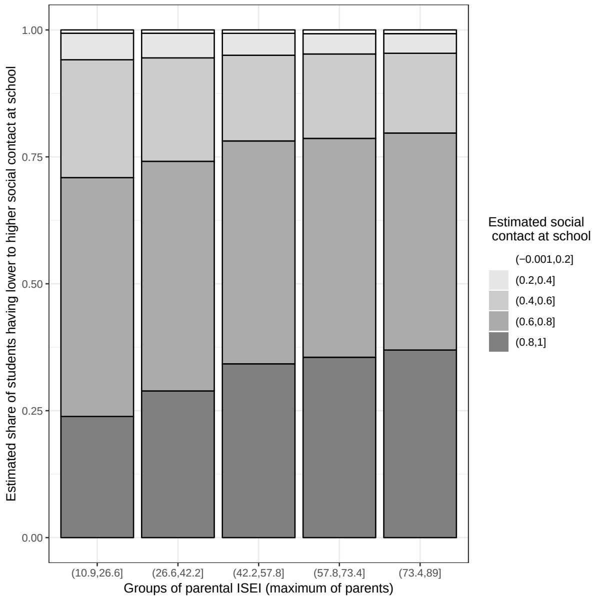


Figure 2.2: Estimated distribution of social contact at school by status background.

school-level variables, school-level compositional differences in terms of ISEI and afterwards sequentially include individual- and school-level effects of social capital. To test the presented theory, we use several multilevel models that try to explain math performance by the socio-economic status of parents and sequentially include social capital indicators that correspond to our hypotheses on influences by social capital. We begin with model 1[28] (table 2.4, p.63) that includes only the parental status, individual level controls for immigration background, gender and school-level controls for private schools and, to capture various regional disparities, is small town schools. Based on model 1, we can estimate that after inclusion of this controls and the parental status 25 percent of the variance is attributed to between-country differences and 25 percent is attributed to the school level.[29] The model predicts that c.p. a change from a family of least status to the highest status background

[28] The asterisks in all subsequent models follow the usual conventions:
$* := p < 0.05, ** := p < 0.01, *** := p < 0.001$

[29] We analyzed a sequence of different models (Supplement section 7.7 p.141). We especially compared models including the mean parental status at school level, which captures various processes, e.g. selection processes according to prior performance, subsequent differences in school quality and confounded with all of this: the potential resources in terms of the status background of classmates that we believe to be associated with cultural capital. The inclusion of the school-level mean ISEI reduces the remaining school-level variance for model 1 by another 5 percent.

would be associated with 55 higher math points. Model 2 additionally includes our estimate for individual student contact (see section 2.3). The model predicts that students who e.g. report 25 percent higher in our proxy index for having social ties will c.p. show a 7 point higher math performance. This effect was tested significant and can, in comparison the effects of other properties of students like e.g. gender, be regarded as being moderate. Given the conceptual problems this result is conform with our hypothesis 1a. The coefficient of parental status background is not drastically reduced. Model 3 extends the preceding model by an interaction term to test for a moderation of the effect of being connected in school by parental status. As expected, we find a negative effect which is significant but of smaller effect size. Hypothesis 3, which stated decreasing returns for social capital of students from higher social status, stands the test. If we again take the prior reference point of an increase of our school-based ties indicator by 25 percentage points, the model estimates that for a student from the lowest status background such will have an overall increase in test scores by 17 math points, while a student stemming from the highest possible status background only would increase the math performance by 11 score points. If this result holds, the decreasing returns of cultural capital in general (or in particular when being embedded in social ties) is a mechanism that allows for reducing IEO by increasing the interconnectedness between students.

In the next step we test hypothesis 2, which stated that the school-level interconnectedness, net of an individual student being strong or weak connected, has an effect on educational outcomes on its own. Figure 2.3a gives an overview on the distribution of school means based on our proxy measure for social ties, which can be interpreted as school-level density. Even without directing the view to special countries, we can see pronounced country-level differences in the distribution of the tie density of schools.[30] Based on our measure, most schools show a relatively high density. Do these school-level differences in the interconnectedness between students explain educational outcomes? Model 4 includes this school mean measure and predicts that e.g. a 10 percent higher tie density[31] is, c.p. and net of the effects of individual students being connected, associated with an increase of 13.57 math points. Because this estimate could be biased by differences in school type, school quality and other sources uncontrolled for, we also analyzed this model under control of the school-level mean of parental ISEI, that we believe to mirror many of such

[30] Note, however, that we can not rule out between-country measurement variance for the items of our index .

[31] Note the change of our exemplary reference point from 25 percent changes in individual social connectedness to 10 percent average class connectedness. This seems a better reference point for the depicted distribution on the class level and respects the fact that mean level changes are at average weaker than individual changes.

processes (Model 5, table 2.5, p.64). This dropped the predicted effects to 9.4 for classes that are reported to be 10 percent denser, but remained significant.

To test hypothesis 4a that suggested an (negative) association of IEO with the average school-level interconnectedness between students, we introduced additional models. Departing from a random slope model that allows for school-level differences in the ISEI effect (model 6) we entered the cross-level interaction (CLI) in model 7, also controlling for school-level mean ISEI (model 8). We found no significant CLI and thus have to reject the hypothesis that IEO is influenced by the school-level interconnectedness between students.[32]

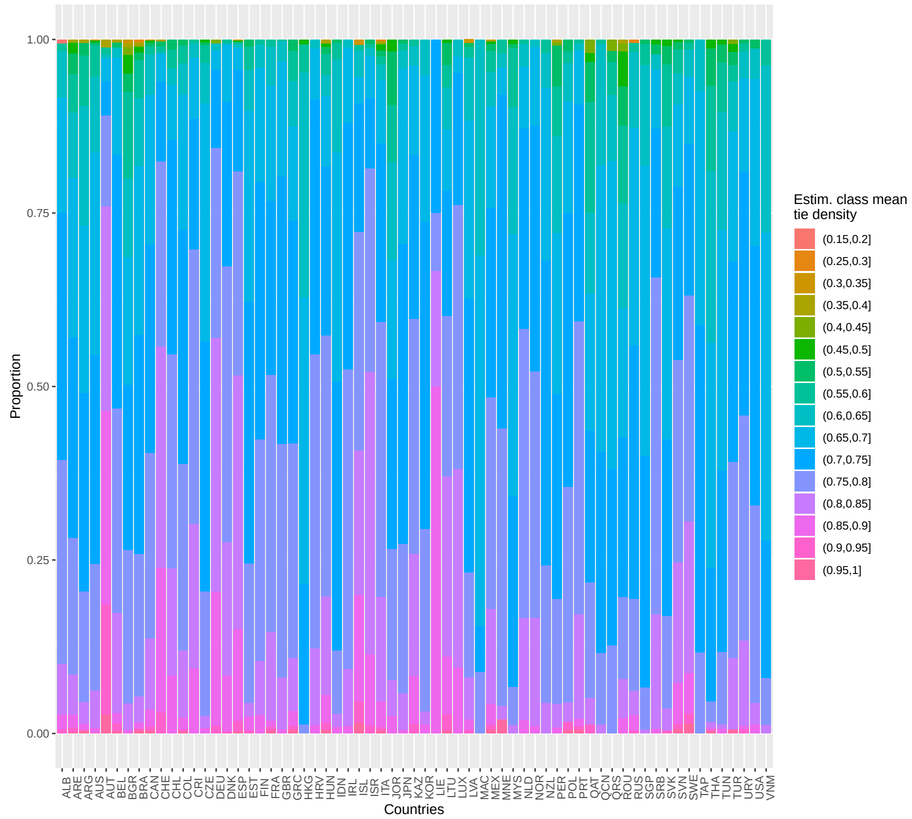
We additionally tested our hypothesis based on parental school involvement. However, since only a few countries participated in the parents questionnaire, the available data is limited to 9 countries. Figure 2.3b shows that the by far largest share of classes has a quite low parental school involvement based on our indicator. Because the low number of 9 countries would violate the assumptions of multilevel models, we decided to compute the same set of models as for the connectedness of students by computing a two-level model with country-fixed effect dummies.[33] Models 9 to 11 included 58270 students from 9 countries. Model 9 predicts that if the own parents participate in school, the results in math score c.p. drop by 20 points. A 10 percent points higher share of parental school involvement on the school-level is predicted to decreases the math scores by 3.3 points. In our opinion, both results on parental involvement mirror weaknesses of cross-sectional analysis and can be explained with mechanisms of self-selection, that we were not able to control for by our design. The test for the estimate of the CLI of the share of parents and parental ISEI also was not significant (model 11).

2.5 Conclusion

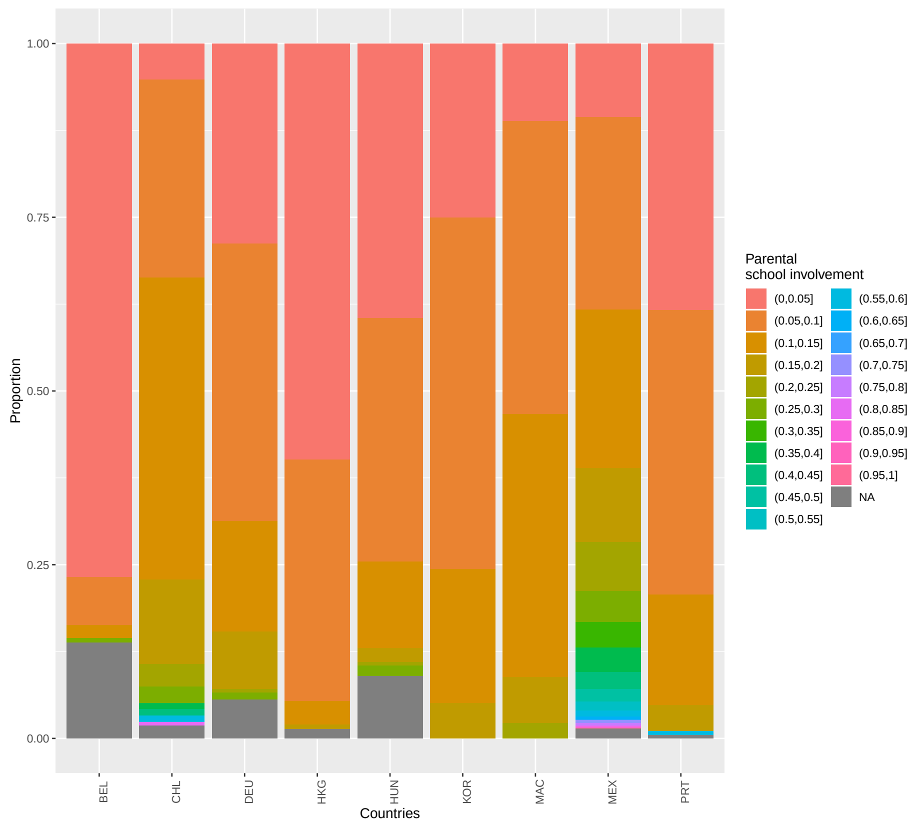
Inequality of educational outcomes (IEO) is, besides genetic variation, a result of differences in social experiences which vary by the societal position one is born into. We tried to analyze how social capital in school-contexts (integration of students and parental school involvement) can help to mitigate such differences by compensating for cultural capital differences due to (prior and actual) out-of-school experience and especially the information environment of families. The presented results are conform with our hypothesis that being better connected inside of school has beneficial effects

[32] We computed the same models also including the estimate for individual ties but also were not able to establish significant cross-level interactions (Supplement table 7.6, p. 147)

[33] For this purpose we used clustering of the standard errors for countries inside the school level.



(a) School-level average of the connectedness of students by country



(b) Mean parental involvement by country

Figure 2.3: School-level average of the connectedness of parental involvement by country

on educational outcomes. Our findings additionally support positive collective effects of the social capital of students on the school level. However, we found mixed results for our questions related to the reduction of the inequality of educational outcomes by collective social capital: While we observed school-specific differences in the math score returns of being individually connected and also decreasing returns of social ties for students from higher status, we were not able to support an additional context cross-level moderation of IEO. The models were not able to support our assumption that, independent of the own ties, the effects of the family status are actual lower in schools where the students are on average more integrated.

We also estimated effects for parental school involvement. The model predicted that students will have lower math scores when their parents are involved at school. We attributed this to uncontrolled differences in school and self-selection of parents whose children had prior performance problems.

This article presented a theory on the relations between social capital and the inequality of educational outcomes and brought up the question if the increase of individual and school-level social ties could be a possible means to decrease inequality. The data source and models, however, are far from perfect. Many possibly interesting class-level variables on sorting processes prior to our analysis were not available. In consequence, we can not reject the possible confoundedness of our results and in combination with the cross-sectional design we can not rule out the possibility of reverse causation. Our results should be taken to be more correlational than causal. In terms of political consequences our preliminary study allows an optimistic guess: School-level relations matter, on the individual and the aggregate, school level. Especially evidence for the hypothesis of decreasing returns of social capital for students from higher family might be a pathway and means to increase the equality of educational outcomes in terms of reducing the dependency from the status of the origin family. Compared to other means, one can expect no drastic effects. However, we believe that we gave enough theoretical and empirical reasons why educational policy and school administrations should take effects of social relations at school into account when they try to reduce IEO. We suggest further research on this questions that should help to clarify this blurred picture.

Table 2.4: 3L MLM: Covariation of math test scores and Cross-level interaction

	Math Performance			
	(1)	(2)	(3)	(4)
Intercept	443.874 ***	422.43 ***	412.939 ***	326.823 ***
	(6.95)	(7.93)	(7.669)	(14.267)
Parental ISEI	0.71 ***	0.7 ***	0.898 ***	0.697 ***
	(0.052)	(0.052)	(0.07)	(0.054)
Est. individual ties		29.644 ***	42.532 ***	24.242 ***
		(3.419)	(5.493)	(3.381)
Est. ind. ties * Par.ISEI			-0.267 **	
			(0.096)	
Est. school-lev aver. ties.				135.667 ***
				(19.89)
– Variance Components –				
$\tau^2_{country}$	2364.674	2337.622	2333.379	2243.313
	(402.653)	(398.695)	(398.292)	(386.447)
τ^2_{school}	2297.243	2244.822	2243.06	2091.329
	(235.646)	(232.487)	(232.503)	(220.794)
σ^2	4616.854	4600.109	4599.335	4603.984
	(211.291)	(211.931)	(212.075)	(212.297)
– Intra Class Correlations				
$\rho_{country}$	0.255	0.255	0.254	0.251
ρ_{school}	0.248	0.244	0.244	0.234
ρ_{σ}	0.498	0.501	0.501	0.515
– Controls –				
Schl Ctrl: SmllTwn,PrvteSch				
Female	-15.272 ***	-15.23 ***	-15.265 ***	-15.391 ***
	(0.983)	(1.006)	(1.008)	(1.001)
1st Gen Immigrant	-16.235 *	-15.567 *	-15.57 *	-14.886 *
	(7.432)	(7.3)	(7.29)	(7.248)
2nd Gen Immigrant	-13.183 **	-13.213 **	-13.256 **	-13.314 **
	(4.637)	(4.654)	(4.668)	(4.657)
n students	236718	236718	236718	236718
n schools	14929	14929	14929	14929
n countries	50	50	50	50
Largest FMI	0.024	0.026	0.042	0.034

Table 2.5: 3L MLM: Covariation of math test scores and Cross-level interaction

	Math Performance			
	(5)	(6)	(7)	(8)
Intercept	259.726 ***	443.368 ***	340.421 ***	272.536 ***
	(14.965)	(6.934)	(20.357)	(19.238)
Parental ISEI	0.59 ***	0.714 ***	0.35	0.256
	(0.057)	(0.052)	(0.32)	(0.327)
Est. individual ties	24.686 ***			
	(3.355)			
Est. ind. ties * Par.ISEI				
Est. school-lev aver. ties.	93.997 ***		140.604 ***	101.194 ***
	(16.979)		(27.8)	(26.926)
Est. schl-l aver. ties *ISEI			0.478	0.442
			(0.445)	(0.452)
School-level mean ISEI	2.147 ***			2.149 ***
	(0.258)			(0.261)
– Variance Components –				
$\tau^2_{country}$	1916.005	2355.984	2236.54	1917.272
	(453.617)	(401.571)	(385.846)	(454.156)
τ^2_{school}	1524.33	2539.595	2282.239	1720.656
	(131.153)	(304.349)	(301.266)	(160.859)
$\tau^2_{school,var(isei\_max)}$		0.17	0.169	0.169
		(0.017)	(0.017)	(0.018)
$\tau^2_{school,cov(ISEI\_max,\_cons)}$		-6.85	-6.365	-6.349
		(1.37)	(1.401)	(1.239)
σ^2	4620.73	4557.247	4562.105	4578.462
	(214.832)	(211.101)	(211.525)	(212.108)
– Intra Class Correlations –				
$\rho_{country}$	0.238	0.249	0.246	0.233
ρ_{school}	0.189	0.269	0.251	0.209
ρ_{σ}	0.573	0.482	0.502	0.557
– Controls –				
Schl Ctrl: SmllTwn,PrvteSch				
Female	-15.66 ***	-15.294 ***	-15.453 ***	-15.728 ***
	(1.064)	(0.98)	(0.977)	(1.042)
1st Gen Immigrant	-14.055	-16.162 *	-15.181 *	-14.347 *
	(7.232)	(7.415)	(7.287)	(7.241)
2nd Gen Immigrant	-13.079 **	-13.077 **	-13.165 **	-12.878 **
	(4.694)	(4.643)	(4.627)	(4.662)
n students	236718	236718	236718	236718
n schools	14929	14929	14929	14929
n countries	50	50	50	50
Largest FMI	0.066	0.215	0.224	0.21

Table 2.6: 2L MLM for Parental School Involvement (with standard errors clustered in countries)

	Math Performance		
	(9)	(10)	(11)
Intercept	505.5 ***	506.6 ***	505.939 ***
	(6.406)	(6.106)	(5.553)
Parental ISEI	0.456 ***	0.453 ***	0.402 ***
	(0.108)	(0.109)	(0.098)
Ind. parental involvement	-20.001 ***	-17.499 ***	-32.000 ***
	(3.001)	(2.523)	(5.623)
School-level average parental involvement		-32.738 ***	
		(6.094)	
Parental School Involvement * ISEI			0.294
			(0.158)
– *Variance Components* –			
τ^2_{school}	2331.568	2310.078	2176.781
	(649.0853)	(660.741)	(600.857)
$\tau^2_{school,var(ISEI)}$			0.143
			(0.062)
$\tau^2_{school,cov(ISEI,\_cons)}$			-1.573
			(1.842)
σ^2	3990.228	3990.574	3946.969
	(407.740)	(407.295)	(393.264)
– *Controls* –			
– *8 Country Dummies* –			
Female	-18.350 ***	-18.380 ***	-18.337 ***
	(2.074)	(2.057)	(2.095)
1st Gen Immigrant	-15.110	-15.077	-15.107
	(13.650)	(13.655)	(13.419)
2nd Gen Immigrant	-11.113	-11.128	-11.026
	(12.926)	(12.926)	(13.419)
Small town school	-28.677 ***	-24.428 ***	-28.437 ***
	(4.235)	(4.630)	(4.310)
Private school	18.782	17.370	17.898
	(10.933)	(10.769)	(10.644)
n students	58270	58270	58270
n schools	2715	2715	2715
n countries	9	9	9
Largest FMI	0.937	0.925	0.8695

Paper 3: Does the segregation of students' relations in secondary school moderate the inequality of educational outcomes? Evidence from two European countries.

Marc Schwenzer

2019/5

Abstract: Residential segregation, national admission policies for higher secondary education and privatization of schooling result in school compositions that are segregated in terms of parental status, which contributes to inequality of educational outcomes (IEO). We give a theoretic conceptional overview of effects of resources available in the network of students and consider possible effects of social relations on inequality. We assume that social networks give access to additional sources of motivation and cultural capital (e.g. through direct sharing of knowledge, co-learning or adoption of educational aspirations), but for the latter with diminishing returns for students from higher status background. We suggest a specification of a status-based resource indicator and apply it to microdata from the Children of Immigrants Longitudinal Survey (CILS4EU) covering school-related networks of about 18700 students from 4 European countries. We find pronounced status differences in terms of the resources that are available to students through their social ties. Our findings support the hypothesis, that educational outcomes are affected by the status composition of the ego-network and also the status homophily on the class level.
Keywords: Inequality of educational outcomes, CILS4EU, social network analysis, school class effects, density of networks, ses homophily

3.1 Introduction

Already canonical sociological literature acknowledged that social ties can be a source of chances and inequality[1] and since then research on education has shown a perceivable interest in the question how social ties are related to educational outcomes and status-specific inequality. The main focus of this paper is how inequality of educational outcomes is moderated by social ties and structural properties of evolved social networks. As other social contexts that were shown to influence educational inequality, e.g. the arrangements of the education systems, we analyze how specific properties of peer networks – particularly density and status-based segregation – genuinely influence the inequality of educational outcomes (IEO).

The article contributes to these topic by trying to answer several basic questions: Do social ties to peers improve the educational outcomes of students? How do network contexts moderate the inequality of educational outcomes? Are educational outcomes in denser (or less homophilous) classes less dependent on parental status?

[1] E.g. Max Weber (1978) already took for granted that "social relationships which are valued as a potential source of present or future disposal are, however, also objects of economic provision".

Despite the simplicity of these questions there are no simple answers and severe conceptual and identification problems make it necessary to deal with them in detail.
After theoretical considerations on the causal processes that shape the inequality of educational outcomes and the possible contribution of social ties (3.2), we give an overview of problems that arise in identifying these processes (3.3). We contribute answers to these questions by using micro-data on the social ties of students in secondary school classes collected by the CILS4EU-project in the European countries Germany and the Netherlands (3.4). Finally, we analyze this data set (3.5) and draw a conclusion (3.6).

3.2 Theory

Learning outcomes have been shown to be a crucial factor in the stratification of modern societies and a main mediator of the status inheritance from families to children. Students from different status backgrounds are prepared very differently to the demands in school. Those, who have acquired less cultural capital than others in consequence of experiences related to familial status background, have to master the task to catch up in learning skills required in school, that some other schoolmates already have, while learning new content. The predominant existence of status-based differences in performance shows, how hard this can be for students from lower status background. As known for the learning of foreign languages of non-native speaking children (e.g. Mashburn, Justice, Downer, and Pianta, 2009), the everyday interactions of students transfer cultural capital (e.g. by word comprehension that is related to the overall comprehension of lessons, workarounds for solving problems, cognitive knowledge and facts about reality). In secondary education many educational processes have already happened. Educational practices like tracked school systems or sorting into classes based on performance, result in school classes, in which students from different status background are already more similar to each other than to the rest of the population. Nonetheless there are still differences that maintain or widen IEO and we expect social networks to be a crucial part in subsequent processes. To understand this, first, we theoretically relate social ties to learning outcomes and, second, conceptualize their possible influences on educational inequality.
Proponents of social resource theory (e.g. N. Lin et al., 2001) have shown that social ties define the communication position of members of society and thus influence

their information intake, they allow for influencing the actions of others, reduce the costs of using economic and cultural resources of others and can be used as credentials which make it easier for strangers to put trust in them (resulting in a Mathew effect for social capital). We build on these ideas by presenting a very simple theory of learning outcomes.

To keep things as lucid as possible, let us think of an imaginary 14-year old student Anne (being one of a classes' individual students denoted by i). Heuristically excluding genetic variation and processes of oblivion we assume that the current educational outcomes of Anne (Y_i) will depend on previous in-school training $T_{.,t-1}$, which is the same for all students inside a school class, her prior available resources ($R_{i,t-1}$) and her prior learning effort ($E_{i,t-1}$): $Y_{i,t} = f(T_{.,t-1}, R_{i,t-1}, E_{i,t-1})$ (1.).[2]

Following the reasoning of Bourdieu (1983), we take for granted fundamental differences in terms of capacities (especially academic ability), habits and other information primarily acquired in the context of a origin family which he termed cultural capital. This differences in experiences result in being better or worse adjusted to the demands in school, which is the main reason for different educational outcomes and can conceptually be treated as familial resources ($R^{(f)}_{i,t-1}$).

Second, educational outcomes are shaped by the learning effort of students (in principle e.g. perceivable by the time and intensity spent for effective learning and repeating educational content related to grades at school). How much (quality) time Anne is spending will depend on her motivation. We expect this motivation to be systematically correlated with the experiences in the family of given socio-economic status (SES), e.g. because familial cultures resulted in character traits like openness or conscientiousness or because economic positions define opportunity and utility structures (Boudon, 1974; Breen & Goldthorpe, 1997), status-specific goals (Raftery & Hout, 1993) and adequate anticipation of likely future outcomes (e.g. by more or less detailed knowledge on the school system, Erikson and Jonsson, 1996). Taking all these mechanisms into consideration we can treat effort as being also strongly shaped by initial familial conditions ($\mathrm{E}^{(\mathrm{f})}_{\mathrm{i,t\text{-}1}}$).

Extending this very basic theory based on two sources of individual educational outcomes, we further acknowledge that the interaction of Anne with classmates will influence her. Thus, her educational outcomes do not only depend on properties of her family but also on the resources of (certain or all) other students (indicated by the letter o) in the same class ($R_{i,t-1} = R^{(f)}_{i,t-1} + R^{(o)}_{i,t-1}$) (2.).[3]

[2] Note this conceptualization implies that having more familial resources, the effort necessary to e.g. achieve an aspired grade will be less.

[3] Note that social ties to classmates will not only directly increase cultural capital, but might also influence other education-related resources. For example, one could think of acquiring

Alike Anne's past motivation and thus effort to learn is unlikely independent of those of other students in the class ($E_{i,t-1} = E^{(f)}_{i,t-1} + E^{(o)}_{i,t-1}$) (3.).
We can conceptually differentiate changes in resources or effort by being a context or a contagion effect. For the parts of the school days where students are not in workgroups we can assume that all students are given the same training $T_{.,t-1}$ (typically a didactic teaching by one teacher). Properties of other individual students that become relevant during lessons are insofar *contextual* as they will affect all class members the same (time). Anne could be influenced independently of her specific social ties to other students in class, e.g. because properties of the students might change the behavior of teachers or the contributions of other students in class change $T_{.,t-1}$.
On the other hand *contagion effects* (DiMaggio & Garip, 2012) denote effects from direct interaction which depend on ties *to other students.* For example, if Anne is changing her behavior because of transfer of information or goods through interaction with a friend or homework partner. Formally this means that outcomes are not only causally dependent on the attributes of other students, but also on the prior realization of ties in a school class network or certain subsets[4] of it. This difference[5] will become more clear in the subsequent analysis of the effects of the social background of students on educational outcomes.
We start the analysis of contagion effects with *cultural capital contagion*[6] by which we denote all kind of transfer of information and educational resources that are beneficial for better performance and thus grades. Imagine in the last lesson Anne was taught the solving of quadratic equations by her math teacher, but she did not understand the formal transformations involved and finally decides to ask for help.[7] Whether she manages to find someone able and willing to help her will depend on Anne's social ties which can be described and compared based on the type of relation (personal friendship, children of parents' friends, homework partners), extensitivity (having many vs. few ties), frequency (meetings being more or less

or borrowing goods (e.g. books, devices) or make use of services (e.g. being allowed to join exhibitions).

[4] An example would be e.g. the subset of direct tie ego network consisting of Anne's best friends.

[5] Note that while contagion and context effects can be distinguished conceptually in reality they can happen sequentially in time. Network properties (higher density) could have effects that *afterwards* influence the behavior of teachers and result in a change of their communication directed to all students which is a mixture of both concepts.

[6] We use the term contagion that has been introduced in epidemiology and subsequently used for information distribution (e.g. Rapoport, 1953).

[7] Note that this deliberate information seeking behavior relying on friends is just one exemplary form how the transfer of $R^{(o)}_{i,t-1}$ can take place, others being e.g. exposure to or occasional co-learning of knowledge, borrowing educational goods, common education-related activities that one interaction partner would take part without the other.

frequently and longer or shorter), intensity (differences in emotional attachment or density of communication).[8] And the likelihood of finding help will also (and probably even more) depend on whether (or how many of) her peers did understand the lesson.[9]. If e.g. many[10] students perceive Anne as friend (indicated e.g. by a higher indegree) she might be able to select from more people willing to help her if they understood the last lesson, but being only befriended with Bea, an idealized class primus who *always* understands everything right from the start, might result in the same (or even better) outcome than being related to many people. (See Figure 3.4, Panel a1 and a2)

Since the likelihood of receiving cultural capital from a certain tie to another

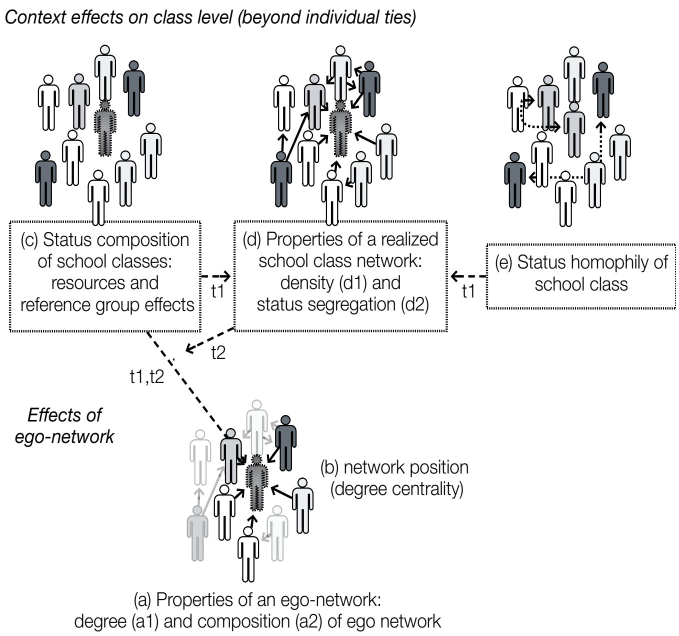


Figure 3.4: Possible influences of social ties, shading symbolizes SES

student j will also depend on j's familial resources ($R_{j,t-1} = R_{f_{j,t-1}} + R_{o.,t-1}$), we expect the utility of ties to others not only to be dependent on their resources but inherently also on the social status of their families.

Before taking all these considerations together, there is a last sophistication stemming from several sources of *saturation effects*. First, having more ties will –

[8] Note that there is no simple theoretical answer to the question which tie characteristics are most relevant and effective in terms of cultural capital contagion.

[9] However, the number (or qualities) of ties can and will be relevant even if all of her ties are less adjusted to the demands of school (which as was previously stated is somehow related to status background), because the likelihood that one of this low performers has acquired the knowledge from another tie.

[10] While we heuristically limit the analysis to the number, in reality the strength of the relation might be also of relevance.

also dependent on the type of relation – be accompanied by the costs of having less time for learning (and also by having less time for interaction with those students decreasing the likelihood getting relevant information). Thus there exists a trade-off and an local optimum for the number of maintained ties in terms of getting additional educational resources. Second, there is always redundancy in the information channeled through social ties that increases with the number of ties(Burt, 2001)[11], which seems to be especially true for understanding school lessons and knowledge. In effect, additional ties will not have the same utility and we expect saturation.

So far we had a narrow focus on effect of ties concerning the diffusion of cultural capital, but there is at least another education-related effect that can be named *motivation contagion*: the changes in learning effort in reaction to all kinds of perception of the behavior of peers or the class. Let us e.g. assume that Anne forms her expectations of the further educational career (Haller, 1968) in part by interaction with her best friends Bea, Charles and Doris who all wanted to go to university even before they entered secondary school which might boost her motivation to devote more time to learning and hence here educational outcomes. In general we can expect that students with social ties to students having high status perform better because they are encouraged by the higher aspiration and motivation of these peers.[12] Since such motivation contagion e.g. described by Harker and Tymms (2004) can be expected being more strongly related to processes of formation of identity and habit shaping we expect this to take more time, happening at more local and intense ties and thus being less prevalent than the diffusion of school-related skills. On the other hand, we expect the possible effects to be longer lasting and possibly more salient.

The major difference of motivation contagion compared to cultural capital contagion is the latter in principle can also have negative effects. While it would be valuable to separate cultural capital and motivation contagion empirically, we here will analyze only both effects together.[13]

In our present analysis we will only take into account the direct ties (or the ego network) of a student, e.g. Anne's friends, but not their friends or other classmates.

[11] Burt (2001) postulate that the foundation of strong ties is often based on structural similarity and the information exchanged will be more redundant. On the other hand, Laumann (1973) assumed that extensive networks show benefits in receiving information.

[12] Possibly adverse findings include the prominent finding of immigrant optimism that is in contrast to this tendency of a at the mean lower aspiration of children from families of lower status (e.g. Kao, Tienda, and Suarez-Orozco, 1995 for the United States).

[13] To be exact, we treat the effort term as part of the resources term. While effort effects could in principle become also negative, we subsequently analyze only the combined effects of familial resources of others.

If we assume Anne's direct tie network of interaction partners is a set N_i containing n_i other students, who might influence both the resources available to Anne and her own effort. In this case the additional resources $R^{(o)}$ from her ties can be assumed to be given by their familial resources
$R^{(o)}_{i,t-1} = r(\sum_{j \in N_i} R^{(f)}_{j,t-1})$ (4.)
where r is a weighting function that takes into account to what extent the resources of her peers are accessible to Anne. [14] Analogously, the impact of the peers in her network on Anne's effort can be written as
$E^{(o)}_{i,t-1} = e(\sum_{j \in N_i} (E_{j,t-1} - E_{i,t-1}))/(n_i))$ (5.)
where e is another weighting function that describes in detail how the effort of her peers affects the effort spent by Anne.[15]
In short, the considerations so far can be combined into two general hypotheses on the educational utility (contribution to beneficial educational outcomes) stemming from all ties to peer students:
Students with more social ties perform better because they can access additional education-related resources. However, the returns to additional ties are decreasing. (H1-1) (utility of ties, decreasing return)
The magnitude of this effect of ties of individuals will depend on the resources controlled by the tie partners. Let us further acknowledge the previous stated assumption that cultural capital is not distributed equally among students but is dependent on the status of the family:
Presupposition 1: Since students stemming from families with higher SES have more cultural capital and higher motivation, ties to such students are more valuable in terms of acquiring cultural capital and adaption of beneficial motivation. We can conclude that the additional cultural capital that can be acquired from the own social network is systematically related to its SES composition:
Students who are connected to peers from higher familial status background will perform better, because they can access more education-related resources (e.g. cultural capital) and at average higher motivation. (H1-2) (utility of the SES composition of tie partners)
While both hypotheses are directed, it is not possible to a priori infer the true functional relation that results from both processes and how one has to weigh the

[14] The weighting function should incorporate that resources within the own family are more accessible than those of others and that there will be a saturation of the benefits due to a large number of peers, as discussed in detail above.
[15] One might e.g. use a function that is negative if the argument is too large, since the student might become discouraged, that is positive for small positive arguments and negative for small negative arguments, and that might eventually become positive again for large negative arguments since the student might define himself as being the best in class.

trade-off between quantity and composition quality on the one hand and saturations on the other hand. However, we can make an educated guess by specifying a special case. We additionally assume that the resources from others are equal to their familial resources, so that the weighting function r is given by the special form: $R^{(o)}_{i,t-1}) = (\log(n_i) * (\sum_{j \in N_i} R_{j,t-1})^{(f)})/n_i)$ (6.)[16]
So far we stated hypotheses only for the direct ties (or the ego network) of a student, while more indirect tie paths and thus the *properties of the total class network* will also be of relevance: Familial resources (and possibly less strongly: motivation) are not only transmitted by direct paths (as stated in hypothesis 1-1 and 1-2) but also influenced by more distant paths. [17] In consequence, given structural properties of the network like density or segregation[18] can also be relevant beyond operationalized effects of direct path contagions.
By simple probabilistic considerations we can e.g. deduce that an information flow from those understanding the solving of quadratic equations to Anne will not only depend on the class-level share of early-adopters, those that understood the lesson (faster), but also on the overall frequency of meetings and the quality of ties (to early-adopters and between others). The likelihood of Anne getting help from her friends Ben and Candy is higher, when those have more ties to other students in class, because this increases their likelihood having been able to previously interact with someone that has understood the previous lesson – even if they also did not understand the lessons at first. Since the likelihood of getting information depends on the overall class level of the tie density, we can hypothesize:
Students in denser classes perform better, because the overall circulation of education-related resources is higher. (H3)[19]

[16] First, we assume a multiplicative effect of resources and number of ties. Second, we model the saturations by taking the log of the individual number of ties (n) and third, include the potential resources of network partners by taking the mean of the parental SES of the partners in the ego network.
[17] One could argue that, if we would observe and measure every interaction in class and reconstruct the process of e.g. mediated cultural capital transfer for all those more distant paths lying between primary sender and receiver of cultural capital, the network structure as separate category was irrelevant. But the existence of those previous paths (formation and dissolution of ties) depends also on former states of the network and thus cannot be ignored. However, network structure is not ignorable anyway, because one can only measure very limited heuristics of the actual communication. Thus structural properties of such heuristics must be used to infer not measured relations.
[18] Note that we here deliberately ignore additional potential relevant sophistications, that might result from differences in power relations that stem from network positions (like centrality) or resulting aggregated class level properties (e.g. centralization).
[19] Another related social mechanism discussed in theory is the fact that interaction with other students can result in the formation of a subculture allowing for turning away from the norms and goals of school education and reducing effort. Because such processes are not well researched we can only hypothesize on this mechanisms. While in principle a whole densely

Results of Van Rossem et al. (2013) who compared the networks of 60 first-grade classes in Dutch elementary schools found that students in denser classes (controlling for various individual and other class characteristics) have higher academic performance. However they also report that "clique-like structures" were associated with lower academic performance and behavioral problems.

Given presupposition 1 that SES is correlated with the distribution of cultural capital, the class-level distribution of cultural capital will be dependent on the absence of barriers to ties of students from different status background:

Students in classes that are less status-homophilious and less segregated perform better, because the overall circulation of education-related resources is higher and less redundant. (H4)[20]

3.2.1 Consequences for educational inequality

While there are other forms of educational inequality to look at (e.g. the distribution of outcomes, Ferreira and Gignoux, 2014) we here are interested in the dependence of educational outcomes on parental status (status-specific educational opportunities) and define inequality of educational outcomes (IEO) in this specific sense.

As for other societal contexts of education, networks will reduce IEO only if they help to mitigate prior differences by compensatory effects. Adding to the theory presented so far, the transfer of educational resources (resulting in an increase of cultural capital or effort and better educational performance) from students of higher status to those of lower status must be higher than the transfer in the opposite direction. As previously explained, we expect networks to play a crucial role in processes of learning. While there exists research on the consequences of given social networks on educational *inequality*, due to the fact of several social mechanism being at work together, theory as well as empirical research, however, is far from being settled.

connected school class can become a subculture in relation to the school culture it is more likely that a densely connected component of the class network becomes a subculture dismissing a school-related goal. We assume that there exists a critical mass of ties to form such a component. We expect that at least one influential students with less motivation could become over-proportionally influential. Given the previous assumption that motivation is related to parental social status this would result in the (here not challenged) hypothesis, that lower status students might have had a stronger impact where components have been established. However, the hypothesis that motivations are shaped at average by direct ties should also be a good heuristic for such constellations.

[20] By exploiting the variation in group size and controlling for selection Boucher et al. (2010) estimate that secondary education students in Quebec perform at average better when their peers have higher average test scores.

N. Lin (2000) is one of the first to think systematically about effects of social networks for proponents of different groups and distinguished two possible sources of inequality: (social) "capital deficit" and a "return deficit" given a specific amount of social capital.

Capital deficit means that students from lower status can gain less educational resources from their social network. Such difference in social capital could have two different reasons: First, students from different socio-economic status groups might differ in their tie patterns and especially the number of ties. Previous research has found students from families of lower social status to have fewer friends and being in higher risk to become isolated (e.g. Hjalmarsson and Mood, 2015).[21] Second, given the same number of ties, ego networks can still deviate in composition, e.g. students from lower status groups having a higher share of ties to students that are less adjusted to the demands of school and of lower utility to educational outcomes. Whether European students from lower social status backgrounds really show a social capital deficit – that is: deviate in number of ties and the status composition of their ego network – is an interesting question that we will address later on.

On the other hand, a *return deficit* of social ties might exist where the social ties of students give access to the same amount of resources, but dependent on the social status of the family those result in different educational returns, e.g. learning achievements or grades. This might be the case for several reasons. First, we can assume that students with low educational resources , e.g. those having no ties to help with school-related problems or to role-models that foster their educational aspirations and motivations, might profit stronger from additional cultural capital which might be irrelevant for a student that has already a high level of cultural capital.[22] Beyond that, we can postulate that the inequality in the distribution of skills across the population of students in class will contribute further to this process. There will exist skills that most other students have and others that can be learned only from a few interaction partners.

Thus for higher levels of cultural capital there should exist a lower likelihood of augmenting it by social interaction (experiencing and acquiring these skills and

[21] Hjalmarsson and Mood (2015) reported that the association of being a poorer student and having less friends is in part mediated by not having an own room. We can hypothesize on other sources beyond the relevance of economic capital which could stem from different experiences resulting in differences in social skills and abilities of networking and maintaining friendships.

[22] Besides that there might exist ceiling effects for students with high cultural capital. Either because there are disproportionalities in the relation between available cultural capital and learning results (e.g. because it requires increased effort or intelligence to make use of remaining cultural capital embedded in social ties) or because grading procedures at school inherently truncate the outcome differences for the highest performers because additional cultural capital cannot have any influence beyond having the maximum grade.

knowledge otherwise not available to the students) with a random tie. For students that have higher cultural capital – which is related to social status of parents – both social processes will result in decreasing returns for cultural resources accessible through additional social ties. [23]

On the other hand, effects of this mechanism might be "overruled" by group-specific differences in abilities to utilize the resources embedded in social ties: For example for students from families that are better equipped with educational resources, new concepts could be understood or linked to previous knowledge more easily.
It is not possible to infer a priori which of both opposite effects or sources of return deficits are of relevance and outweighs the other. Therefore we here make a mere heuristic decision by stating the following hypothesis:
Students from lower socio-economic status have higher educational returns to social ties, because of a higher likelihood of augmenting their cultural capital and higher benefits, given the same information input. (H1-1i)
A higher SES composition of ties is especial beneficial for lower SES students, because their return of gaining from the transfer of resources is higher. (H1-2i)

DiMaggio and Garip (2012) deal with the consequences of adoption of behavior on equality, which is quite congruent with our previous focus on the spread of information as a key component of the effects of social ties, and hypothesize that "inequality in the adoption of beneficial practices" is exacerbated by social networks when a group first has an initial *advantage* in performing this behavior and second their social network shows patterns of *homophily*.
Students from lower SES backgrounds have a higher performance gain in classes that are less status-homophilous, because of enhanced transfer of education-related resources because of their higher educational returns to education-related input resources. (H4i)

[23] Note that the assumptions are quite plausible, but there might be additional complicating limitations to acquiring cultural capital: It could be possible that usage of available cultural capital/information requires prior knowledge and thus less accessible to children from families with lower cultural capital.

3.3 Identification problems and modeling strategy

While conceptual relatively simple, there are several obstacles in testing the theory presented so far, because several processes have happened already before, that might be related to given networks in school classes and also to the performance of students:
Status-specific experiences result in a set of education-related resources (cultural capital and motivation). The surveyed students have already acquired such a set and almost everything of this biographical processes is latent. They have experienced years of experiences. They have also shaped and adjusted their preferences related to learning in consequence of prior feedback to their performance in primary school, which is part of the main social mechanism, we are interested in.
First, the students have already been selected or selected themselves into a certain school (of specific type) based on their academic outcomes, which results in a *presorting of classes* in terms of composition of performance and socio-economic status of the family for performance is dependent on $R^{(f)}_{i,t-1}$.
In consequence, the students of the analyzed school classes are more similar to each other than to students of other classes. Comparison of the performance of students across classes and schools additionally suffers from possibly different grading procedures[24] that result in a *measurement variance* between schools.[25]
Second, a network of in and out-of-school ties has already formed prior to our analysis – based on latent criteria, but certainly not at random. Ties of students are in part product of *preferences and interests* of students and in part related to the *opportunity structure* (J. M. McPherson & Smith-Lovin, 1987).[26] An important example of an opportunity structure that influences to whom one will have ties is co-residence, since e.g. when Anne is living in the same suburb as Ben, this can lead to non-random likelihood of contacts – be it by taking the same school bus or occasionally meeting each other in the streets – or having lower transaction costs for maintaining ties. Anne and Ben on the other hand might choose each other as friends because they both share the same preference for riding horses[27] ("choice

[24] Teachers can be expected to somehow react to the average performance in class and since tests and assignments are widely not standardized, this will result in a class-specific bias in grading.

[25] The same is true for countries, however, we tried to pseudo-harmonize the grades of the Netherlands and Germany by bringing them into the same scale.

[26] We assume that social interactions of partners depend on the willingness of both and social ties are somewhat exclusive, so that having an (intenser) relation to one student is at the cost of not having such a relation to some other.

[27] Expensive leisure activities might result in the pattern of higher status students having more contacts to students from higher status and reverse.

homophily" in terms of M. McPherson et al., 2001), they might be more willing to communicate and eventually will become friends.[28] Particularly, it cannot be neglected, that ties in a given school class might also be product of preferential tie formation ("choice homophily") based on performance criteria. The problem is that "when there is latent homophily, contagion effects are unidentifiable, and even the presence of contagion cannot be distinguished observationally from a causal effect of the homophilous trait" (Shalizi & Thomas, 2011). For our study, that tries to explain grades by network parameters, this would mean running into the problem of reverse causality – the network structure could be a consequence of the grades and not the other way around.
Finally we expect the class-level context to have aforementioned context effects beyond networks that can also lead to the confusion of effects. The class-level performance composition can e.g. result in reference group effects on motivation and effort (e.g. Big fish little pond, Marsh and Parker, 1984). Alike there is no good control for the variance in teaching quality from school class to school class.
Our analysis strategy will not be able, to rule out all of this mechanisms. Ideally, we aim at isolating the influences of social ties and segregation of school networks from compositional differences, opportunity structure and latent tie formation preferences (M. McPherson et al., 2001). In accordance with the presented theory, we compare students in school classes and try to explain their individual performance measured in t by ties of the class network and individual performance in $t-1$ by using a value-added model. We try to cancel out the hidden network preferences based on status by obtaining estimates for SES homophily from simulations of Exponential Random Graph-Models, which will be detailed in the analysis.
Alternative ways for solving these problems, might be specification of matching-procedures for schools.

3.4 Used data set and operationalization

For our analysis we used the Children of immigrants Longitudinal Survey (CILS4EU, Kalter et al., 2017) which surveys and follows 18700 initially 14 year-old students in 4 European countries[29] as well as their parents and teachers. The panel started

[28] Possible are also mixtures of both preference and opportunity structure by e.g. meeting at the same organized leisure activity and thus having a higher likelihood to get into contact. For a more detailed typology see Shalizi and Thomas (2011).

[29] The total sample of primarily 14-year old students was sampled by classes of 9th graders in Germany, a 3rd graders in the Netherlands, a 8th graders in Sweden, and a 10th graders in Great Britain.

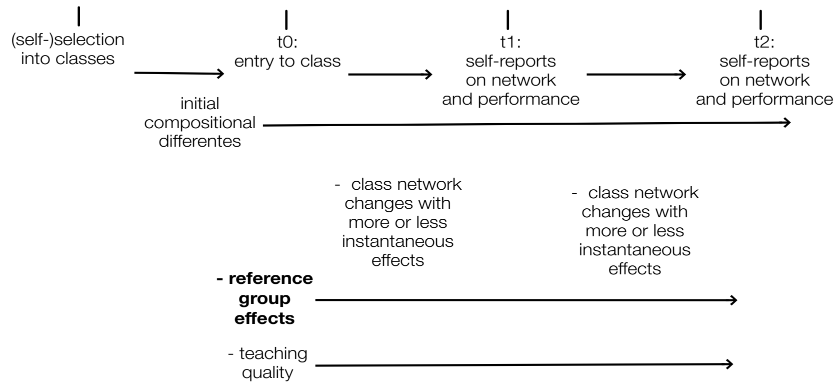


Figure 3.5: Timestructure of other social processes

in 2010/11 and there is a yearly follow-up with 5 waves being released. The sample structure is a stratified random-sample which departs from simple-random sampling at the most in two aspects: First, the survey design is complex and consisting of a selection of schools in countries, a subsequent selection of classes within schools and finally the inclusion of every student within those classes. Second, the designers, matching their main research interest, have chosen to oversample classes with a high proportion of students either having migrated or being child of migrants (CILS4EU, 2016a). We chose this data set despite the oversampling of migrants because of its comparably rich social network data that allows to analyze the interplay of effects of social ties (and tie formation) on the educational outcomes (e.g. measured by performance tests and grades) and resulting inequality. By allowing for direct comparison of social networks between classes, it offers the opportunity to address the effect of collective social capital and structural properties like e.g. status segregation.
We used self-reports of annual school grades of students in math (reading, science) as central outcome variable and related those grades to the SES of their parents (measured in ISEI points, Ganzeboom et al., 1992) treating the according coefficient as a measure of IEO. We believe that school grades capture, however imperfect, the success of in-school learning of the students – either perceivable as being directly correlated with learning skills and knowledge in the later occupational career or part of a credential that determines entrance opportunities to subsequent career steps. Since grades were measured only for Netherlands and Germany we restricted our analysis to those two countries [30] and were able to include the reported grades of 6467 students that are part of 496 classes in 234 schools.

[30] While the data set contains also performance scores, these are not comparable across countries.

To control for prior differences, we used two waves starting in 2010/11 and the second measurement in 2011/12.
We analyzed several dimensions of the multiplex and directed social peer networks and did deliberately not mutualize these ties by either taking one-way ties as indicator for mutual relations or ignorance of unreciprocated ties.[31]
The students in the survey were asked several aspects and contexts of relation. While we generated and had a look at all those networks, we focused our analysis especially on three of them, that appear to be the most related to our question: The *spent-time network* (stn, CILS4EU, 2016b, p.335) was based on reports with whom of their classmates they have previously spent time (allowing for deviation in the number of reports). The *homework-network* (hwn, CILS4EU, 2016b, p.353) was based on reports with whom of their classmates they spent time with. The *best-friend network* (bfn, CILS4EU, 2016b, p.330) was based on reports of at maximum five best friends. We perceive this restriction to the five best friends as a form of forced choice that psychologically involves some kind of (however conceptually rather unclear) ranking which e.g. might be based on the perceived quality or the perceived individual importance of the tie.
As we were interested in the influence of properties of the network, we restricted our analysis to those classes having at least 10 students and excluded special needs classes altogether for their small number and mostly small class sizes.
We also included several control variables, however rather sparsely. Since our focus lies on the influence of parental SES on the educational outcomes of students – indifferent to the social mechanisms this relation realizes, we are in danger of drawing from this variance when including correlated variables. We thus did not include other variables correlated with ISEI (like familial wealth indicators) or educational resources (e.g. books) because they are part of the social mechanism in central focus. However, we intended to separate the effects of SES from those of *migration* (recognizing other compositional differences related to migration) by inclusion of a dummy variable which indicates the students having either migrated

[31] There is a trade-off in the decision for using directed or undirected networks. Because directed networks are at average more informative for they include relations forgotten by one participant or relations that might exist but not pass the threshold of being perceived by one of the participants, restricting the analysis to undirected networks by artificial mutualizing ties is in fact dropping information. Whether this reduction of information would be more adequate depends on the proportion of coverage errors, concrete: whether participants more often forget to report ties to others (under-reporting) or more often over-report ties that are not reciprocated. Beyond coverage errors, mutuality can also be seen as a quality of relations on its own, that gives an answer to a different question. Lastly, mutuality could also be taken as a kind of additional indicator for tie strength. In our opinion we took a more conservative approach in regarding *every* information available.

or having parents who are migrants. We also included the variable *gender,* that can be expected being associated with different tie patterns as well as math performance. For the same reason we controlled for age.[32]

3.5 Analysis

The aim of this study is not primarily country comparison but we want to identify general social mechanism that should exist more or less in classes all over the world. We restrict our main analysis on the Netherlands and Germany which are quite similar, e.g. in the average availability of other resources[33]. Nonetheless, we value the comparative opportunities of the data set by reporting certain aspects and differences.

To get a first impression on the existence of a resource deficit for students from lower status families, we grouped students based on their parental occupational status in terms of resource differences. Figure 3.6 shows mean values[34] of the number of other students that reported them as having a tie to them (indegree[35]). First, there exist remarkable differences between the four countries in terms of the number of classmates the students spent time with and how many are perceived as friends. Overall Great Britain shows the lowest means in reported contact between students, while the social contacts based on the reported indegrees at average are highest in Germany. Doing homework together seems to be more typical in Germany and the Netherlands than in Sweden and Great Britain. Second, in all countries we can observe a clear tendency for students of higher status families to be reported more often having spent time and done homework together, while this association is weaker for reported best friends (and not existent for Germany). Figure 3.6b shows the relation between the status of the own parents and the parents of the interaction partners. Besides differences in the average ISEI of partners, in all countries there is

[32] We included age, although it might be related to the SES status inheritance process. Since age is correlated with the decision of parents to sent their children a year later to school, although they would be qualified going there. We can assume that this decision is correlated with SES-specific preferences.

[33] For example in the Netherlands there is a lower number of books available (estimated average 115) and more students do have an own room (93 percent compared to around 84-85 percent in the other countries). 97 percent of the students in Germany, compared to 98 percent in England and 99 percent in Netherlands and Sweden do have access to internet

[34] Note that while we weighted the descriptive results by the total weights given by the data providers, due to the sampling process one should not expect this results to represent the population of the respective countries.

[35] We use indegree-based measures as indicator of resources for it corrects for the potential overestimation of isolated students.

a clear correlation between own status background and the average parental status of interaction partners. This association is least in the Netherlands and seems to be strongest in Great Britain and Germany. We expect this pattern to be strongly caused by previous performance selections into school tracks and the opportunity structure of the status compositions of schools and school classes. Nonetheless, this graphics show a remarkably high segregation of a very relevant part of everyday interactions of students. Taken both aspects together, students from families of lower status have a prominent social resource deficit in terms of the number of ties and the actual resources that can be accessed through them.

To test our hypotheses we computed several multi-level models that pooled the Netherlands and Germany and applied a simple value-added model (Hanushek & Rivkin, 2010). Since network effects take time to become relevant and despite changes in ties, we assume a larger part of ties stay the same, we used the math grades and network properties reported in wave 1 to explain math grades reported in wave 3. Table 3.7 shows the results on effects of doing homework together.[36] We first tested our theoretically deduced resource indicator (equation 6). This resulted in better fits than only the indegree, the mean ISEI of network partners or the interaction of both. However, the scale becomes unintuitive since indegree and mean ISEI of the network are entered together. Therefore we report the according margin plot in figure 3.7. Since the dependent variable was transformed into a scale between 0 and 100 being the maximum grade in both countries, we can see a rather small but significant effect in model 2.[37] In Model 3 we additionally include the effect of homophily to test H4 that stated that an absence of segregation or homophily is beneficial for learning outcomes. To derive these values we used a, as far as we know, novel method.[38] We computed Exponential Random Graph (ERG) Models[39] to estimate the configuration 'absolute difference in parental ISEI'. This way we were able to estimate a parameter for the tendency to choose tie partners with the same ISEI background.[40] It is based on deviations of the socio-economic status of

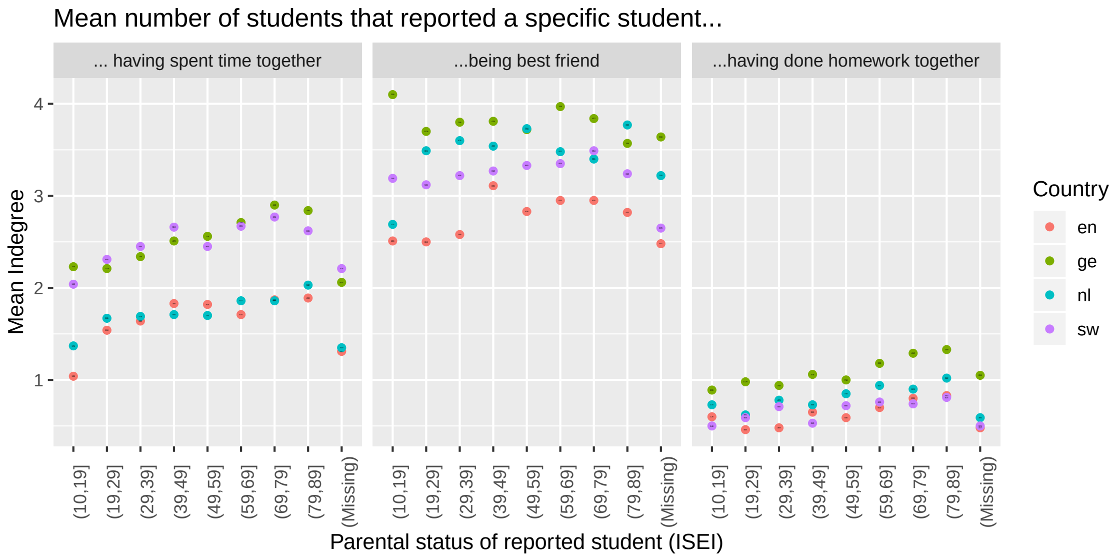
[36] The asterisks in all subsequent models follow the usual conventions:
$* := p < 0.05, ** := p < 0.01, *** := p < 0.001$

[37] Note that model 1 to 4 are not directly comparable due to the different case numbers due to missingness, for which we did not correct because of the low power of the model.

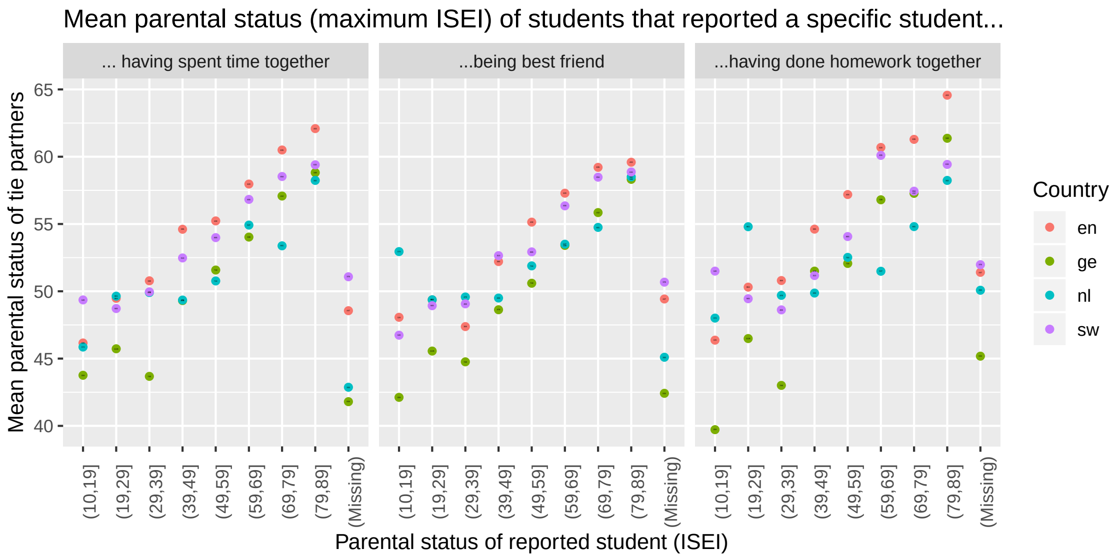
[38] With reasonable search time we found no other sources. Since almost everything has been done before by someone, the author would like to ask for your forgiveness, if his fallacy resulted in not giving credit.

[39] In essence, ERG models try to estimate latent processes in the formation of ties by giving a model for the likelihood of ties based on given attributes of nodes and structural network properties (Harris, 2013; Lusher, Koskinen, & Robins, 2013).

[40] We used the R-package `ergm` (David, Mark, Carter, Steven, & Martina, 2008; Mark et al., 2018).

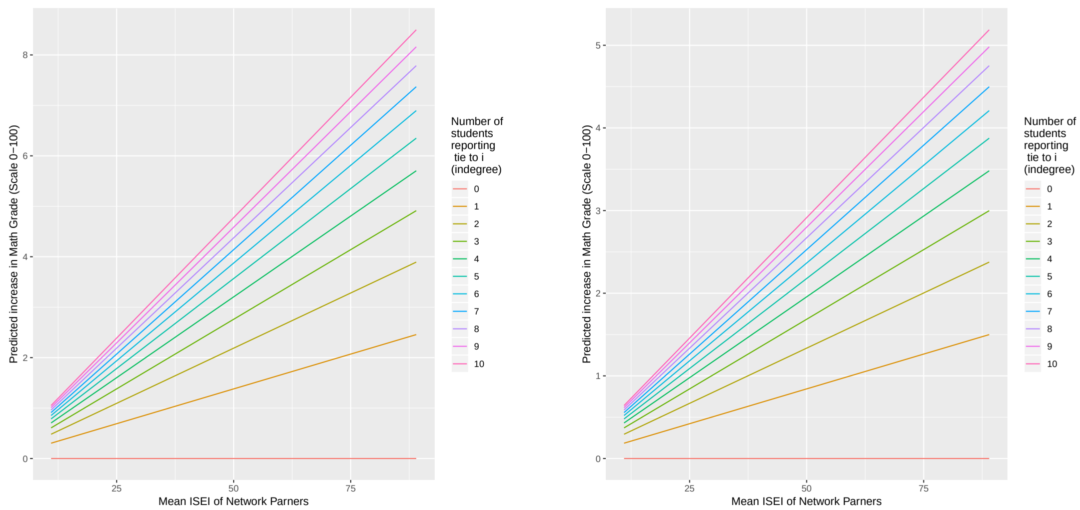


(a) Number of ties (indegree) by own parental status



(b) Mean parental status of interaction partners by own parental status

Figure 3.6: Resource Deficit of lower status students
Numbers in points report cases in this category.



(a) Model 2 (b) Model 3

Figure 3.7: Marginal Effects Plots for resource indicator of Model 2 and 3 (homework network)

tie partners from the SES of the own family. The distribution of this deviations is compared with the distribution under the assumption of random choices and can be used to compute a measure of the level of homophily in a specific class. To test the main part of our theory, we would have to introduce interactions between parental ISEI and our resource indicator or the homophily indicator. But as one can see, in the value added specification of model 1, the math score at $t = 1$ already took the whole variance of the parental ISEI which seems like it mediates the biggest part of the ISEI. Beyond the especially strong impacts of early childhood development inside of families, processes related to cultural capital and grades span a much longer time and can be reinforced by feedback processes and thus have become more relevant. In essence, the parental background is much less relevant when math at $t = 1$ is already controlled for. Due to the relatively small sample size, thus, parental ISEI becomes insignificant.

3.6 Conclusion

We presented a detailed theoretic specification of effects of networks on the inequality of educational outcomes and performed a first empirical test. The descriptive analysis documented a pronounced status segregation resulting from the selection into schools. This has consequences for the everyday interactions and also the available resources of students. Given that the SES of interaction partners is correlated with their cultural capital, this also means that there exists a strong gap in the resources accessed by social ties which mirrors the prior educational resource gap between families of different SES. Our proposed specification of network resources proved quite feasible and showed a good fit. The value added specification that was used to isolate effects of previous selection into school classes could give support to peer composition effects and additionally gave first clues, that homophily is related to educational outcomes. However, we were not able to test our hypothesis on IEO, which is left to future research.

Table 3.7: 2L MLM. Dep.: math grade

	Math grade			
	(1)	(2)	(3)	(4)
Intercept	36.14 ***	34.05 ***	28.34 ***	29.85 ***
	(1.5)	(1.82)	(3.57)	(2.89)
parental ISEI	0.02	0.02	-0.01	0.01
	(0.01)	(0.01)	(0.03)	(0.02)
Math grade t-2 years	0.46 ***	0.46 ***	0.49 ***	0.49 ***
	(0.02)	(0.02)	(0.03)	(0.03)
Homework Log Resource Indic		0.03 *	0.02	
		(0.01)	(0.02)	
Class.Lev Homophily (ERG AbsDiff ISEI)			-1.09	-1.01 **
			(0.56)	(0.4)
τ^2_{school}	20.09	26.52	41.61	36.69
	(6.06)	(8.03)	(16.72)	(13.57)
τ^2_{class}	2.15	0	0	0
	(2.85)	(0)	(0)	(0)
σ^2	218.45	209.7	214.06	217.62
	(10.06)	(10.88)	(16.3)	(14.29)
– *Intra Class Correlations* –				
ρ_{school}	0.08	0.11	0.16	0.14
ρ_{class}	0.01	0	0	0
ρ_{σ}	0.91	0.89	0.84	0.86
– *Controls* –				
L1: Female	-2.55 ***	-2.08 **	-0.62	-2.11 *
	(0.55)	(0.73)	(1.08)	(0.85)
n students	5006	3081	1186	1940
n classes	459	423	162	176
n schools	231	226	121	128

4 Conclusion: Contextual Social capital and IEO

As conceptualized by e.g. Bourdieu (Bourdieu, 1982; Bourdieu & Passeron, 1971), the reason for the pronounced IEO in modern societies are early and long-lasting differences in information environments and resulting experiences. The main question of this dissertation was how various forms of social capital are related to inequality of educational outcomes (IEO) and especially if a higher amount of social capital of aggregates might reduce IEO. In essence, such a reduction of IEO – be it specified as conditional chance by socio-economic status, as implicitly used by our approach or as a distribution of outcomes by social ties and networks – can be achieved only if the benefits for students from higher status are lower than those from lower status. What is true for societal changes and policy interventions, of course is also true for social capital, collective social capital and aggregate social capital. Even if all gain from collective social capital (e.g. generalized trust) or aggregate social capital (e.g. denser school class networks), some students from families that have a SES higher than the average must gain less, when IEO should be reduced. While the overall IEO in society is drastically shaped by differences in cultural capital, this differences in educational outcomes are naturally limited by the heterogeneity of social experiences. We stated earlier, that contextual and institutional settings determine the strength of the link between individual experiences in a specific (and individually different) social world and educational outcomes.

Our aim was to test the hypothesis that contextual effects of social capital on an aggregate level does actually reduce IEO. As was detailed before, this hypothesis of effects of network contexts seems plausible to us for several reasons: First, the value of social ties depends on the resources that are accessible through them and we expect a decreasing utility of this additional resources, e.g. because redundancy makes additional cultural capital irrelevant. Second, given that students from families of higher SES already have more social ties, they might gain less education-related resources (e.g. cultural capital) from the additional social ties associated with higher social capital contexts. Both mechanism can be expected to reduce IEO, given that there are no adverse mechanisms like e.g. status-based social closure or latent status segregation. Thus, especially the social interaction of students from different status backgrounds should at average decrease IEO.

The three studies of this dissertation tried to analyze effects of social capital on three different aggregate levels: countries (paper 1), schools (paper 2) and school class networks (paper 3). Paper 2 and 3 found *individual* benefits from having social ties. Paper 1 and 2 supported also that living in denser aggregates is positively related to educational outcomes. Paper 3 gave additionally support, that students in less homophilous classes have higher educational outcomes. However, the results on the association of social capital on aggregate levels with IEO were mixed.

In Paper 1 we tried the theory that cultural properties, which increase the likelihood of tie formation and the overall density of the social network of a society, also reduce IEO. While we found both forms of collective social capital, generalized trust and the membership in associations, to be associated with higher educational outcomes, these higher levels were opposite to our hypothesis accompanied by even higher levels of IEO. While for reasons we explained in detail, we have to be very cautious to draw conclusions out of model results based on the 50 country cases we analyzed, one could infer that students from higher socio-economic status profited over-proportionally from cultural properties that increase the density of a society.

Paper 2 compared schools by proxy measures of the connectedness of students and school-based volunteering of parents. As in paper 1, we found educational outcomes to be positively correlated with the individual connectedness of students. Additionally and separate of it, we found also beneficial effects of what we previously called aggregate social capital. Students that go to denser connected schools profit independent of their own ties. This is in accordance with our theory that relates the aggregate density to the availability of resources by an additional tie to a random other student. However, also opposite to our main hypothesis, we found the aggregate social capital context to increase IEO. Although we analyzed more units compared to paper 1, our analysis also showed the limits of cross-sectional modeling. We estimated negative "effects" of parental volunteering, which, in our opinion, are best explained as being a result of self-selections of parents that participated in school *because* of previous performance problems of their children that we were not able to control for.

Paper 3 researched the same question based on micro data of social tie networks of school classes. This required and allowed for a more detailed specification of the resources embedded in a network which according to our theory can be understood as linked to the socio-economic background. While we mirror the previous findings in terms of utility of social ties, this paper contributes a specification of the effect of the composition of this ties. We were also able to give support to the assumption, that a lower average homophily as an aggregate property of classes does increase educational outcomes.

As a byproduct of our studies we documented the pronounced social "resource deficit" (N. Lin, 2000) of students from lower status families, that we distinguished by a deficit in social ties and the composition of their interaction partners. First, students from lower status families have less ties at schools, which might result from different opportunity structures and school climates. Second, we reported a pronounced difference in the composition in terms of status background, which in large parts is a result of tracking and selection into schools based on performance. We keep it to future research to analyze this aspect in detail.

Taken altogether, we found no evidence that IEO is associated with social capital on higher aggregate levels. Nonetheless, in our opinion future research should retest the presented hypotheses that related cultural or network properties to IEO – ideally by directly controlling for the confounding influence of segregation and hopefully by usage of better data.

The author does not want to conceal that the work was accompanied by a large skepticism. We used common large-scale cross-sectional data sets that surveyed students in secondary education and deployed methods that are still frequently used by educational research. Nonetheless, the list of what can go wrong is too long. Thus, the author regards benevolent and optimistic skepticism to be the only way to deal with the current state of cross-country research. Hopefully the large data providers, like those of PISA and WVS, decide to switch to longitudinal and more modern approaches of surveying society. Besides that, the author is optimistic about and wants to encourage the combined secondary usage and aggregation of micro data sets of single-issue studies.[1] Until this wishlist is fulfilled, we have to live

[1] This could be achieved by several measures: First, a general higher standardization of items and codebooks in micro data sets and practices of catalogueing items across data sets. Second, a standardization and multi-use license contracts that allow for maximum access by the scientific

with biased results and a blurred picture of reality from large-scale comparative studies.

Leaving the framework of the current work, we can take an even more general view on IEO. The author perceives historical changes of higher functional differentiation of occupational tasks and differentiation and specialization that also hold for preference patterns and ways of enjoying leisure time, in tendency to increase differences in experiences. Whether these differences widen the gap of children in the adjustedness to the demands of school depends on the connectedness of societal sub-domains. Societal organizations and institutions (e.g. the previously analyzed membership in associations or involvement of parents in school) are opportunities to bridge domains and components of the societal social networks. Societies in which social experiences of different status groups and especially their information environments are at average more similar, which can be addressed by politics and society by inciting opportunities for less homophilous social ties, will also be more educational equal societies.

community. Third, simplified access to data, that is aggregated from micro data sets. Fourth, maintenance of meta-data sets and automated generation of aggregated variables from data sets of different sources, which at best should be accomplished by a consortium maintained by the scientific community.

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6 Supplement Paper 1

6.1 Application of weighting procedures

We had to account for the complex survey structure of PISA. The specific mixture of clustered sampling and stratified sampling (OECD, 2009) compels the usage of weighting procedures and modelling methods that consider the deviations from simple random sampling induced by increased similarities inside of clusters like schools and countries (Lohr, 2010).

For descriptive statistics and at step/at stop one of the computed two-step models we weighted by the final student weights which are the inverse of the probability being selected inside a country. The sum of final student weights in every country equals the number of eligible students.

But multi-level modelling also "may lead to biased estimates when employed in samples that include unequal probability of selection" and thus requires scaling of the weights (Carle, 2009). We applied a scaling of the raw weights that is advised by PISA-Team and described e.g. by Snijders and Bosker (2012, p. 231): We scaled the L1-weight (individual-level) with the formula

$$w_{1ij} = \frac{n_j (W\_FSTUWT)_{ij}}{\sum_k (W\_FSTUWT)_{ik}}$$

and the L2-weight (school-level) with the formula

$$w_{2j} = \frac{M(W\_FSCHWT)_j}{\sum_h n_h (W\_FSCHWT)_h}.$$

with i denoting any individual, j denoting any school, n_j denoting the number of students per school, M denoting the total number of sampled students in the country, n_h denoting the number of schools in the country and year of PISA. In effect for every country and year the sum of the student level weights $\sum_{ij} w_{1ij}$ resulted in the number of survey participants in the school they were attending and the sum of the school weights $\sum_j w_{2j}$ resulted in the total number of students sampled in a country of a certain PISA wave.[1]

6.2 Application of Plausible Values

We analyzed the PISA data in accordance with the suggestions of the technical manual and utilized plausible values (PV) to estimate performance scores and covariation with other student properties. Plausible values are draws from a posterior-distribution (Wu, 2005). PISA provides 5 (2000-2012) to 10 (2015) plausible value-scores (PV) for the math performance estimated based on a Rasch (or 1PL)-measurement model OECD, 2009, p.79.

Statistics for the Models that explain performance scores were based on the mean of computations of the separate models for each PV, that are equal to the standard formulas of Multiple Imputation (Rubin, 1987):

$\theta_k = 1/M \sum_{i=1}^{M} \theta_{ik}$.

Simulations show that estimates based on this formula are unbiased and more efficient compared with other estimates. This is true for estimates of means as well as variances, regression coefficients and standard errors, but also the between- and in-group-variance of a population (Monseur & Adams, 2008).

[1] We did not used replicate weights due to unavailability of technical applications suited for multi-level models, missing simulation studies and insufficient resources (requiring 60 imputations to be estimated for each model calls). In consequence, estimates of variances might or might not additionally be biased.

6.3 Used country samples

6.3.1 Country set 1: Valid responses for 50 countries participating in PISA waves 2006-2015 (n=~1.54 million)

cnt	2006	2009	2012	2015
AUS	13646	13346	13619	13076
AUT	4790	6169	4560	6586
BEL	8543	8163	8154	8870
BGR	4206	4094	4800	5050
BRA	8767	19063	17814	18980
CAN	21776	21816	20131	17763
CHE	12022	11596	10995	5476
CHL	5007	5411	6499	6425
COL	4250	7370	8529	10594
CZE	5773	5880	5122	6403
DEU	4498	4396	4034	5329
DNK	4276	5578	6982	6111
ESP	19084	24843	24906	6320
EST	4785	4583	4636	5310
FIN	4587	5734	8527	5630
FRA	4431	3993	4342	5530
GBR	12399	11541	11949	12265
GRC	4737	4847	4947	5085
HKG	4455	4625	4307	4753
HRV	5025	4820	4769	5393
HUN	4203	4399	4471	5178
IDN	9751	4729	4982	6095
IRL	4397	3777	4843	5398
ISL	3696	3547	3304	3178
ISR	3852	5155	4531	5879
ITA	21344	30427	30223	10843
JOR	5302	5747	5389	5915
JPN	5453	5579	5725	6009
KOR	5113	4908	4939	5373
LTU	4560	4261	4379	5690
LUX	4357	4431	4937	4772
LVA	4507	4251	4118	4449
MEX	29923	36841	32382	7157
MNE	3890	4388	4005	4647
NLD	4734	4580	4229	5084
NOR	4510	4519	4459	5091
NZL	4625	4449	4021	4112
POL	5380	4736	4441	4231

PRT	4956	6156	5468	6925
QAT	3679	7309	9074	10125
ROU	4736	4482	4589	4058
RUS	5621	5141	5018	5372
SVK	4526	4362	4319	5584
SVN	6387	5786	5648	6035
SWE	4334	4414	4508	4992
THA	5890	5622	5850	6405
TUN	4414	4747	3967	4288
TUR	4522	4438	4262	5149
URY	4627	5694	5059	5507
USA	5221	4989	4708	5259

6.3.2 Country set 2: Valid responses for 34 countries participating in PISA waves 2000-2012 (n=~1.34 million)

cnt	2000	2003	2006	2009	2012
AUS	4939	11894	13646	13346	13619
AUT	4635	4435	4790	6169	4560
BEL	6371	8293	8543	8163	8154
BRA	4469	4105	8767	19063	17814
CAN	28751	25929	21776	21816	20131
CHE	5880	8142	12022	11596	10995
CZE	5273	6071	5773	5880	5122
DEU	4934	4252	4498	4396	4034
DNK	3953	4106	4276	5578	6982
ESP	5923	10378	19084	24843	24906
FIN	4770	5715	4587	5734	8527
FRA	4389	4113	4431	3993	4342
GBR	8843	8965	12399	11541	11949
GRC	4468	4354	4737	4847	4947
HKG	4224	4290	4455	4625	4307
HUN	4746	4501	4203	4399	4471
IDN	6811	9806	9751	4729	4982
IRL	3737	3726	4397	3777	4843
ISL	3298	3273	3696	3547	3304
ITA	4864	11395	21344	30427	30223
JPN	2019	4180	5453	5579	5725
KOR	4617	5308	5113	4908	4939
LUX	3201	3782	4357	4431	4937
LVA	3713	4476	4507	4251	4118
MEX	4222	28594	29923	36841	32382
NLD	2438	3722	4734	4580	4229
NOR	4037	3939	4510	4519	4459
NZL	3523	3794	4625	4449	4021
POL	3396	4285	5380	4736	4441
PRT	4426	4477	4956	6156	5468
RUS	6512	5848	5621	5141	5018
SWE	4313	4503	4334	4414	4508
THA	4798	4950	5890	5622	5850
USA	3242	5154	5221	4989	4708

6.3.3 Country set 3: Valid responses for 38 countries participating in PISA waves 2003-2012 (n=~1.23 million)

cnt	2003	2006	2009	2012
AUS	11894	13646	13346	13619
AUT	4435	4790	6169	4560
BEL	8293	8543	8163	8154
BRA	4105	8767	19063	17814
CAN	25929	21776	21816	20131
CHE	8142	12022	11596	10995
CZE	6071	5773	5880	5122
DEU	4252	4498	4396	4034
DNK	4106	4276	5578	6982
ESP	10378	19084	24843	24906
FIN	5715	4587	5734	8527
FRA	4113	4431	3993	4342
GBR	8965	12399	11541	11949
GRC	4354	4737	4847	4947
HKG	4290	4455	4625	4307
HUN	4501	4203	4399	4471
IDN	9806	9751	4729	4982
IRL	3726	4397	3777	4843
ISL	3273	3696	3547	3304
ITA	11395	21344	30427	30223
JPN	4180	5453	5579	5725
KOR	5308	5113	4908	4939
LUX	3782	4357	4431	4937
LVA	4476	4507	4251	4118
MEX	28594	29923	36841	32382
NLD	3722	4734	4580	4229
NOR	3939	4510	4519	4459
NZL	3794	4625	4449	4021
POL	4285	5380	4736	4441
PRT	4477	4956	6156	5468
RUS	5848	5621	5141	5018
SVK	7074	4526	4362	4319
SWE	4503	4334	4414	4508
THA	4950	5890	5622	5850
TUN	4478	4414	4747	3967
TUR	4263	4522	4438	4262
URY	5226	4627	5694	5059
USA	5154	5221	4989	4708

6.4 Social Capital Indicators (Used sources)

Table 6.4: Overview of used indicators for Collective Social Capital and Association Membership

Source	Variable	
	Trust in strangers	Association Member
WVS1981-1984	V27	-
WVS1990-1994	V94	V87
WVS1995-1998	V27	-
WVS1999-2004	V25	
WVS2004-2009	V23	
WVS2010-2014	V24	
EVS1981-1984	v208	v160
EVS1990-1993	q241	q234d
EVS1999-2001	v66	
EVS2008-2009	v62	
ESS2002	pplhlp	
ESS2004	pplhlp	
ESS2006	pplhlp	fltlnl
ESS2008	pplhlp	
ESS2010	pplhlp	fltlnla
ESS2012	pplhlp	fltlnl
ESS2015	pplhlp	fltlnl

6.5 Distribution of context variables (1): Collective social capital

6.5.1 Generalized trust

Table 6.5: Live-time context of trust in strangers by country and wave

	cnt	2000	2003	2006	2009	2012	2015	
1	ALB	0.29			0.23	0.24	0.25	0.06
2	ARG	0.21		0.18	0.18	0.18		0.03 (-)
3	AUS	0.42	0.42	0.43	0.44	0.47	0.48	0.06 (+)
4	AUT	0.33	0.36	0.40	0.42	0.44	0.48	0.15 (+)
5	AZE			0.21	0.20			0.01 (-)
6	BEL	0.32	0.34	0.36	0.39	0.42	0.44	0.12 (+)
7	BGR	0.30		0.29	0.28	0.28	0.29	0.02
8	BRA	0.08	0.08	0.08	0.09	0.09	0.09	0.01 (+)
9	CAN	0.47	0.45	0.43	0.42	0.42	0.42	0.05 (-)
10	CHE	0.45	0.46	0.48	0.51	0.53	0.55	0.1 (+)
11	CHL	0.23		0.21	0.19	0.17	0.15	0.08 (-)
12	COL			0.12	0.12	0.11	0.10	0.02 (-)
13	CZE	0.28	0.30	0.32	0.33	0.37	0.40	0.12 (+)
14	DEU	0.34	0.37	0.40	0.42	0.46	0.49	0.15 (+)
15	DNK	0.61	0.62	0.62	0.63	0.62	0.61	0.02
16	DOM						0.28	0
17	DZA						0.16	0
18	ESP	0.34	0.36	0.37	0.38	0.39	0.41	0.07 (+)
19	EST			0.31	0.35	0.39	0.44	0.13 (+)
20	FIN	0.57	0.56	0.55	0.56	0.58	0.58	0.03
21	FRA	0.23	0.26	0.30	0.34	0.38	0.42	0.19 (+)
22	GBR	0.39	0.40	0.41	0.44	0.48	0.53	0.14 (+)
23	GEO				0.21		0.18	0.03 (-)
24	GRC	0.24	0.25	0.26	0.27	0.28	0.30	0.06 (+)
25	HKG	0.41	0.41	0.41	0.42	0.43	0.44	0.03 (+)
26	HRV			0.23	0.23	0.25	0.29	0.06 (+)
27	HUN	0.25	0.27	0.30	0.32	0.37	0.42	0.17 (+)
28	IDN	0.51	0.51	0.50	0.48	0.46	0.45	0.06 (-)

Table 6.5: Live-time context of trust in strangers by country and wave

	cnt	2000	2003	2006	2009	2012	2015	
29	IRL	0.43	0.46	0.48	0.50	0.54	0.58	0.15 (+)
30	ISL	0.43	0.44	0.48	0.50	0.53	0.58	0.15 (+)
31	ISR	0.24		0.30	0.35	0.40	0.46	0.22 (+)
32	ITA	0.33	0.34	0.34	0.33	0.34	0.36	0.03
33	JOR			0.28	0.28	0.27	0.24	0.04 (-)
34	JPN	0.43	0.43	0.42	0.42	0.41	0.40	0.03 (-)
35	KAZ				0.38	0.38		0
36	KGZ			0.18	0.21			0.03 (+)
37	KOR	0.32	0.31	0.29	0.28	0.28	0.27	0.05 (-)
38	LBN						0.15	0
39	LTU			0.26	0.27	0.31	0.35	0.09 (+)
40	LUX	0.26	0.29	0.33	0.35	0.36	0.37	0.11 (+)
41	LVA	0.21	0.21	0.22	0.24	0.29	0.35	0.14 (+)
42	MDA				0.18		0.14	0.04 (-)
43	MEX	0.31	0.29	0.25	0.21	0.17	0.15	0.16 (-)
44	MKD	0.12					0.18	0.06 (+)
45	MLT				0.22		0.22	0
46	MNE			0.32	0.31	0.29	0.28	0.04 (-)
47	MYS				0.09	0.09		0
48	NLD	0.55	0.56	0.56	0.55	0.56	0.55	0.01
49	NOR	0.64	0.64	0.63	0.63	0.62	0.62	0.02 (-)
50	NZL	0.49	0.49	0.50	0.51	0.53	0.54	0.05 (+)
51	PER	0.07			0.08	0.08	0.08	0.01 (+)
52	POL	0.26	0.25	0.25	0.29	0.32	0.37	0.12
53	PRT	0.18	0.20	0.24	0.27	0.32	0.37	0.19 (+)
54	QAT			0.21	0.21	0.21	0.21	0
55	ROU	0.16		0.17	0.19	0.19	0.17	0.03
56	RUS	0.31	0.29	0.28	0.30	0.33	0.37	0.09
57	SGP				0.21	0.25	0.29	0.08 (+)
58	SRB			0.24	0.21	0.17		0.07 (-)
59	SVK		0.24	0.28	0.30	0.33	0.38	0.14 (+)
60	SVN			0.27	0.31	0.36	0.40	0.13 (+)
61	SWE	0.63	0.63	0.62	0.62	0.62	0.60	0.03 (-)
62	THA	0.42	0.42	0.42	0.41	0.40	0.38	0.04 (-)

Table 6.5: Live-time context of trust in strangers by country and wave

	cnt	2000	2003	2006	2009	2012	2015	
63	TTO				0.04		0.04	0
64	TUN		0.17	0.17	0.17	0.17	0.17	0
65	TUR		0.12	0.16	0.18	0.19	0.20	0.08 (+)
66	URY		0.24	0.25	0.25	0.24	0.23	0.02
67	USA	0.42	0.40	0.38	0.37	0.37	0.37	0.05 (-)
68	VNM					0.48	0.50	0.02 (+)

6.6 Additional Figures

6.6.1 Results of alternative Two-step models

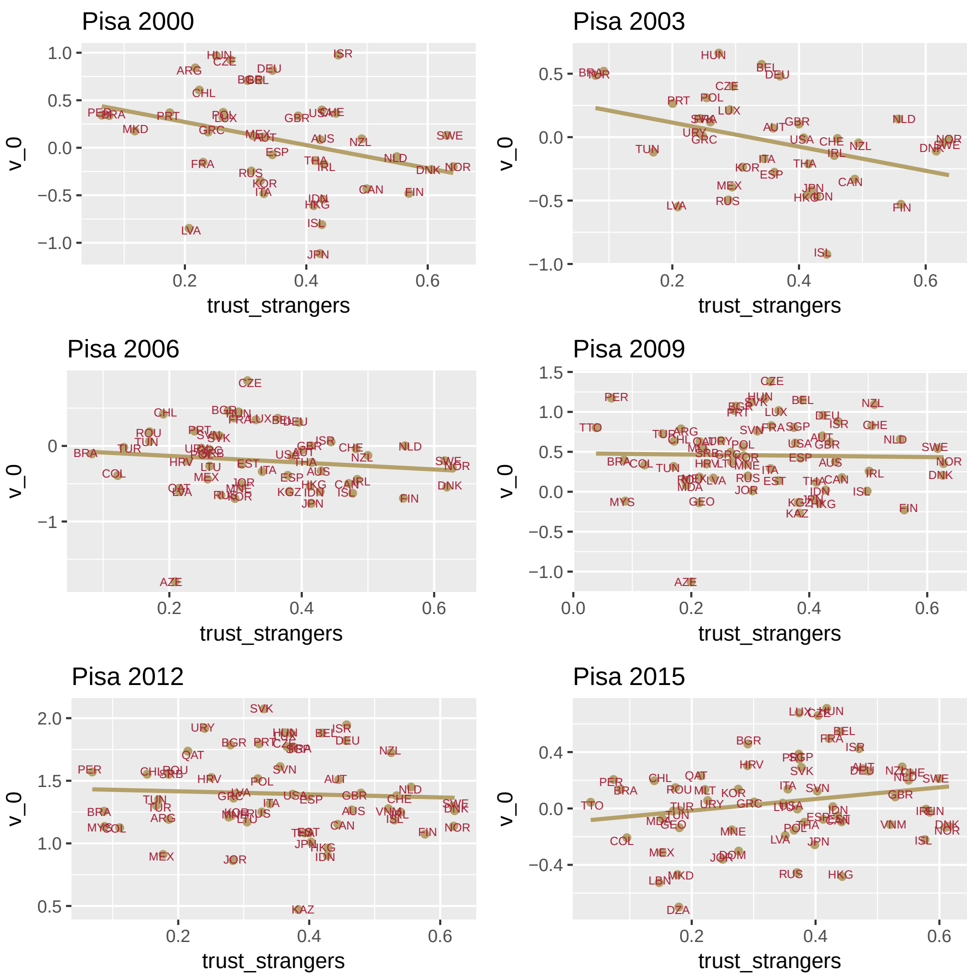

Figure 6.1: Results from a Two-Step Model: Country deviations of the influcence of $ISEI_{max}$ and $Generalized\ Trust$

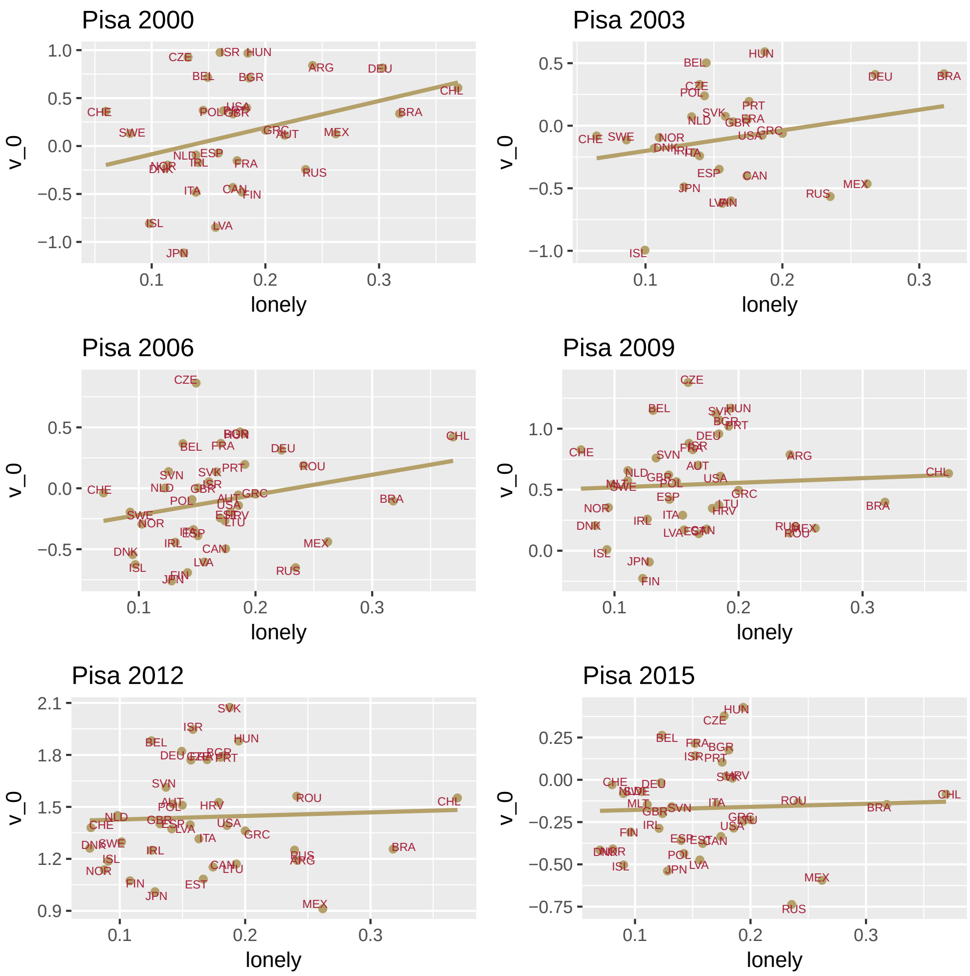

Figure 6.2: Results from a Two-Step Model: Country deviations of the influcence of $ISEI_{max}$ and loneliness

6.6.2 Distribution of Math performance

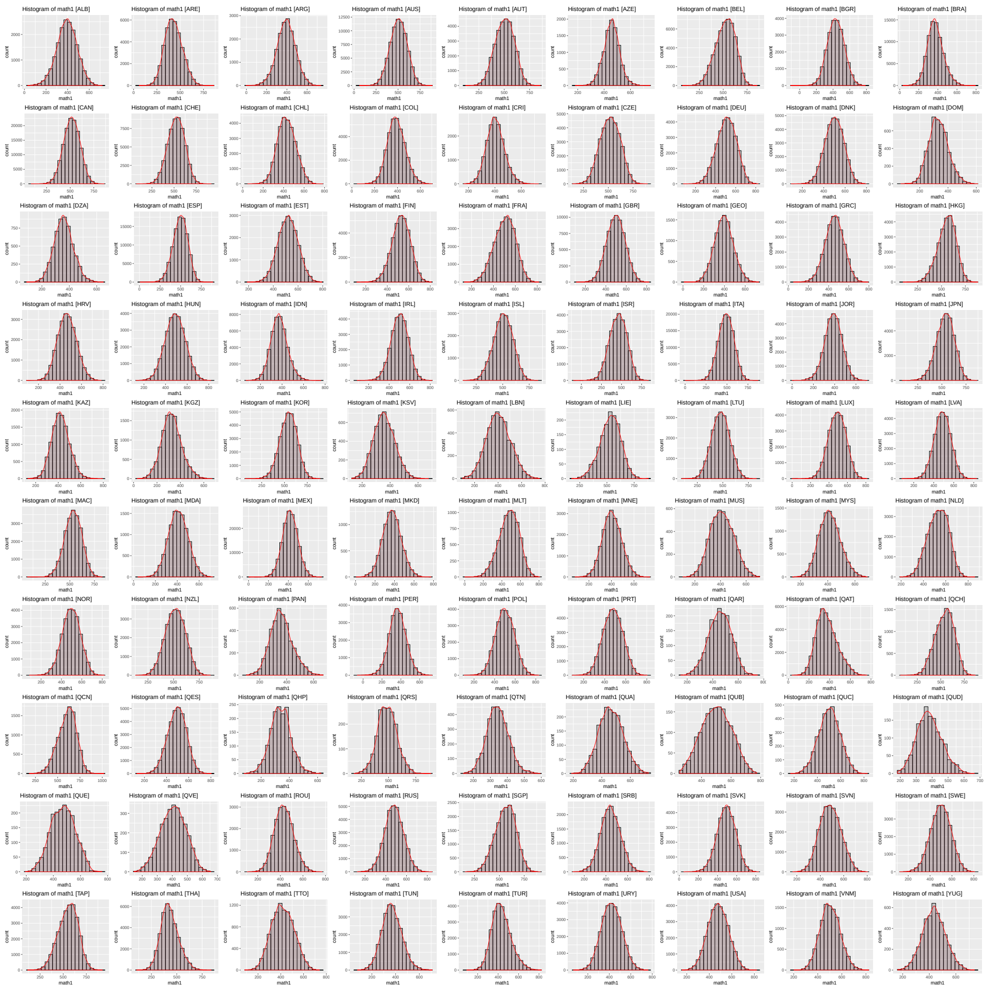

Figure 6.3: Distribution of math scores across country (unimputed, only first math score)

6.6.3 Estimated share of generalized trust based on WVS, EVS, ESS

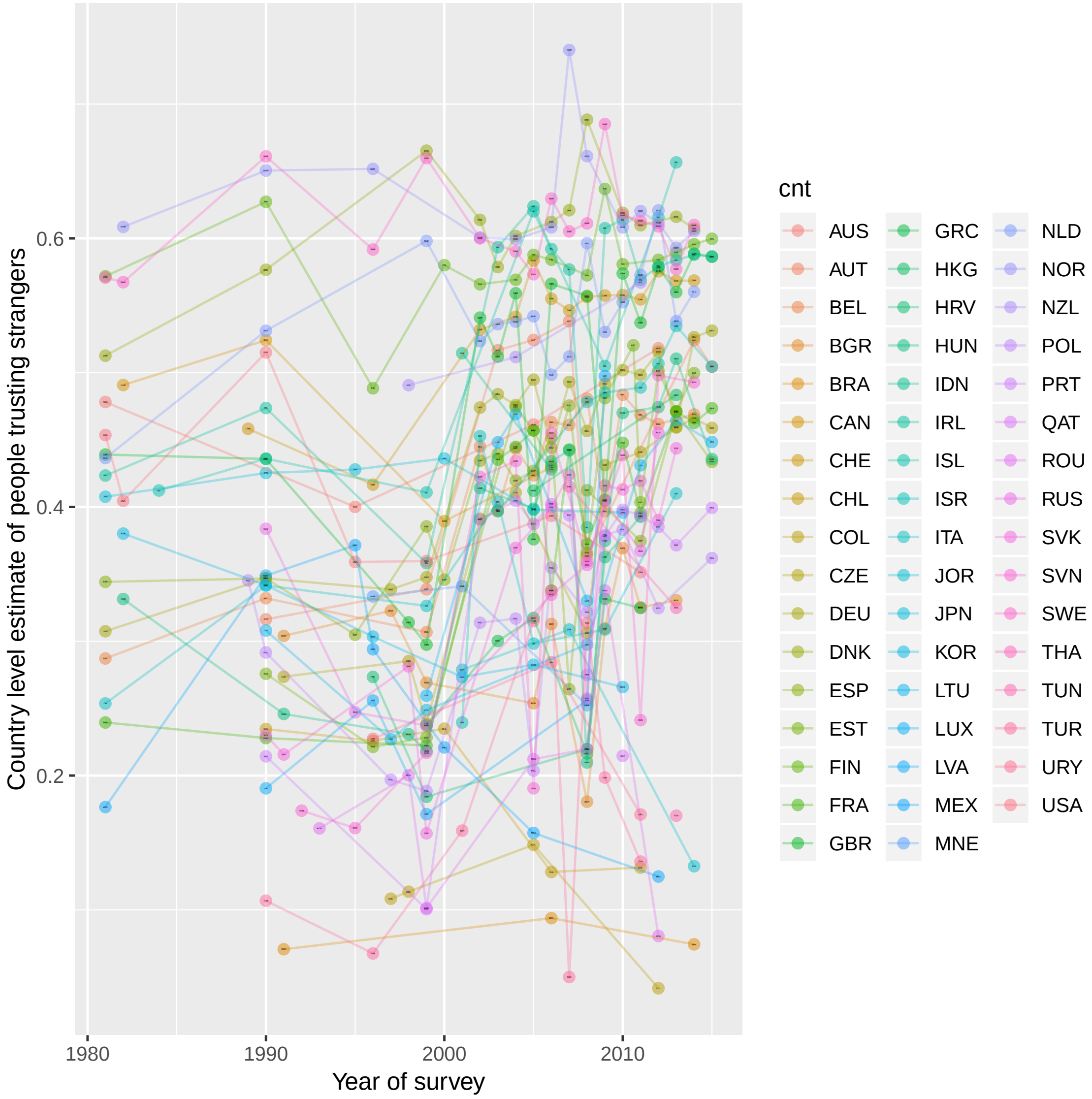

Figure 6.4: Degree of trusting strangers by country

6.6.4 Estimated share of members in voluntary associations based on WVS,EVS

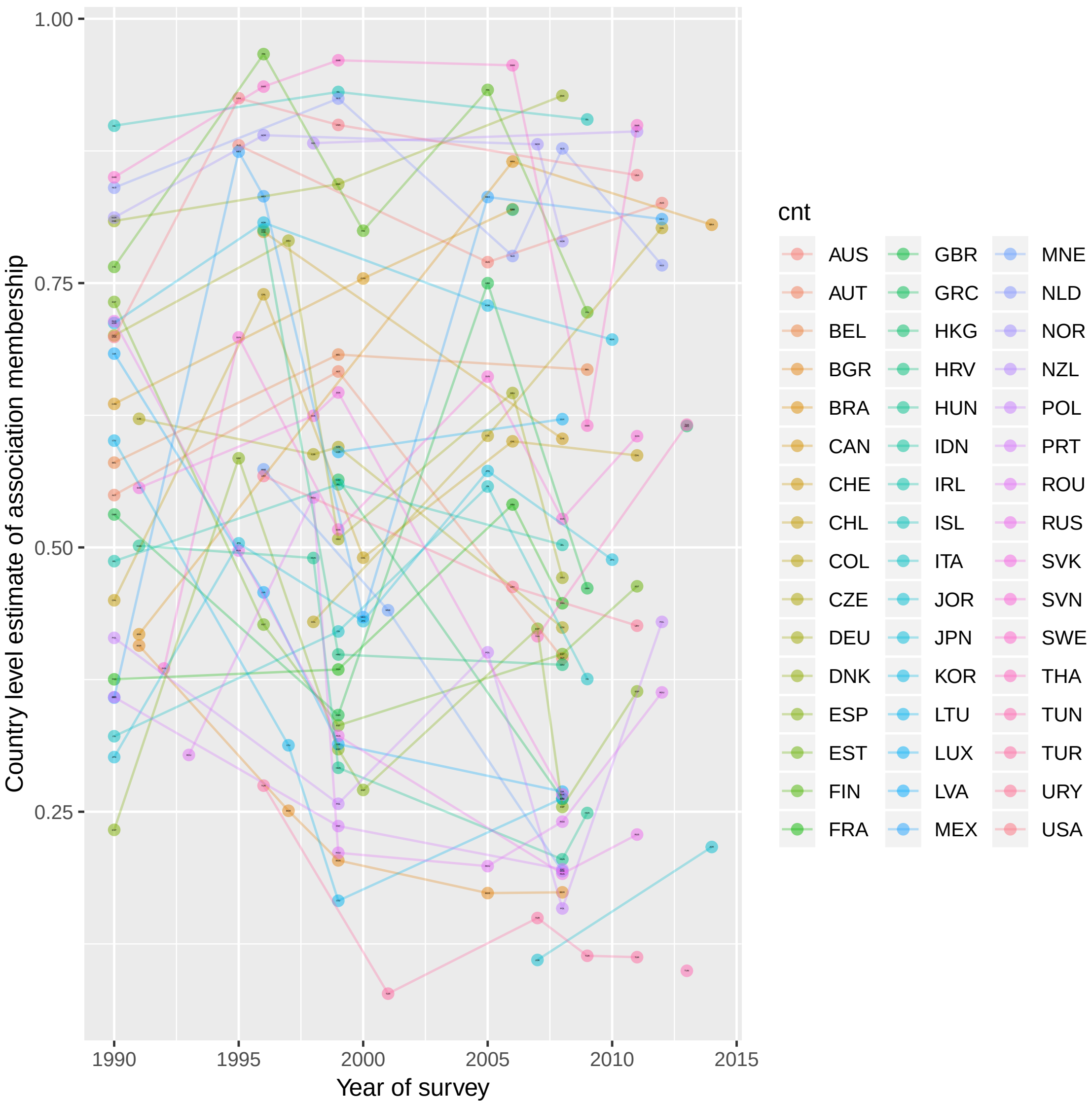

Figure 6.5: Estimated share of members in voluntary association by country

6.6.5 Estimated share of being lonely based on WVS, EVS, ESS

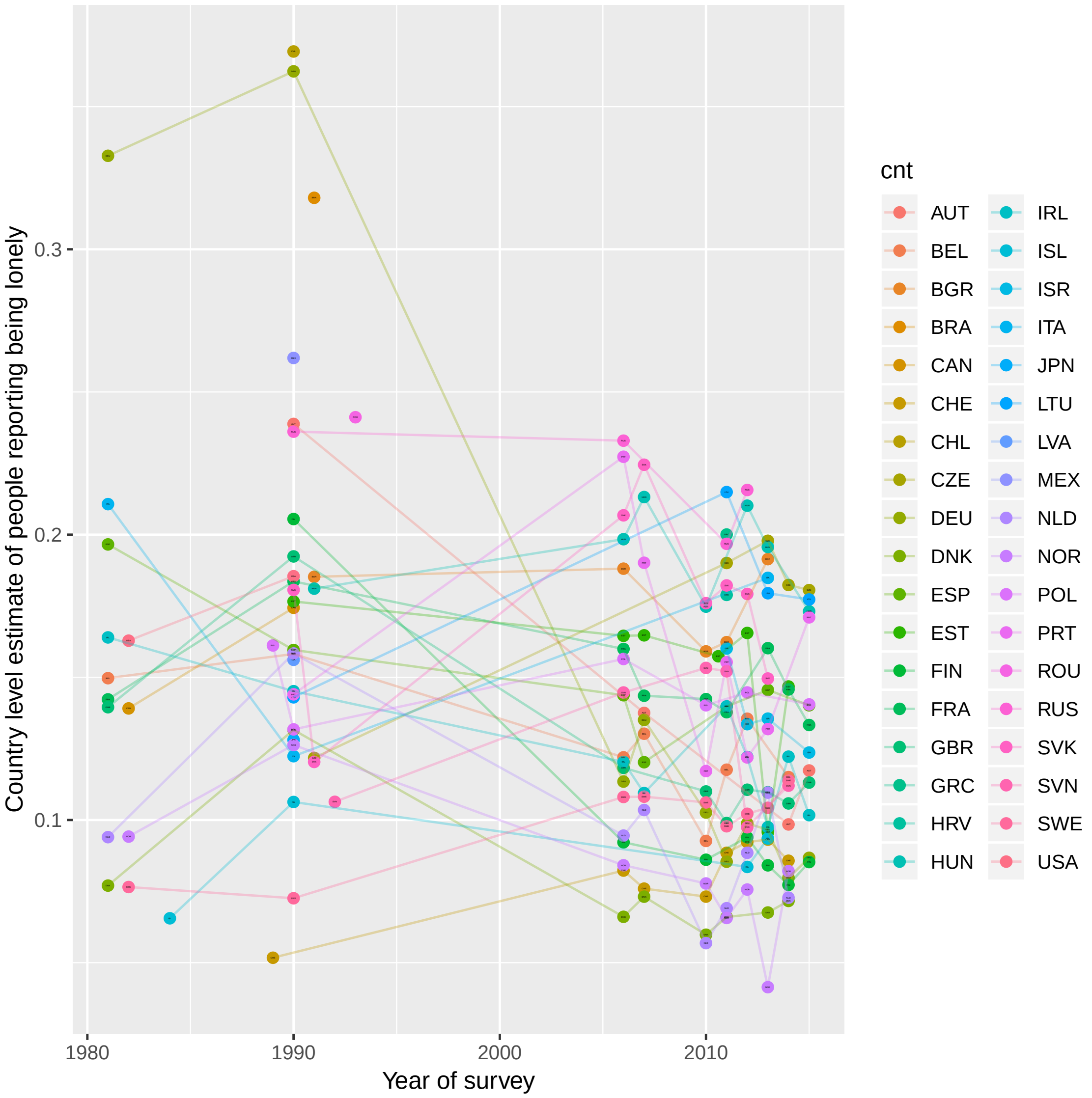

Figure 6.6: Degree of reporting being lonely by country

6.6.6 Gross domestic product (GDP)

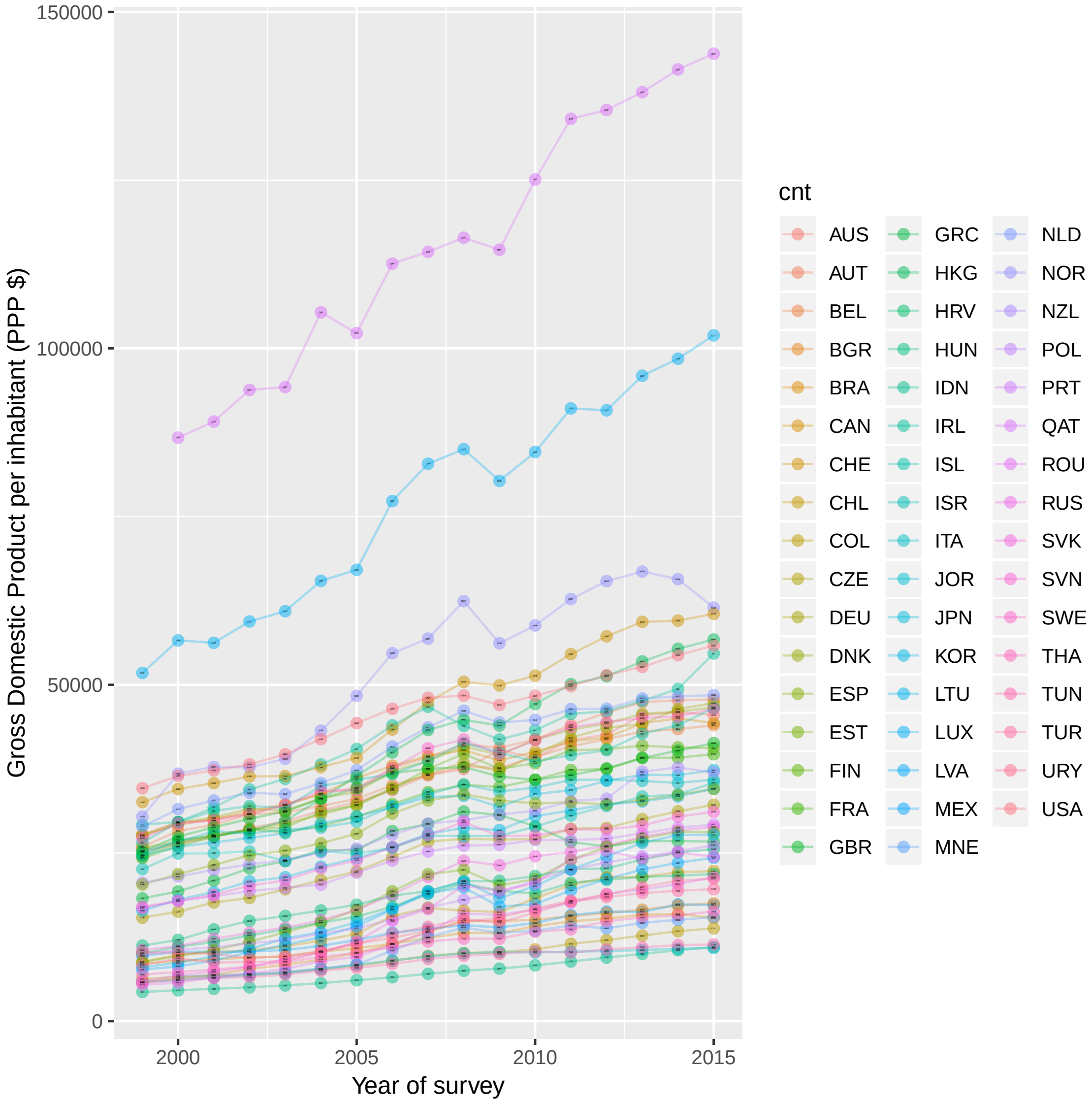

Figure 6.7: GDP by country and year

6.6.7 Educational expenditure (Percentage of GDP per capita)

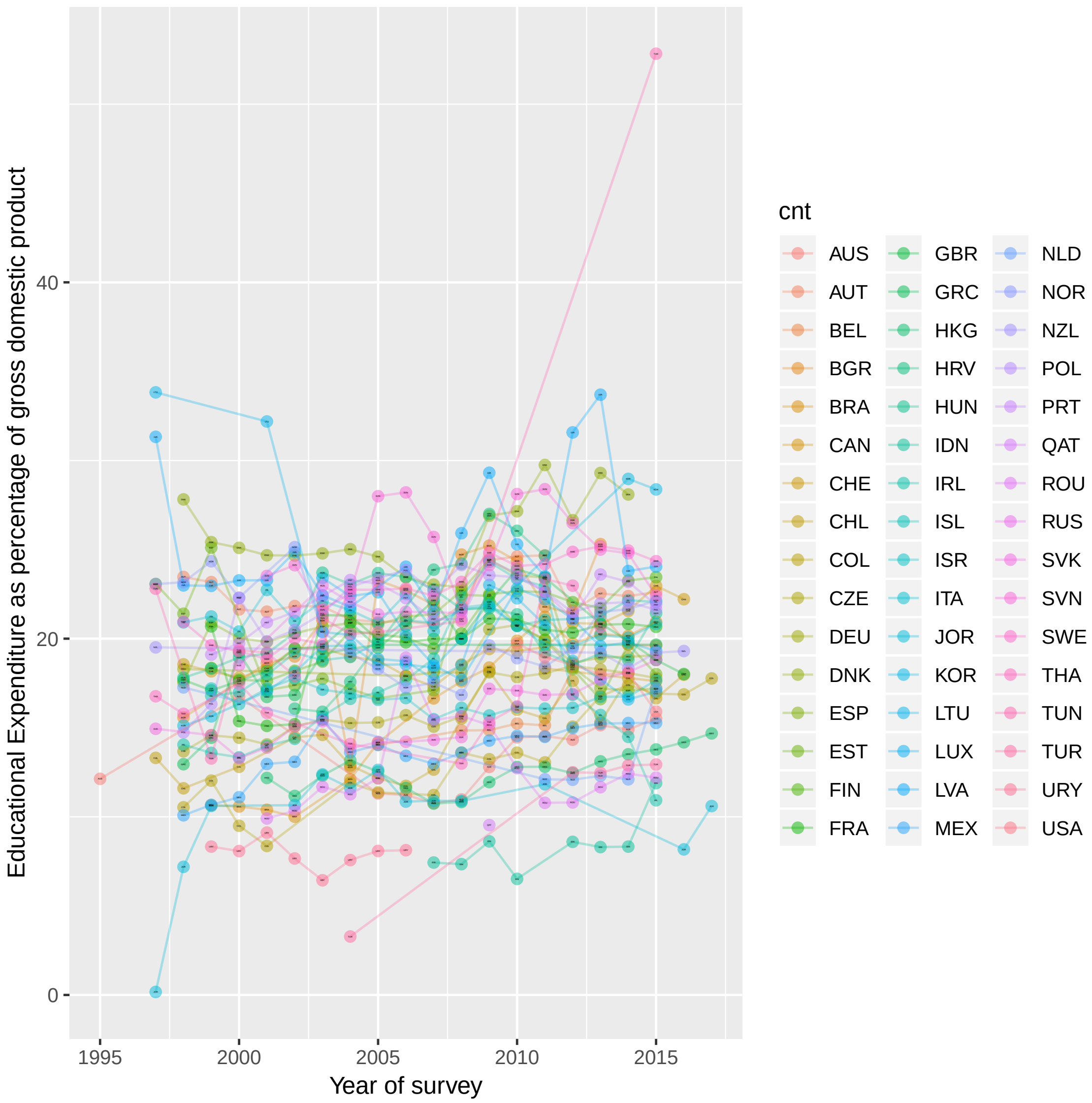

Figure 6.8: Proportion of educational expenditure per student as share of GDP per capita

6.6.8 Official entrance age to primary education

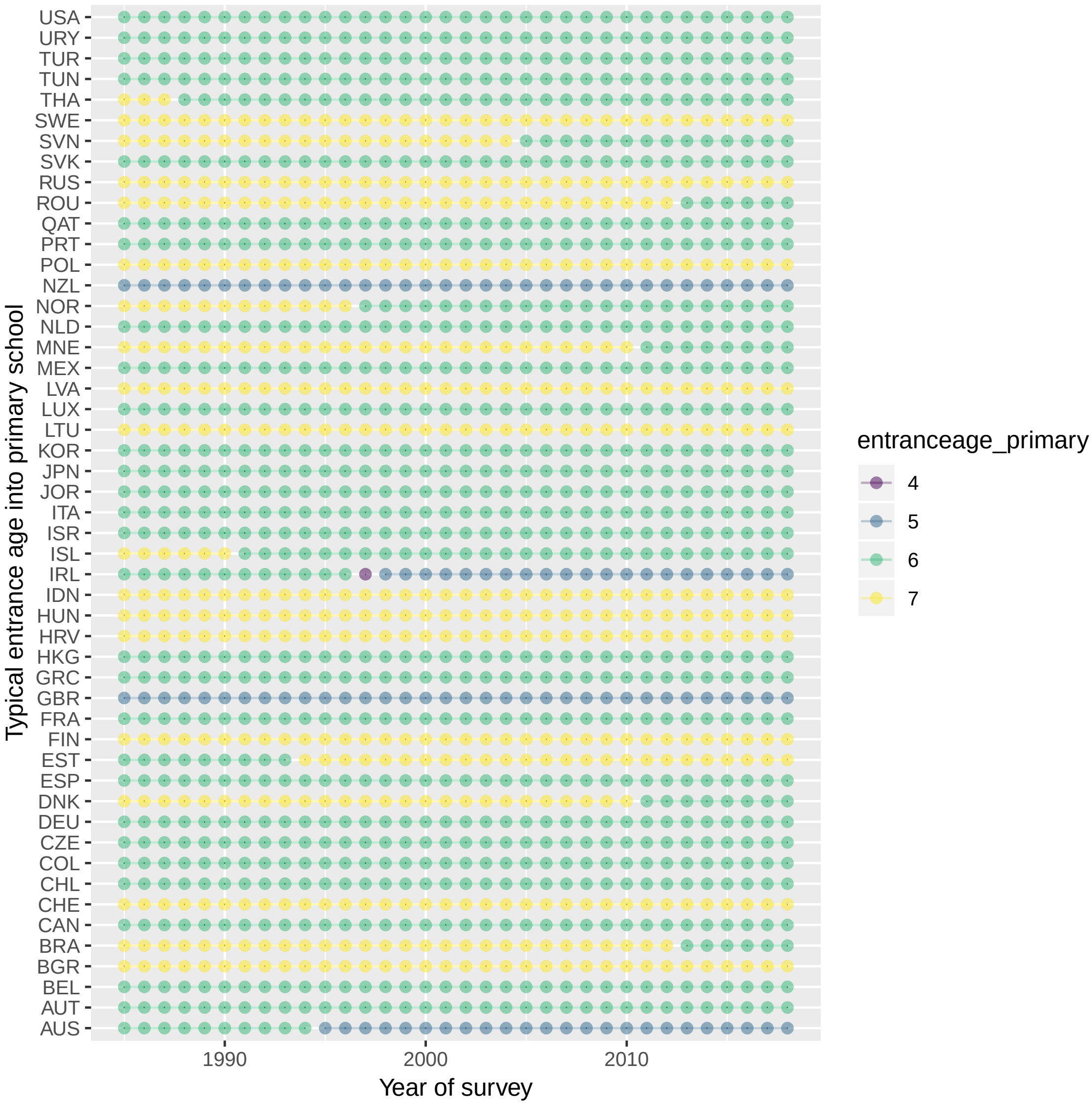

Figure 6.9: Official entrance age to primary education country and year

6.6.9 Covariation of Macro Level Controls with Generalized Trust

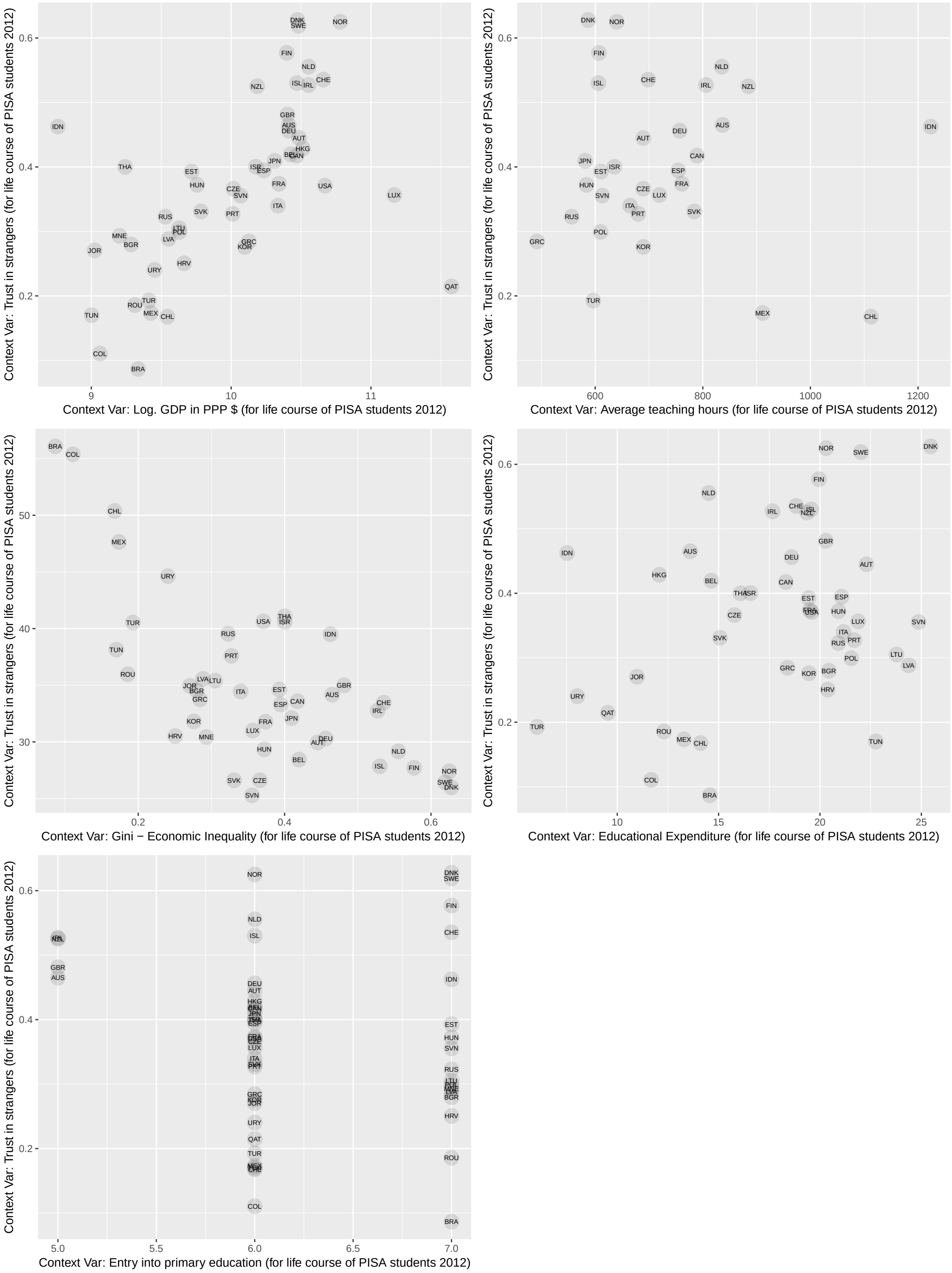

Figure 6.10: Covariation of Macro Level Controls with Generalized Trust

6.6.10 Dependence of Math scores on ISEI

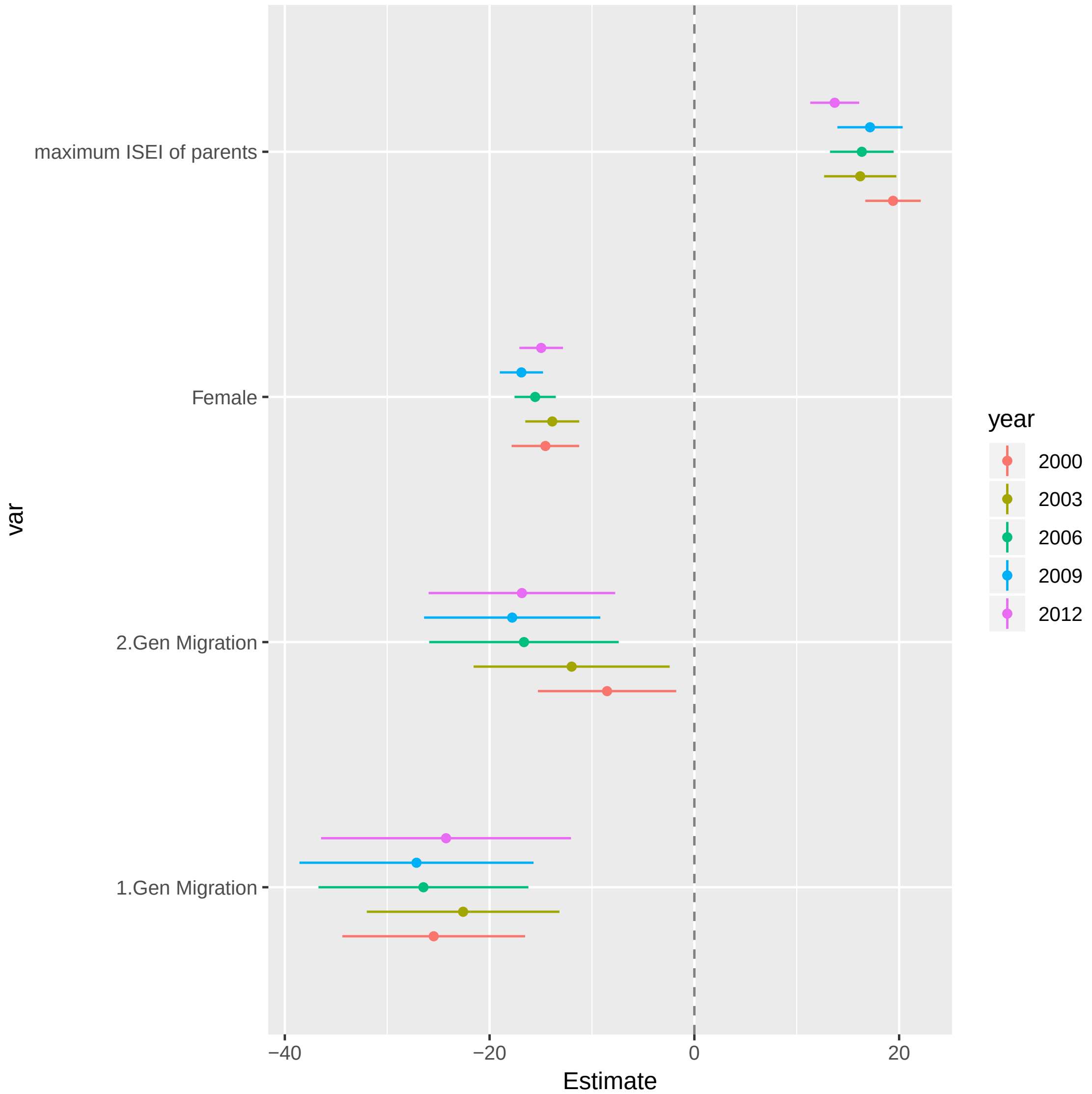

Figure 6.11: Estimated MLM (standardized) coefficients of various L1 variables for model explaining Math Scores (for PISA wave) and 95%CI
Countries: Country set 3 (6.3.3)

6.6.11 Dependence of Science scores on ISEI

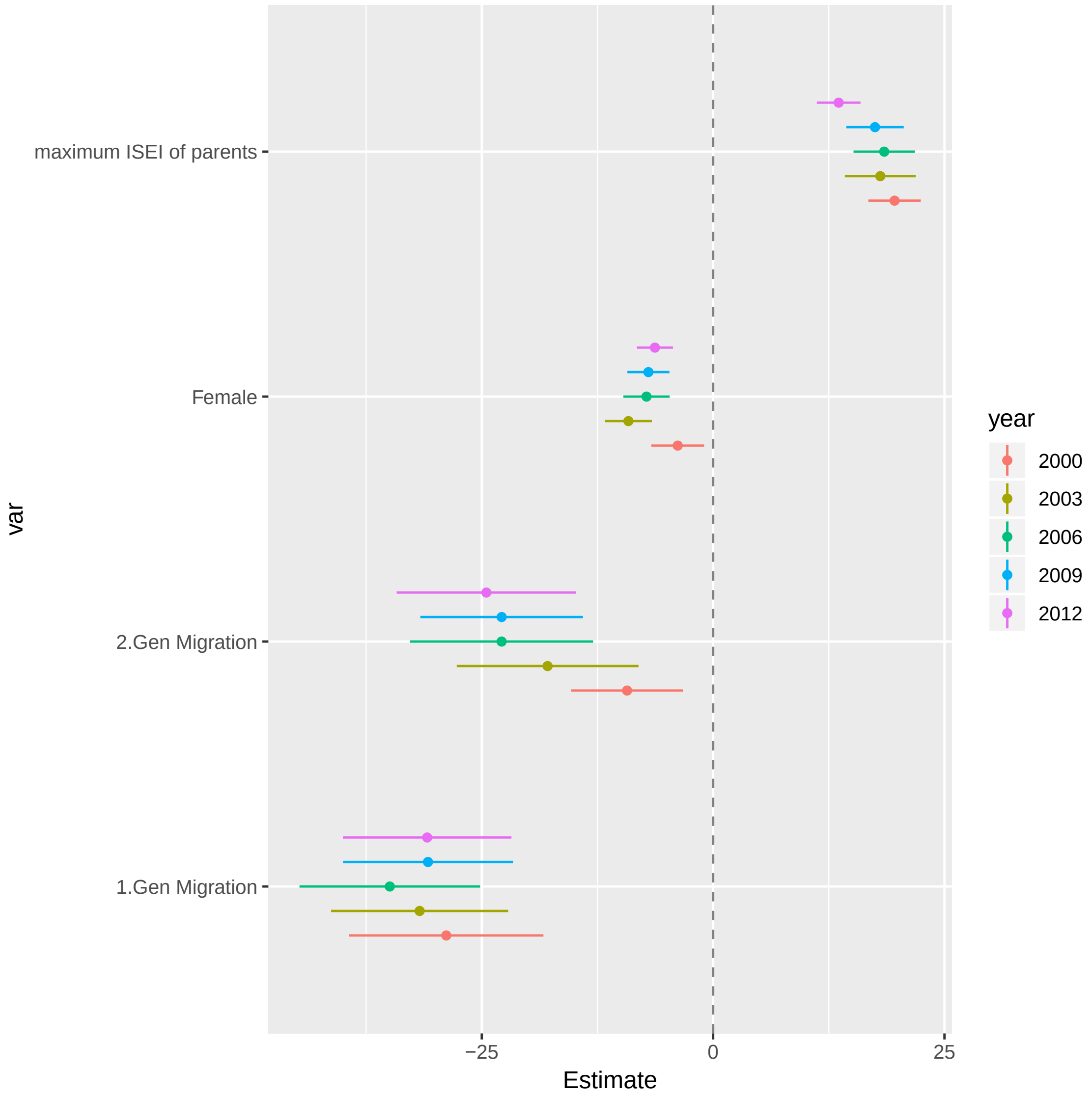

Figure 6.12: Estimated MLM (standardized) coefficients of various L1 variables for model explaining Science Scores (for PISA wave) and 95%CI Countries: Country set 3 (6.3.3)

6.7 Additional Model Results

6.7.1 Individual Level Controls (Generalized Trust Model)

Table 6.6: 3L MLM: Extended Individual level controls (Math Performance, PISA 2012, Country set 1)

	Math Performance				
	(13)	(14)	(15)	(16)	(17)
Intercept	460.782 ***	468.304 ***	469.294 ***	470.48 ***	437.541 ***
	(7.603)	(7.515)	(7.598)	(7.724)	(7.039)
Par.ISEI					0.698 ***
					(0.053)
IndLvlCtr					
Female		-15.917 ***	-15.859 ***	-15.847 ***	-14.971 ***
		(1.082)	(1.062)	(1.057)	(1.007)
1G Mig			-18.467 *	-21.469 **	-17.935 *
			(8.193)	(8.388)	(7.473)
2G Mig				-17.256 ***	-12.33 **
				(5.091)	(4.559)
Var. Comp.					
$\tau^2_{country}$	2823.144	2842.626	2842.908	2872.795	2561.052
	(448.101)	(450.228)	(449.49)	(451.793)	(433.237)
τ^2_{school}	3237.318	3306.918	3273.469	3253.525	2704.001
	(284.019)	(289.802)	(274.906)	(271.569)	(244.034)
σ^2	4825.29	4763.186	4752.337	4742.217	4622.175
	(236.446)	(240.344)	(237.967)	(237.244)	(211.478)
ICCs –					
$\rho_{country}$	0.259	0.26	0.262	0.264	0.259
ρ_{school}	0.297	0.303	0.301	0.299	0.273
ρ_{σ}	0.443	0.436	0.437	0.436	0.467
n students	371305	371305	371305	371305	371305
n schools	15485	15485	15485	15485	15485
n countries	50	50	50	50	50
FMI	0.003	0.004	0.007	0.008	0.011

6.7.2 School-Level Controls (Generalized Trust Model)

Table 6.7: 3L MLM: Extended School level controls (Math Performance, PISA 2012, Country set 1)

	Math Performance				
	(18)	(19)	(20)	(21)	(22)
Intercept	446.817 ***	441.984 ***	420.951 ***	422.283 ***	326.586 ***
	(6.952)	(7.202)	(7.362)	(6.961)	(12.802)
Par.ISEI	0.693 ***	0.688 ***	0.684 ***	0.684 ***	0.603 ***
	(0.054)	(0.054)	(0.055)	(0.054)	(0.058)
SchoolCtrl –					
Small Town	-20.038 ***	-17.384 ***	-6.209 **	-6.275 **	7.151 **
	(2.937)	(2.585)	(2.401)	(2.404)	(2.372)
School		20.418 ***	25.548 ***	25.534 ***	2.658
		(4.036)	(3.813)	(3.805)	(3.928)
School Size			0.027 ***	0.028 ***	0.018 ***
			(0.005)	(0.005)	(0.004)
Stu-Teach-R				-0.143	-0.083
				(0.13)	(0.074)
Mea.Par.ISEI					2.248 ***
					(0.262)
IndLCtrl –					
Female	-15.024 ***	-15.026 ***	-15.067 ***	-15.066 ***	-15.279 ***
	(1.02)	(1.017)	(1.022)	(1.022)	(1.048)
1G Mig	-18.052 *	-18.108 *	-18.147 *	-18.155 *	-17.374 *
	(7.598)	(7.527)	(7.47)	(7.472)	(7.438)
2G Mig	-12.287 **	-12.286 **	-12.381 **	-12.394 **	-12.536 **
	(4.716)	(4.738)	(4.724)	(4.722)	(4.788)
$\tau^2_{country}$	2539.214	2494.707	2528.901	2502.004	2017.381
	(419.972)	(417.677)	(439.893)	(434.357)	(482.726)
τ^2_{school}	2629.102	2573.403	2416.962	2415.549	1747.001
	(259)	(263.105)	(251.203)	(250.625)	(145.007)
σ^2	4642.069	4642.83	4642.826	4642.705	4652.322
	(209.433)	(209.769)	(210.002)	(209.987)	(212.101)
$\rho_{country}$	0.259	0.257	0.264	0.262	0.24
ρ_{school}	0.268	0.265	0.252	0.253	0.208
ρ_{σ}	0.473	0.478	0.484	0.486	0.553
n students	329788	329788	329788	329788	329788
n schools	13624	13624	13624	13624	13624
n countries	49	49	49	49	49
Largest FMI	0.041	0.092	0.102	0.102	0.074

6.7.3 Country Level Controls (Generalized Trust Model)

Table 6.8: 3L MLM: Extended Country level controls for Generalized Trust Model (Math Performance, PISA 2012, Country set 1) (1: Economic Situation - Log. GDP, Gini)

	Math Performance			
	(23)	(24)	(25)	(26)
Intercept	354.036 ***	210.18	355.536 ***	439.464 ***
	(15.111)	(183.742)	(13.59)	(57.168)
Parental ISEI	0.683 ***	0.683 ***	0.671 ***	0.671 ***
	(0.054)	(0.054)	(0.056)	(0.056)
Generalized Trust	240.066 ***	199.14 **	233.345 ***	169.938 **
	(34.266)	(76.028)	(32.295)	(57.152)
– *Cnt Level Controls* –				
Log GDP		15.88		
		(20.996)		
Gini				-1.743
				(1.019)
– *Lower Lvl Ctls* –				
Small Town	-18.334 ***	-18.331 ***	-18.547 ***	-18.54 ***
	(2.722)	(2.721)	(2.785)	(2.784)
Private School	18.645 ***	18.631 ***	19.352 ***	19.37 ***
	(4.04)	(4.04)	(4.186)	(4.187)
Female	-14.947 ***	-14.947 ***	-15.179 ***	-15.179 ***
	(1.019)	(1.019)	(1.03)	(1.03)
1st Gen Immigrant	-18.198 *	-18.204 *	-25.119 ***	-25.119 ***
	(7.443)	(7.445)	(5.953)	(5.953)
2nd Gen Immigrant	-12.703 **	-12.707 **	-17 ***	-17.001 ***
	(4.681)	(4.682)	(4.192)	(4.192)
$\tau^2_{country}$	1467.854	1408.025	1167.049	1082.911
	(362.537)	(355.778)	(308.776)	(275.152)
τ^2_{school}	2556.219	2556.108	2534.06	2533.92
	(257.343)	(257.319)	(266.405)	(266.367)
σ^2	4624.572	4624.583	4555.826	4555.84
	(213.942)	(213.944)	(223.307)	(223.309)
$\rho_{country}$	0.17	0.164	0.141	0.133
ρ_{school}	0.296	0.298	0.307	0.31
ρ_{σ}	0.535	0.538	0.552	0.557
n students	363623	363623	342664	342664
n schools	15104	15104	14460	14460
n countries	50	50	46	46
Largest FMI	0.055	0.055	0.05	0.05

Table 6.9: 3L MLM: Extended Country level controls for Generalized Trust Model (Math Performance, PISA 2012, Country set 1) (2: Average teaching hours in primary to secondary education and Educational Expenditure adjusted for Gini and Inhabitants)

	Math Performance			
	(27)	(28)	(29)	(30)
Intercept	357.614 ***	319.308 ***	397.085 ***	474.888 ***
	(15.073)	(23.74)	(22.582)	(48.885)
Parental ISEI	0.694 ***	0.694 ***	0.69 ***	0.69 ***
	(0.056)	(0.056)	(0.074)	(0.074)
Generalized Trust	230.906 ***	197.667 ***	150.966 **	141.503 **
	(34.389)	(41.65)	(50.341)	(45.931)
– *Cnt Level Controls* –				
Educational Expenditure		2.847		
		(1.508)		
Average Teaching Hours				-0.103 *
				(0.047)
– *Lower Lvl Ctls* –				
Small Town	-18.46 ***	-18.459 ***	-19.106 ***	-19.093 ***
	(2.696)	(2.696)	(3.128)	(3.124)
Private School	18.578 ***	18.624 ***	17.92 ***	18.008 ***
	(4.1)	(4.097)	(4.237)	(4.234)
Female	-14.979 ***	-14.979 ***	-15.39 ***	-15.389 ***
	(1.038)	(1.038)	(1.228)	(1.228)
1st Gen Immigrant	-18.422 *	-18.422 *	-25.981 ***	-25.983 ***
	(7.494)	(7.495)	(6.589)	(6.589)
2nd Gen Immigrant	-12.917 **	-12.917 **	-18.752 ***	-18.754 ***
	(4.726)	(4.727)	(4.876)	(4.876)
$\tau^2_{country}$	1355.574	1199.474	1264.919	1017.1
	(358.597)	(270.194)	(435.926)	(272.925)
τ^2_{school}	2527.024	2526.981	2593.515	2593.389
	(260.004)	(260.003)	(344.2)	(344.168)
σ^2	4638.924	4638.928	4781.501	4781.514
	(219.717)	(219.718)	(274.554)	(274.549)
$\rho_{country}$	0.159	0.143	0.146	0.121
ρ_{school}	0.297	0.302	0.3	0.309
ρ_{σ}	0.544	0.555	0.553	0.57
n students	353982	353982	250787	250787
n schools	14864	14864	10682	10682
n countries	48	48	32	32
Largest FMI	0.05	0.05	0.04	0.04

Table 6.10: 3L MLM: Extended Country level controls for Generalized Trust Model (Math Performance, PISA 2012, Country set 1) (3: Typical Entrance age to Primary School)

	Math Performance	
	(31)	(32)
Intercept	354.036 ***	358.948 ***
	(15.111)	(62.504)
Parental ISEI	0.683 ***	0.683 ***
	(0.054)	(0.054)
Generalized Trust	240.066 ***	239.633 ***
	(34.266)	(35.418)
– *Cnt Level Controls* –		
Age entering Primary Educ		-0.759
		(9.389)
– *Lower Lvl Ctls* –		
Small Town	-18.334 ***	-18.334 ***
	(2.722)	(2.722)
Private School	18.645 ***	18.644 ***
	(4.04)	(4.04)
Female	-14.947 ***	-14.947 ***
	(1.019)	(1.019)
1st Gen Immigrant	-18.198 *	-18.199 *
	(7.443)	(7.444)
2nd Gen Immigrant	-12.703 **	-12.703 **
	(4.681)	(4.681)
$\tau^2_{country}$	1467.854	1467.62
	(362.537)	(361.895)
τ^2_{school}	2556.219	2556.216
	(257.343)	(257.342)
σ^2	4624.572	4624.573
	(213.942)	(213.942)
$\rho_{country}$	0.17	0.17
ρ_{school}	0.296	0.296
ρ_{σ}	0.535	0.535
n students	363623	363623
n schools	15104	15104
n countries	50	50
Largest FMI	0.055	0.055

6.7.4 Country Level Controls (Association Membership Model)

Table 6.11: 3L MLM: Extended Country level controls for Association Membership Model (Math Performance, PISA 2012, Country set 1) (1: Economic Situation - Log. GDP, Gini)

	Math Performance			
	(33)	(34)	(35)	(36)
Intercept	413.952 ***	-188.807 *	407.944 ***	546.093 ***
	(15.714)	(96.495)	(14.831)	(29.327)
Parental ISEI	0.673 ***	0.673 ***	0.667 ***	0.667 ***
	(0.055)	(0.055)	(0.056)	(0.056)
Association Member	58.58 *	-22.888	62.847 *	51.761 *
	(26.539)	(22.449)	(26.468)	(22.987)
– *Cnt Level Controls* –				
Log GDP		64.82 ***		
		(10.306)		
Gini				-3.813 ***
				(0.593)
– *Lower Lvl Ctls* –				
Small Town	-18.603 ***	-18.587 ***	-18.463 ***	-18.459 ***
	(2.746)	(2.746)	(2.815)	(2.817)
Private School	19.012 ***	19.008 ***	19.439 ***	19.448 ***
	(4.131)	(4.122)	(4.184)	(4.186)
1st Gen Immigrant	-23.427 ***	-23.442 ***	-25.34 ***	-25.344 ***
	(5.903)	(5.903)	(6.041)	(6.041)
2nd Gen Immigrant	-15.804 ***	-15.816 ***	-17.517 ***	-17.523 ***
	(4.225)	(4.225)	(4.324)	(4.325)
$\tau^2_{country}$	2176.403	1211.179	1973.258	1228.124
	(465.434)	(267.397)	(427.892)	(273.537)
τ^2_{school}	2539.939	2539.335	2521.938	2521.825
	(263.646)	(263.553)	(268.806)	(268.767)
σ^2	4592.776	4592.837	4540.127	4540.139
	(220.622)	(220.627)	(225.761)	(225.76)
$\rho_{country}$	0.234	0.145	0.218	0.148
ρ_{school}	0.273	0.304	0.279	0.304
ρ_{σ}	0.493	0.55	0.502	0.548
n students	350406	350406	338248	338248
n schools	14778	14778	14291	14291
n countries	48	48	45	45
Largest FMI	0.043	0.043	0.048	0.048

Table 6.12: 3L MLM: Extended Country level controls for Association Membership Model (Math Performance, PISA 2012, Country set 1) (2: Average teaching hours in primary to secondary education and Educational Expenditure adjusted for Gini and Inhabitants)

	Math Performance			
	(37)	(38)	(39)	(40)
Intercept	417.504 ***	338.551 ***	440.612 ***	527.071 ***
	(15.316)	(26.851)	(18.916)	(38.094)
Parental ISEI	0.684 ***	0.684 ***	0.685 ***	0.685 ***
	(0.057)	(0.057)	(0.074)	(0.074)
Association Member	52.362 *	54.707 *	31.479	68.523 **
	(26.36)	(24.121)	(30.044)	(25.512)
– Cnt Level Controls –				
Educational Expenditure		4.331 **		
		(1.453)		
Average Teaching Hours				-0.149 ***
				(0.045)
– Lower Lvl Ctls –				
Small Town	-18.735 ***	-18.737 ***	-19.02 ***	-19.008 ***
	(2.719)	(2.719)	(3.175)	(3.172)
Private School	18.948 ***	18.991 ***	18.004 ***	18.093 ***
	(4.201)	(4.202)	(4.22)	(4.223)
Female	-15.102 ***	-15.101 ***	-15.324 ***	-15.324 ***
	(1.042)	(1.042)	(1.247)	(1.247)
1st Gen Immigrant	-23.725 ***	-23.728 ***	-26.275 ***	-26.277 ***
	(5.928)	(5.929)	(6.702)	(6.701)
2nd Gen Immigrant	-16.078 ***	-16.079 ***	-19.508 ***	-19.512 ***
	(4.264)	(4.265)	(5.08)	(5.08)
$\tau^2_{country}$	2039.063	1642.708	1587.555	1122.63
	(464.166)	(356.107)	(459.173)	(268.528)
τ^2_{school}	2509.17	2509.164	2577.854	2577.804
	(266.438)	(266.453)	(348.749)	(348.735)
σ^2	4606.697	4606.698	4764.062	4764.067
	(226.843)	(226.843)	(278.915)	(278.907)
$\rho_{country}$	0.223	0.188	0.178	0.133
ρ_{school}	0.274	0.286	0.289	0.305
ρ_{σ}	0.503	0.526	0.534	0.563
n students	340765	340765	246371	246371
n schools	14538	14538	10513	10513
n countries	46	46	31	31
Largest FMI	0.04	0.04	0.037	0.037

Table 6.13: 3L MLM: Extended Country level controls for Association Membership Model (Math Performance, PISA 2012, Country set 1) (3: Typical Entrance age to Primary School)

	Math Performance	
	(41)	(42)
Intercept	413.952 ***	448.314 ***
	(15.714)	(76.272)
Parental ISEI	0.673 ***	0.673 ***
	(0.055)	(0.055)
Association Member	58.58 *	56.077 *
	(26.539)	(28.512)
Age entering Primary Educ		-5.268
		(11.217)
Small Town	-18.603 ***	-18.602 ***
	(2.746)	(2.746)
Private School	19.012 ***	19.008 ***
	(4.131)	(4.129)
– *Individual Level Controls* –		
Female	-15.067 ***	-15.067 ***
	(1.022)	(1.022)
1st Gen Immigrant	-23.427 ***	-23.427 ***
	(5.903)	(5.903)
2nd Gen Immigrant	-15.804 ***	-15.804 ***
	(4.225)	(4.224)
$\tau^2_{country}$	2176.403	2166.644
	(465.434)	(455.487)
τ^2_{school}	2539.939	2539.92
	(263.646)	(263.64)
σ^2	4592.776	4592.777
	(220.622)	(220.622)
$\rho_{country}$	0.234	0.233
ρ_{school}	0.273	0.273
ρ_{σ}	0.493	0.494
n students	350406	350406
n schools	14778	14778
n countries	48	48
Largest FMI	0.043	0.043

7 Supplement Paper 2

7.1 Application of weighting procedures

See section 6.1 of the Supplement of Paper 1, p.106.

7.2 Application of Plausible Values

See section 6.2 of the Supplement of Paper 1, p.107.

7.3 Used Country samples

See section 6.3 of the Supplement of Paper 1, p.108.

7.4 Social capital indicators (English question wording)

Items were taken from OECD (2014b).

1. Items used to measure students' social integration
   - "I feel like an outsider (or left out of things) at school."
   - "I feel awkward and out of place in my school."
   - "I make friends easily at school."
   - "Other students seem to like me."
   - "I feel lonely at school."

2. Items used to measure the parental school involvement 1: School engagement (OECD, 2014a) *During the last <academic year> have you participated in any of the following school-related activities*

    - "Volunteered in physical activities, e.g. building maintenance, carpentry, gardening or yard work."
    - "Volunteered in extra-curricular activities, e.g. book club, school play, sports, field trip."
    - "Volunteered in the school library or media center."
    - "Appeared as a guest speaker."
    - "<Assisted a teacher in the school.>
    - "Volunteered in the school <canteen>."
    - "Participated in local school <government>, e.g. parent council or school management committee."

7.5 School-specific variation in IEO (Two-step approach)

Figure 7.1 shows estimates of school-level linear relations between the maximum parental occupational status (measured in ISEI points) and math scores. It contains so-called spaghetti-plots that consist of semi-transparent lines that represents a linear model for every school with more than 5 students that explain math scores by the occupational status background of parents. These plots are grouped in panels that correspond to countries.

Ignoring single atypical lines and looking at the densest parts in the distribution that form trapeze-like patterns one can see a mean pattern inside of countries, that consist of three types of differences: The overall location in the y-axis reflect the country-differences in math performance, the skew of the trapeze corresponds to mean (school-level) differences in IEO (e.g. due to tracking and streaming schools based on previous performance or school quality differences) and the skews at the left and right boundaries of the trapeze is caused by schools that are outliers in terms of the common pattern of other schools (schools with more or less IEO or where students from lower strata are estimated to perform even better than those from higher).

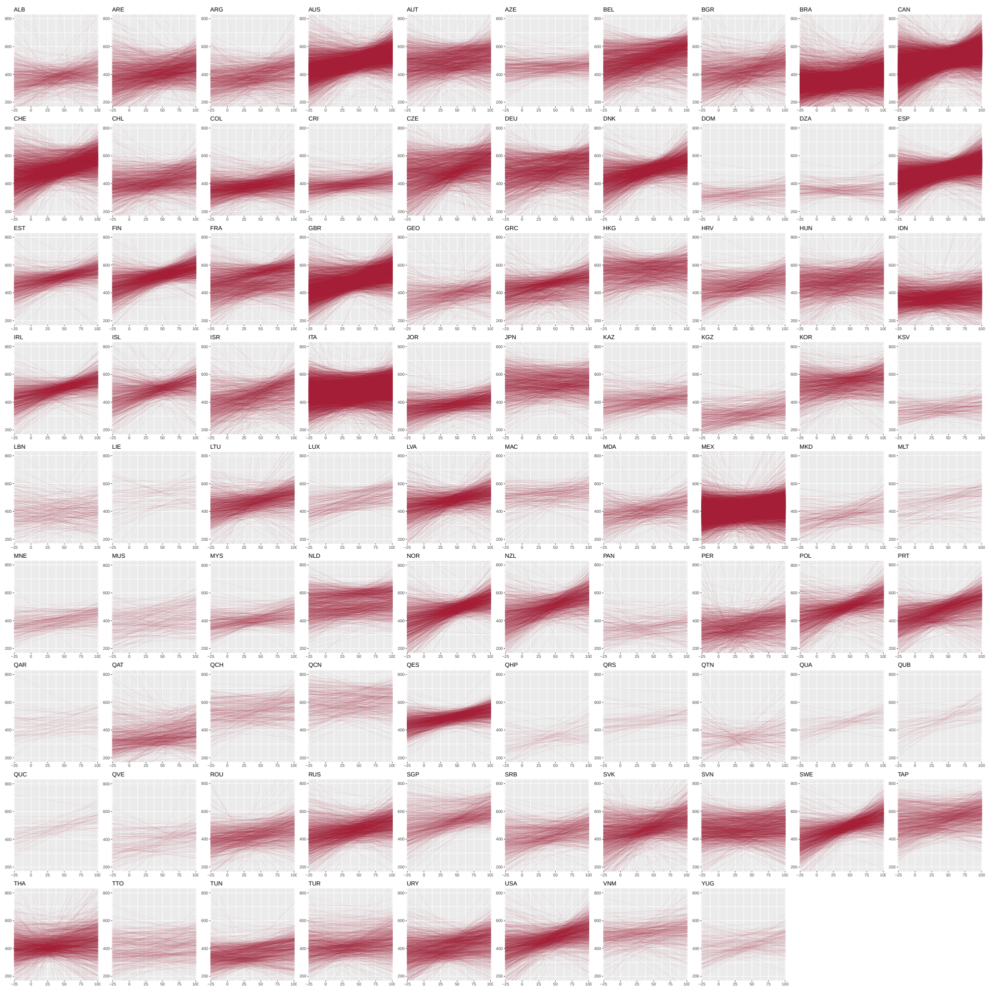

Figure 7.1: School-level variation in IEO by country (2 Step-Approach)

7.6 Distribution of students' school integration by country

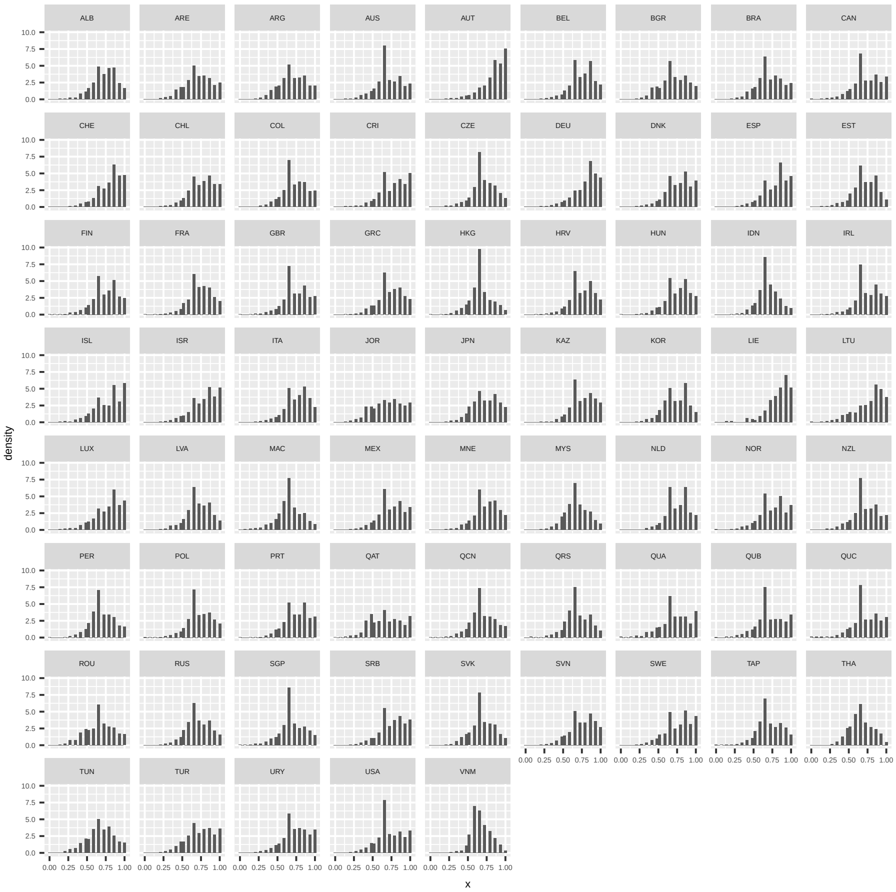

Figure 7.2: Histogram of students' school integration over all schools

7.7 Additional Model Results

Table 7.1: 3L MLM: Covariation of math test scores with parental occupational status and *individual ties and school tie density* (0): School Controls

	Math Performance			
	(10)	(11)	(12)	(13)
Intercept	465.352 ***	440.19 ***	443.874 ***	339.689 ***
	(7.428)	(6.916)	(6.95)	(12.498)
Parental ISEI		0.732 ***	0.71 ***	0.598 ***
		(0.049)	(0.052)	(0.057)
– *School Level Controls* –				
School-Level Mean ISEI (Composition)				2.293 ***
				(0.258)
Small Town			-16.507 ***	0.986
			(2.71)	(2.32)
Private School			19.096 ***	-2.257
			(4.198)	(4.772)
– *Individual Level Controls* –				
Female		-15.2 ***	-15.272 ***	-15.567 ***
		(0.973)	(0.983)	(1.048)
1st Gen Immigrant		-15.673 *	-16.235 *	-15.227 *
		(7.685)	(7.432)	(7.367)
2nd Gen Immigrant		-12.544 **	-13.183 **	-12.976 **
		(4.595)	(4.637)	(4.681)
– *Variance Components* –				
$\tau^2_{country}$	2693.74	2437.005	2364.674	1949.246
	(432.924)	(416.485)	(402.653)	(470.281)
τ^2_{school}	2925.722	2417.273	2297.243	1627.424
	(264.628)	(226.609)	(235.646)	(136.638)
σ^2	4818.635	4617.385	4616.854	4635.271
	(235.032)	(211.018)	(211.291)	(214.171)
– *Intra Class Correlations* –				
$\rho_{country}$	0.258	0.257	0.255	0.237
ρ_{school}	0.28	0.255	0.248	0.198
ρ_{σ}	0.462	0.487	0.498	0.564
n students	236718	236718	236718	236718
n schools	14929	14929	14929	14929
n countries	50	50	50	50
Largest FMI	0.008	0.014	0.024	0.067

Table 7.2: 3L MLM: Covariation of math test scores with parental occupational status and *individual ties and school tie density* (1)

	Math Performance			
	(14)	(15)	(16)	(17)
Intercept	422.43 ***	319.937 ***	412.939 ***	310.82 ***
	(7.93)	(11.907)	(7.669)	(10.799)
Parental ISEI	0.7 ***	0.589 ***	0.898 ***	0.781 ***
	(0.052)	(0.057)	(0.07)	(0.075)
Indiv. ties	29.644 ***	29.071 ***	42.532 ***	41.529 ***
	(3.419)	(3.493)	(5.493)	(5.562)
School-Level Mean ISEI (Composition)		2.266 ***		2.265 ***
		(0.259)		(0.258)
– Controls: – SmllTown,PrvteSchl – Fem,1G Im,2G Im – Variance Components –				
$\tau^2_{country}$	2337.622	1937.406	2333.379	1935.315
	(398.695)	(466.137)	(398.292)	(466.587)
$\tau^2_{country,var(isei\_max)}$				
$\tau^2_{country,cov(ISEI\_max,\_cons)}$				
τ^2_{school}	2244.822	1591.556	2243.06	1590.577
	(232.487)	(134.752)	(232.503)	(134.738)
σ^2	4600.109	4618.477	4599.335	4617.69
	(211.931)	(214.719)	(212.075)	(214.888)
n students	236718	236718	236718	236718
n schools	14929	14929	14929	14929
n countries	50	50	50	50
Largest FMI	0.026	0.067	0.042	0.068

Table 7.3: 3L MLM: Covariation of math test scores with parental occupational status and *indlividual ties and school tie density* (2):

	Math Performance			
	(18)	(19)	(20)	(21)
Intercept	326.722 ***	259.9 ***	326.823 ***	259.726 ***
	(14.285)	(14.972)	(14.267)	(14.965)
Parental ISEI	0.705 ***	0.598 ***	0.697 ***	0.59 ***
	(0.053)	(0.057)	(0.054)	(0.057)
Indiv. ties			24.242 ***	24.686 ***
			(3.381)	(3.355)
School-Level Mean Tie (Density)	159.675 ***	118.542 ***	135.667 ***	93.997 ***
	(19.457)	(17.145)	(19.89)	(16.979)
School-Level Mean ISEI (Composition)		2.14 ***		2.147 ***
		(0.259)		(0.258)
– Controls: –				
SmllTown,PrvteSchl –				
Fem,1G Im,2G Im –				
Variance Components –				
$\tau^2_{country}$	2240.714	1915.243	2243.313	1916.005
	(386.131)	(452.756)	(386.447)	(453.617)
τ^2_{school}	2083.946	1520.818	2091.329	1524.33
	(220.508)	(131.21)	(220.794)	(131.153)
$\tau^2_{school,var(isei\_max)}$				
$\tau^2_{school,cov(ISEI\_max,\_cons)}$				
σ^2	4621.134	4637.897	4603.984	4620.73
	(211.974)	(214.522)	(212.297)	(214.832)
n students	236718	236718	236718	236718
n schools	14929	14929	14929	14929
n countries	50	50	50	50
Largest FMI	0.034	0.066	0.034	0.066

Table 7.4: 3L MLM: Covariation of math test scores with parental occupational status and *individual ties and school tie density (3):*

	Math Performance			
	(22)	(23)	(24)	(25)
Intercept	326.823 ***	259.726 ***	412.939 ***	310.82 ***
	(14.267)	(14.965)	(7.669)	(10.799)
Parental ISEI	0.697 ***	0.59 ***	0.898 ***	0.781 ***
	(0.054)	(0.057)	(0.07)	(0.075)
Indiv. ties	24.242 ***	24.686 ***	42.532 ***	41.529 ***
	(3.381)	(3.355)	(5.493)	(5.562)
Indiv.ties*ISEI			-0.267 **	-0.258 **
			(0.096)	(0.096)
School-Level Mean Tie (Density)	135.667 ***	93.997 ***		
	(19.89)	(16.979)		
School-Level Mean ISEI (Composition)		2.147 ***		2.265 ***
		(0.258)		(0.258)
– Controls: – SmllTown,PrvteSchl – Fem,1G Im,2G Im – Variance Components –				
$\tau^2_{country}$	2243.313	1916.005	2333.379	1935.315
	(386.447)	(453.617)	(398.292)	(466.587)
τ^2_{school}	2091.329	1524.33	2243.06	1590.577
	(220.794)	(131.153)	(232.503)	(134.738)
$\tau^2_{school,var(isei\_max)}$				
$\tau^2_{school,cov(ISEI\_max,\_cons)}$				
σ^2	4603.984	4620.73	4599.335	4617.69
	(212.297)	(214.832)	(212.075)	(214.888)
n students	236718	236718	236718	236718
n schools	14929	14929	14929	14929
n countries	50	50	50	50
Largest FMI	0.034	0.066	0.042	0.068

Table 7.5: 3L MLM: Covariation of math test scores with parental occupational status and *individual ties and school tie density*: (4.1) Random Coef Par. ISEI

	Math Performance			
	(26)	(27)	(28)	(29)
Intercept	443.368 ***	339.378 ***	326.046 ***	259.163 ***
	(6.934)	(12.519)	(14.292)	(14.93)
Parental ISEI	0.714 ***	0.587 ***	0.705 ***	0.584 ***
	(0.052)	(0.058)	(0.054)	(0.058)
School-Level Mean Tie (Density)			160.078 ***	119.269 ***
			(19.399)	(17.113)
School-Level Mean ISEI (Composition)		2.305 ***		2.15 ***
		(0.26)		(0.261)
– Controls: – SmllTown,PrvteSchl – Fem,1G Im,2G Im – Variance Components –				
$\tau^2_{country}$	2355.984	1949.661	2231.08	1914.392
	(401.571)	(471.961)	(385.317)	(455.026)
τ^2_{school}	2539.595	1857.458	2265.748	1708.965
	(304.349)	(158.029)	(297.48)	(158.316)
$\tau^2_{school,var(isei\_max)}$	0.17	0.169	0.169	0.17
	(0.017)	(0.018)	(0.017)	(0.018)
$\tau^2_{school,cov(ISEI\_max,\_cons)}$	-6.85	-6.662	-6.197	-6.237
	(1.37)	(1.268)	(1.359)	(1.239)
σ^2	4557.247	4575.55	4562.358	4578.576
	(211.101)	(211.899)	(211.53)	(212.148)
n students	236718	236718	236718	236718
n schools	14929	14929	14929	14929
n countries	50	50	50	50
Largest FMI	0.215	0.207	0.235	0.214

Table 7.6: 3L MLM: Covariation of math test scores with parental occupational status and *individual ties and school tie density* (4.2): CLI School-level ties - Par. ISEI

	Math Performance			
	(26)	(27)	(28)	(29)
Intercept	340.421 ***	272.536 ***	340.731 ***	272.559 ***
	(20.357)	(19.238)	(20.344)	(19.219)
Parental ISEI	0.35	0.256	0.337	0.243
	(0.32)	(0.327)	(0.32)	(0.328)
Indiv. ties			24.242 ***	24.68 ***
			(3.385)	(3.362)
School-Level Mean Tie (Density)	140.604 ***	101.194 ***	116.3 ***	76.385 **
	(27.8)	(26.926)	(28.152)	(26.955)
School-Level Mean ISEI (Composition)		2.149 ***		2.156 ***
		(0.261)		(0.26)
Schl MeanTie*ISEI (CLI)	0.478	0.442	0.485	0.449
	(0.445)	(0.452)	(0.445)	(0.453)
– Controls: – SmllTown,PrvteSchl – Fem,1G Im,2G Im – Variance Components –				
$\tau^2_{country}$	2236.54	1917.272	2239.154	1918.013
	(385.846)	(454.156)	(386.143)	(454.989)
τ^2_{school}	2282.239	1720.656	2289.059	1721.878
	(301.266)	(160.859)	(300.732)	(160.11)
$\tau^2_{school,var(isei\_max)}$	0.169	0.169	0.168	0.168
	(0.017)	(0.018)	(0.017)	(0.018)
$\tau^2_{school,cov(ISEI\_max,\_cons)}$	-6.365	-6.349	-6.349	-6.309
	(1.401)	(1.239)	(1.388)	(1.231)
σ^2	4562.105	4578.462	4545.115	4561.529
	(211.525)	(212.108)	(211.849)	(212.447)
n students	236718	236718	236718	236718
n schools	14929	14929	14929	14929
n countries	50	50	50	50
Largest FMI	0.224	0.21	0.231	0.216

8 Supplement Paper 3

8.1 Estimates for homophilic preferences for parental ISEI (based on ERG-Models)

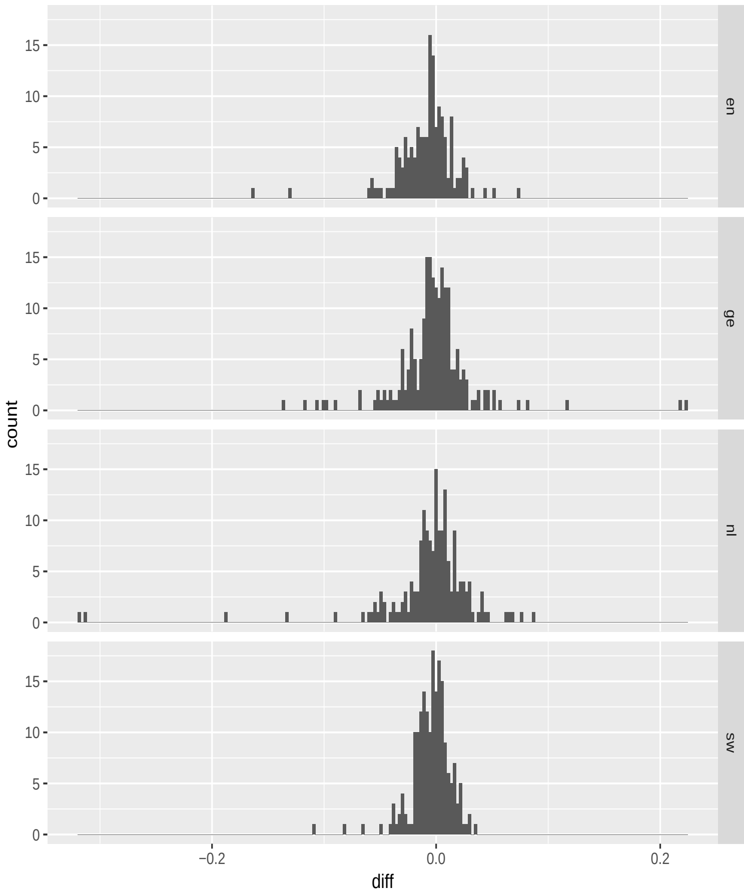

Figure 8.1: Histogram of homophily estimates as properties of class level (estimate via ERG models ; explaining configuration: absolute diff (parental isei)

8.2 Extreme examples of segregation in best friend networks by gender and ISEI

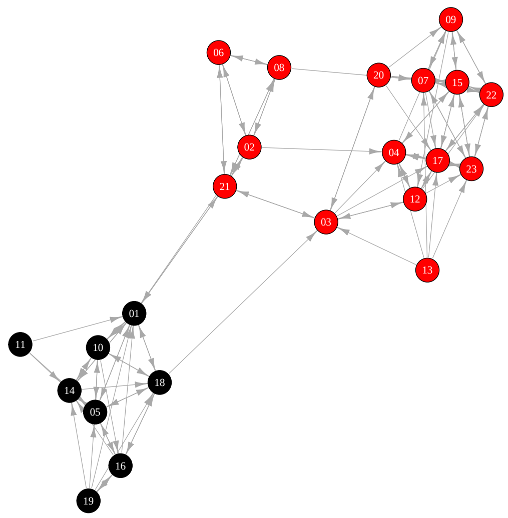

Figure 8.2: Example of segregation based on gender
Color: Female (red) Male (black) ; blue: missing value, class id: 405002

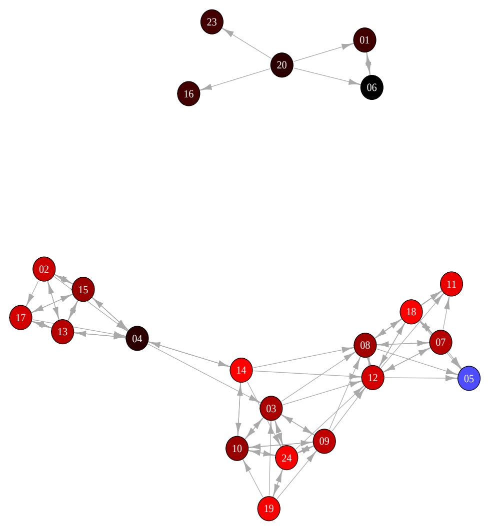

Figure 8.3: Example of segregation based on socio-economic status
Color: Higher (red) to lower (black) parental ISEI; blue: missing value, class id: 405202