LUND UNIVERSITY
School of Economics and Management

Master's Programme in Economic Development and Growth

Bad Apples, Social Capital and Human Capital in El Salvador

Evidence from Salvadoran High School Students

by

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Abstract: This study investigates the impact of classroom conflict and social capital on different measures of human capital accumulation in middle school and high school students from El Salvador. Using class-level measures of mutual enmity and friendship obtained through network analysis and exploiting exogenous variation in the proportion of students who have repeated the school year, I obtain consistent estimates of gendered and non-linear effects on different academic outcomes. The thesis' main findings reveal that class conflict, mediated by mutual enemy relationships, impacts various educational outcomes differently for boys and girls, including enrollment likelihood in university and expected years of schooling. Additionally, lower-quality social capital accumulation at the classroom level is associated with improved performance in cognitive skills and increases educational continuation for girls, but reduces schooling expectations for certain students at the bottom of the human capital distribution. Gang activity appears to exacerbate these effects, particularly affecting girls and students with less potential educational benefit, while bullying is shown as a potential mechanism further elucidating gender differences in preferences for investments in social and human capital.

EKHM51
Master's Thesis (15 credits ECTS)
June 2024
Supervisor: Prof. Martin Dribe
Examiner: Kirk Scott
Word Count: 15,505

Acknowledgements

I would like to extend my gratitude to Prof. Martin Dribe for his exceptional supervision and guidance. Furthermore, thanks are owed to Prof. Pablo Brañas Garza, Diego Jorrat, Mónica Vasco and the TeensLab research team for providing me with access to the data, for their support, and for their insightful suggestions. I acknowledge comments from Cyprien Duhamel and Raquel Carrasco. I am also grateful to Koen Deconinck and Céline Giner. Their contributions have been invaluable to the successful completion of this thesis.

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Introduction

The academic debate that has emerged in the field of economic growth and development around the question of proximate and fundamental factors of growth has seen social capital as a central aspect of study (Acemoglu et al., 2005). Understood as the set of resources embedded within social networks, encompassing trust, shared norms, and interconnected relationships, which facilitate collective action and enhance overall societal productivity through coordinated efforts (Putnam, 1993), social capital is shown to be probably one of the most fundamental sources of economic growth, capable of influencing other more proximate aspects such as the accumulation of other forms of capital like physical or human capital (Bourdieu, 2018).

Moreover, there is a vast literature showing how violence and conflict impact different measures of economic development in a country where they are as prevalent as El Salvador, including education and human capital formation (Blattman et al. (2021); Brown et al. (2021); Melnikov et al. (2020)). Additionally, evidence has been found showing how social capital (when considered as a proxy for trust or cohesion at different levels of social grouping) could influence human capital formation and other economic outcomes, even as early as in adolescence (Goldin and Katz, 1998; Braatz and Putnam, 1996; Coleman, 1988; Temple, 2002).

In such a convulsive context, it is to be expected that conflictive behaviors and poor social capital formation begin to occur in childhood and adolescence, especially among those who develop in the most vulnerable contexts and are exposed to violence, potentially hindering their educational potential and that of their environment.

Drawing on existing literature and social capital theory, this study delves into the impact of conflict and negative social capital on various aspects of human capital development in El Salvador. Examining potential gender differences and the non-linearity of outcomes, the thesis also investigates gang violence at the municipal level as a determinant of students' social capital accumulation and bullying as a potential explanatory mechanism. Utilizing data from middle and high school students across 12 schools in El Salvador, I exploit exogenous variation in the proportion of students that have repeated their current school year in different classrooms to assess the effects of class-level enmity and social capital on educational outcomes. To the best of my knowledge, this is the first study to consider in-class peer conflict and social capital transmission as determinants of educational outcomes in the Salvadoran context. The key findings are the following: (1) Class conflict, characterized by mutual enemy relationships, diminishes consistency in the development of time discounting and risk preference tasks, university enrollment likelihood for girls, and future schooling expectations of girls in the bottom 5% of expected future human capital accumulation, while enhancing financial abilities in boys. (2) Poorer social capital quality correlates with improved cognitive performance and increases educational continuation for girls but decreases expected schooling for students initially considering higher education. (3) Gang activity appears to exacerbate enmity effects, potentially affecting girls and students with less potential educational benefit and explaining gendered impacts and non-linearities. (4) Bullying further elucidates gender differences, suggesting that boys may struggle to socialize in classrooms with low social capital due to increased victimization.

The rest of the thesis is structured as follows. Section 2 discusses the main theoretical insights relating social capital with human capital accumulation and reviews the most relevant previous literature on the topic. Section 3 briefly contextualizes the Salvadoran education system as well as the general development of violent conflict in the country. Section 4 presents a description of the data and the main variables that are used in the analysis. Section 5 describes the methodological approach and potential endogeneity issues as well as threats to internal validity. Section 6 presents and discusses the main results obtained from the empirical analysis. Section 7 concludes.

2

Theory

2.1 Theoretical Approach

2.1.1 Social Capital and Human Capital

The inclusion of social capital in the development and growth economics literature has been relatively recent. Along with other aspects such as institutions, geography, or culture, it is usually considered as one of the fundamental factors of economic growth (Acemoglu et al., 2005). The concept was popularized by Putnam (2000) and could be defined as those elements within social structures, like trust, customs, and network-dirven connections, which enhance societal efficiency by enabling coordinated endeavors (Putnam, 1993). Like other more traditional forms of capital, social capital also has the potential to boost productive capacities through, for example, greater ease in associating with others to carry out projects or investments of common interest due to greater trust (either in other members of the community to which one belongs, or towards the institutions that regulate it) or social cohesion. Bourdieu (2018) defines social capital as "a 'credential' which entitles [social agents] to credit, in the various senses of the word." Additionally, for this author, the network of relationships emerges from deliberate or subconscious efforts to establish or sustain social connections that serve immediate or future purposes, such as transforming casual relations into vital and chosen ones, like those within neighborhoods, workplaces, schools, or families. This demands investment of time, energy, and economic capital, contingent upon a specific set of skills (Bourdieu, 2018). However, a combination of its still recent incorporation into the intellectual discussion and its sometimes relatively ambiguous definition causes many to view the study of the economics of social capital with some skepticism (Temple, 2002).

Nevertheless, Woolcock (1998) advanced the theoretical development of social capital by deepening its definition and by proposing four dimensions which can be summarized as (1) the role and importance of "horizontal associations"; (2) the character of interpersonal bonds within societies; (3) the connection between civil society and the government; and (4) the nature of existing institutional frameworks. Despite the fact that the fourth dimension clearly overlaps with the classical notion of institutions that has long been studied by economists, the latter categorization has made it possible to quantitatively study the growth effects of social capital, which will be discussed in the next subsection. In particular, it is the second and third dimensions that have usually been considered to proxy social capital with variables such as different measures of general trust towards other community members or voter turnout, respectively. Network analysis also appears as an increasingly frequent alternative for analyzing the economic effects of social capital accumulation (Jackson et al., 2017), something which has the additional virtue of being closer to Putnam's initial notion. Along the same lines, this thesis employs network measures of friendship and enmity relationships at the class level that are consistent with the third dimension in Woolcock (1998), which capture social ties that arise within communities (school classrooms in this case).

This is especially relevant for the present work because understanding how social capital, measured by the nature of friendship-enemy networks, affects human capital accumulation might not necessarily align with previous findings that used different proxies for social capital. Although a general review of existing evidence might show mixed results due to not considering these distinctions, it can still be argued that various aspects of social capital may not be comparable. This non-comparability makes it challenging to determine potential expected effects when using network variables at the classroom level as proxies, as is done in this study.

More interesting is the interaction between social capital and other forms of proximate causes of growth such as human capital accumulation. Glaeser et al. (2002) state that "the connection between social capital and human capital is one of the most robust empirical regularities in the social capital literature". In this sense, the authors claim that investments in both human and social capital may reasonably be considered as complements, as it is expected that those engaging in the former somehow implicitly also invest in the latter. One of the first and most interesting theoretical developments of the relationship between both forms of capital is presented by Coleman (1988), who identifies three aspects of social capital that act as mechanisms for human capital formation: expectations and responsibilities (which are determined by trust), the capacity for information flow within the social network (which may facilitate education peer effects), and norms paired with consequences.[1] The study also shows how the effects of social capital on human capital may arise both at the family level and in groups outside the family (e.g., friends or classmates), which conforms the main interest of this thesis.

In this regard, social capital can improve human capital investment in several ways. On the one hand, it generates in individuals a certain degree of trust in the community and institutions that provides assurance that these investments will be effectively translated into future valuable economic outcomes (for example, by improving expectations of access to the labor market). On the other hand, it facilitates communication and collaboration during the educational process itself, enabling the most advantaged students to promote the knowledge of their peers, for which the quality of friendship and enmity networks in the classroom is key. Finally, social capital generalizes behaviors and attitudes that would become normalized and positively perceived by the whole, making it possible for aspects such as effort and the desire to study in order to achieve more ambitious goals in the future of the students'

[1] It is the third element that is studied in greater depth in this thesis.

economic life to be seen as socially desirable.[2]

An important insight that is also highlighted by Coleman (1988) is that, unlike other manifestations of capital, social capital exhibits a public good nature that leads to under-investment in it. This is because the benefits that arise from investing in this type of capital as a result of individual rational decision-making are mostly enjoyed by third parties. The author also points out the consequences this could have for the accumulation of human capital. An example related to the one presented in this thesis may be illustrative: when deciding to put effort into creating a better environment within the classroom (for example by having a less conflictive or friendlier attitude towards classmates), taking into account that this could have an improvement mainly on the academic success of their classmates (and not so much on their own), any school student would probably decide not to commit so much at the individual level.

Social capital can, in turn, be conditioned and altered by structural factors such as war and conflict (see Colletta and Cullen, 2000; Nunn and Wantchekon, 2011). This is important, since, as pointed out by Justino (2011), in contexts of violent conflict, returns to education may be altered as a consequence of job scarcity, thus making it only attractive for households to invest in the education of children who might profit more from it in the future, usually boys. The author especially highlights how this could potentially impact educational and future labor market gender inequality. In the specific context of El Salvador, gang violence has been found to cause such labor-scarcity effects as reported by Melnikov et al. (2020) and Brown et al. (2021). This could explain possible heterogeneous effects of the worsening of social capital on educational achievement brought about by violent conflict.

Other authors like Helliwell and Putnam (1999) suggest that the direction of cause to effect might rather be the opposite, with education at the group level effectively increasing social capital. In fact, these differences in interpretation could indicate that the mechanism may go both ways. Whatever the direction of causation, all of the above seems to show that investments in social capital and human capital are indeed closely related.

It should be noted that all of the above insights point to a clear distinction between social capital at the individual level (more closely linked to relational networks of each agent) and at the community level (which focuses more on group cohesion). While classical social capital theorists like Putnam and Bourdieu seem to mostly consider community-level social capital accumulation, my analysis in this thesis is rather halfway between the individual and the community levels. Despite classrooms representing independent social networks in which individual children interact, the interest of this thesis is on the effects of aggregate class social capital on different individual academic outcomes. This may not directly relate to what other authors have considered in bigger or more general groups of individuals, whose works mostly focus on neighbourhoods, towns, or even larger sized communities.

[2]Note that the opposite is also true. Communities may lead to standards that are not conducive to academic achievement, for example, if child labor or criminal activity, for which no formal education is required, were normalized or generalized.

2.1.2 Peer Effects and Human Capital

Many aspects of social capital, especially those that are more related to networks, cannot be understood if it is not through the so-called peer effects. These can be defined as the influences that certain characteristics at the group level have on individual behaviors or results. In the context of this study, understanding peer effects is key to analyzing how social capital of school peers might be able to affect individual academic performance. Given the latter, peer effects are often considered as a form of externality (Sacerdote, 2001).

Many scholars have focused their attention on peer effects in education, not only because they manifest themselves more explicitly than in other contexts, but also because of their relevance at the public policy level (Castilla, 2024). Hoxby and Weingarth (2005) provide a categorization of seven different peer effects that can potentially be found in human capital investment contexts, some (but not all) of which are related to social capital. Of this taxonomy, the first two configurations are the most relevant for this thesis. The first of these, the *linear-in-means model*, focuses on peer effects that arise from group average of certain characteristics, including measures of social capital. The second, *bad apple*, occurs when conflicting students affect the academic performance of their peers.

Jackson et al. (2017) discuss the importance of network effects in determining different individual economic behaviors, including human capital investments. Among the different reflections drawn by the authors, one of the most relevant is the fact that the centrality of friendship or enmity within a network can promote or hinder cooperative behavior which, in turn, can affect the academic performance of individuals. This is because networks that show better and more clustered social capital facilitate the exchange of favors and are capable of perpetuating and spreading beneficial behaviors. The opposite is true of networks that are less integrated or have poorer levels of social capital (for example, those that show higher levels of enmity or conflict). Note that the validity of the above interpretation could be given for any network composition. However, it is more plausible that these effects on peer educational outcomes occur in social network contexts (i.e., friendship and enmity) at smaller scales, with the school class level being the most obvious.

2.2 Previous Literature

Since its popularization in the economics intellectual discussion, there has been a growing body of (mostly empirical) literature centered around the economic effects of social capital. As shown above, it seems to be precisely the effects on education and human capital accumulation that are usually given greater consideration. Looking at the "high school movement" in the US during the first decades of the twentieth century, Goldin and Katz (1998) find that what catalyzed the establishment of public secondary education in Iowa were the relatively higher levels of social capital. Notably, it was a combination of the small size of towns in this State, lower economic inequality, community stability and cultural, religious, and ethnic homogeneity that ensured a more intense manifestation of the high school movement. The authors also report that these impacts continue to determine human capital formation today, suggesting the persistence of social capital effects over time. In a similar vein, Braatz and Putnam (1996) explore empirical evidence relating parental involvement and school quality in the US, with the former (as a proxy for social capital) positively affecting the latter. The authors also provide evidence on the association between social capital (measured by an index including survey measures of social trust levels,[3] memberships to associations per capita, voting turnout, and the number of non-profit organizations) and different variables capturing academic achievement (results in national standardized tests and dropout rates), finding positive results. Both papers explore the relationship between social and human capital from a more communitarian and even intergenerational approach to the former, without paying too much attention to the possible intra-group dynamics of the students themselves. Additionally, even though the potential positive effects that social capital might have for human capital are largely discussed, the authors in both studies are cautious not to interpret their empirical results as causal and stress the importance of overcoming certain methodological issues regarding endogeneity that future research should address as well as the mechanisms operating through these effects.

Despite being more instrumental in defending their main arguments, other studies find empirical evidence in favor of the accumulation of social capital, especially at the family and religious community levels, as well as membership to different organizations, as a determinant of human capital through lower dropout rates and more years of schooling (Coleman, 1988; Glaeser et al., 2002; Narayan and Pritchett, 1999). It is also important to note that Glaeser et al. (2002) provide a theoretical framework describing optimal social capital accumulation, but which is not supported by the evidence shown earlier by the authors as the prediction that social capital should be inversely related to the opportunity cost of time is inconsistent with the positive correlation between social and human capital.[4] Similarly to Goldin and Katz (1998) and Braatz and Putnam (1996), the focus is again on community-level social capital and methodological considerations addressing potential endogeneity are left rather uncovered.

Although most of the studies on the relationship between social capital accumulation and education cover developed economies, the literature on this topic in poorer countries is rather scarce. Even so, some authors have focused their attention on the role that social capital could play at the level of community trust in countries such as Tanzania, Colombia, Argentina, Chile, Venezuela, Peru, or Uruguay (Narayan and Pritchett, 1999; Cárdenas and Carpenter, 2005; Cárdenas et al., 2013; Nunn and Wantchekon, 2011). Interestingly, it is these few studies that pay most attention to the identification strategy, employing experimental methodologies as well as instrumental variables (IV) approaches. Not only are higher levels of trust and community cohesion shown to have positive effects on schooling, but the authors also strongly emphasize the need of addressing social capital in studying poverty and development, as, unlike the more urbanized West, community dynamics might

[3] Trust is defined as the binary response to the question "Generaly speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?"

[4] For further detail, see Glaeser et al. (2002, pp. 8–10) where the first order condition of the social capital accumulation optimization problem and comparative statics are discussed.

probably play a key role in certain developing regions.[5] The above shows an interesting dichotomy: while most of the academic literature studying the effects of social capital on education and other aspects of development has focused primarily on developed contexts, the study of social capital seems even more relevant in communities in the developing world. The most plausible explanation for this is not academic disinterest, but probably lack of data.[6] In this sense, the present thesis aims to shed some more light with an approach to social capital at the level of the general influence of interpersonal networks.

Regarding the role that network peer effects play in determining individual educational outcomes, Jackson et al. (2017) discuss several pieces of evidence showing how different social network configurations affect investments in human capital, with homophily (i.e., individual preferences towards peers that share similar characteristics) and centrality (measures of relative importance of individuals in the network with respect to the rest) as main factors. It is important to note that, although centrality does seem to have undoubtedly positive effects, homophily is identified by the authors as a potential source of unequal human capital investments. This might be since, if the networks that host valuable social capital (e.g., of friends) are only composed of individuals who are very similar in certain characteristics (e.g., ethnic, religious, or social class), only these could benefit from the positive externalities that the network provides. Additionally, Calvó-Armengol et al. (2009) provide results along the same lines, showing that the centrality of a student in a network of friends is associated with increases in school performance, likely due to positive externalities through peer effects.

The most relevant work considering the *bad apples* category in Hoxby and Weingarth (2005) are Carrell and Hoekstra (2010) and Carrell et al. (2018), who find that the number of disruptive students (measured as those who have experienced domestic violence) reduces future enrollments, the likelihood of college graduation, and even the average earnings upon entering the labor market of their classmates. Bursztyn and Jensen (2015) and Bursztyn et al. (2019) take a distinct approach and focus on investigating the impact of peer pressure and social norms on students' educational investment. Their research reveals that classmates wield a magnifying effect on both social pressure and norms, shaping individual decision-making of students.

The latter can be considered together with other relevant empirical results showing that the peer effects of troubled students and a poor transmission of social capital within the classroom have effects on non-academic outcomes such as worse health habits and even involvement in criminal activity (Calvó-Armengol and Zenou, 2004; Ballester et al., 2010; Jackson et al., 2017; Gaviria and Raphael, 2001; Deming, 2011; Eren et al., 2022). The latter is of particular interest when considering a context such as that in El Salvador, where several studies have shown how gang violence and

[5] In the words of Putnam (2000), people in less developed countries are not yet *bowling alone*.

[6] For instance, the fact that it is this literature that is most concerned with causal inference could be related to the scarcity of data. As these countries probably have fewer statistical sources from official national censuses or surveys, it would not be unreasonable to think that most of the evidence is collected directly by researchers and teams from the academic world who, being more concerned about possible endogeneity problems, could deliberately introduce experimental or quasi-experimental elements into the data collection.

conflict cause detrimental impacts in different measures of economic development, including education and human capital formation (Blattman et al., 2021; Brown et al., 2021; Melnikov et al., 2020). All the above could be suggestive of a gang-driven potential interpretation driving *bad apple* peer effects in the event of finding significant effects of the latter on human capital. In such case, gang violence in El Salvador could have additional indirect effects acting as a channel through social capital deterioration, with the aggravating effects that these peer effects could have by increasing the likelihood of joining a gang in the future.

There is also a large body of literature that studies these effects in the context of natural experiments, usually taking advantage of exogenous variations in the composition of the networks that are given by movements of people or by random assignment of individuals in the same network (Angrist and Lang, 2004; Imberman et al., 2012; Sacerdote, 2001; Zimmerman, 2003; Carrell et al., 2009), both being two types of shocks to social capital structures. These are usually shown to be the most methodologically rigorous and accurate. Even so, some of them, as well as many others that apply non-experimental methodologies, agree that the effects of social capital through networks are often non-linear and heterogeneous (Hoxby and Weingarth, 2005; Imberman et al., 2012; Sacerdote, 2001; Carrell et al., 2009; Castilla, 2024). In fact, only about half of the studies investigating peer effects in education use the *linear-in-means model* that was famously popularized by Manski (1993) (Sacerdote, 2014).

In the case of PE-driven social capital impacts on human capital, the literature provides a wider coverage of developing countries (see, for example, Duflo et al., 2011; Figlio and Özek, 2019; Altmejd et al., 2021; Bobonis and Finan, 2009; Barrios-Fernández, 2022; Corno et al., 2022; Helmers and Patnam, 2014). However, these works tend to deviate from peer effects that could be associated to what is defined as social capital as they usually consider those that arise from pairing students with peers who are more academically dedicated, who have higher educational achievement, or who have been exposed to an experimental treatment that could generate spillover effects on other untreated students (i.e., *shining light* or *boutique/tracking* peer effects as described by Hoxby and Weingarth (2005)).

2.3 Summary and Hypotheses

In conclusion, there is a growing academic consideration of social capital as well as its interaction with human capital. Whether through aggregate measures more at the community level or through peer effects within a network of social relationships such as friendship or enmity, there are mechanisms that point to greater accumulation of social capital being associated with better academic performance. While most of the literature so far has focused on the study of social capital at one of these two levels (community or individual), in this thesis I focus on a more intermediate level by studying the effect of class-level conflict or *bad apple* peer effects on individual human capital measures. Moreover, relatively few publications have covered developing countries, regions where the role of social capital and its impact on different dimensions of economic development (including education) may be even more relevant than in more prosperous economies.

From all of the above, several hypotheses can be proposed:

1. Higher enmity levels and *bad apple* social capital affects human capital accumulation negatively in Salvadoran high school children, both in cognitive abilities as well as expectations for the continuation of studies.

2. These effects are heterogeneous and gender-dependent as well as non-linear across the human capital distribution.

3. Gang violence and bullying inside the classroom are determinants of worse and lower social capital accumulation, with the former being able to make sense of possible heterogeneities and non-linearities and the latter acting as a causal channel through which educational outcomes are reduced.

The validation or refutation of the three hypotheses could depend to a large extent, on the one hand, on considerations related to the quantitative (and not qualitative) aspect of my measures of social capital, and on the other hand, by the fact that these would be measured at the aggregate level of the network within the classroom, something rather unexplored by previous literature.

3

Context

This section presents a basic contextualization of El Salvador in terms of education and conflict. This is useful to better understand some of the results presented in the *Empirical Analysis* section, as well as the different interpretations I present to make sense of the various findings.

3.1 Educational System in El Salvador

Education in El Salvador is overseen by the Ministry of Education (MINED) and comprises several levels of schooling: basic education, divided into three cycles of three grades each, and secondary education followed by higher education. Basic education includes the 1st to 3rd grades, 4th to 6th grades, and 7th to 9th grades (which correspond to middle-school education). Secondary education includes a two-year general high-school and an optional third year of technical high school. All students, whether in public or private schools, are required to take a national test (*Learning and Skills Test for Secondary School Graduates*, or PAES for its acronym in Spanish) during their second year of high-school needed for graduation and accession into higher education (Posner et al., 2019). This exam assesses their proficiency in mathematics, Spanish language and literature, as well as general natural and social science.

Despite this structured system, socioeconomic disparities significantly impact educational access and quality in El Salvador. This is especially evident in rural areas of the country, where the population experiences higher poverty rates, contributing to educational inequalities (López, 2000). Many poor families cannot afford to keep their children in school, leading to high dropout rates as children often have to work to support their families (MINED, 2010). Close to 2 million children, especially those living in rural households, are found to engage in child labor, limiting their academic opportunities and future prospects (Acosta, 2011). Additionally, Dahbura (2018) finds that crime is one of the main reasons why secondary and higher education students drop out of school.

Limited resources are often identified as the main factor hindering the development and improvement of the public education system. This, in turn, translates into overcrowded classrooms, with classes in public school often exceeding forty students per teacher, particularly in rural areas, making it difficult for children to receive adequate attention and support. As a result, families are reluctant to send their children to public schools (McConnell-Farmer et al., 2012). In response to all these deficiencies, several interventions and initiatives by national institutions as well as international development agencies have been implemented in El Salvador to improve public schooling in the last decades (Posner et al., 2019). However, the Salvadoran educational system still faces ongoing challenges, most of which are related to the lack of public resources (Posner et al., 2019; McConnell-Farmer et al., 2012).

3.2 Violent Conflict and Gangs in El Salvador

Since the end on the decade of the 1990s, El Salvador has experienced unprecedented levels of criminal activity and violence, mostly gang-related (UNODC, 2019). These gangs (the so-called *maras*) were mostly originated in the US after the 1980s and were transferred to Central America and, in particular, to El Salvador as a consequence of massive deportations starting in 1996 with the US Illegal Immigration Responsibility Act. The reason why Salvadoran gangs were born in the US is related to previous migration which took place in the 1980s as a consequence of the Civil War in El Salvador (DeCesare, 1998; Dunn, 2007; Lopez and Connell, 1996). Two of the largest gangs, Mara Salvatrucha (MS-13) and 18th Street, control much of the criminal activity (e.g., drug trafficking, murder, or human smuggling) across the whole country and, even though the last years have seen a massive decrease in their presence as a consequence of harsh governmental measures, they still have territorial influence over different municipalities.

Upon returning to El Salvador, deported gang members brought with them American gang culture, including distinctive features such as gang names, clothing styles, hand signs, tattoos, and a significant emphasis on violence and criminal activities like extortion and drug trafficking (Giralt and Concha-Eastman, 2001; Cruz, 2007). This introduction has led over the years to a significantly high homicide rate in El Salvador peaking in 2015, with a rate of 103 homicides per 100,000 inhabitants, largely driven by violent conflicts between gangs vying for control over the drug trade and extortion schemes (Sviatschi, 2022).

Many economists have studied the effects of gangs on different measures of economic development in El Salvador, including human capital investments (Blattman et al., 2021; Brown et al., 2021; Melnikov et al., 2020; Sviatschi, 2022; Dahbura, 2018). However, less attention has been paid to studying how gang violence might be channeled through children and adolescents to manifest itself in disruptive behavior at the school level toward other classmates, thus influencing human capital investment decisions. In El Salvador, many families are directly or indirectly in contact with gangs, either through extortion relationships or by belonging to territories under their control (see Brown et al., 2021; Melnikov et al., 2020), making children often susceptible to their influence. This is mostly the case in more impoverished areas of the country, where most schools in my sample are located. This is relevant as Salvadoran gangs mostly start recruiting at early ages, with more than 60% of members in different *maras* joining before turning 15 years old (Cruz et al., 2017).[1]

[1] Note that children of this age range make up about 45% of my sample in this study.

4

Data

4.1 The Dataset

The data used in this study were sourced from a survey conducted within the framework of the program known as *Mapping of Competencies and Abilities of Secondary School Students* (COM-PHAS, for its acronym in Spanish), carried out by a team of researchers affiliated with the Loyola Behavioral Lab, a Behavioral Economics research institute, in collaboration with the ETEA Foundation-Development Institute and Universidad Loyola Andalucía.[1]

The data were collected in collaboration with the foundation *Fe y Alegría El Salvador*, a Jesuit association comprising 12 public secondary schools in low-income areas of El Salvador. Although three waves of data collection were carried out between the years 2021 and 2023, permission was only granted to use the data obtained from the second wave. This second survey was carried out by enumerators of the research team during the months of March to May 2023 in the schools themselves for all groups going from 7th to 9th grades of middle school education and from 1st to 3rd year of high school education. A large sample of Salvadoran secondary school students will be used in the analysis ($N = 2,649$). The attrition rate was low, with a total of 2,528 students finishing the whole survey (i.e., completing all the information that was asked). However, some children skipped specific sections or individual tasks. In total, the number of students that provided complete information for all of the variables considered in the main analysis of this thesis was 2,571.

The sampling was made possible through the local partnership with *Fe y Alegría*, which, aided by a field coordinator overseen by the Spanish research team, facilitated recruitment. A local team of pedagogues adjusted the survey for the social context of children, which was then piloted with students from El Salvador to evaluate the modifications. The recruitment procedure was uniform across the different waves of data collection and did not involve self-selection. School administrators and officials agreed to incorporate the experiment into their educational curriculum and administer it as a class activity by signing an agreement. For further details about how the sampling protocols were carried out, see Gaviria and Raphael (2001).

[1]The project received ethical approval from the Ethical Committee of Universidad Loyola Andalucía and was supported by the Spanish Ministry of Economy and Competitiveness, Excelencia-Junta, and the Agencia Andaluza de Cooperación Internacional para el Desarrollo.

A latent limitation of these data is that the non-random way in which the sampling has been carried out probably does not allow for representativeness of the general population of high school students in El Salvador. Most of the children come from families in disadvantaged socioeconomic contexts and all of them attend public schools run by the Catholic association *Fe y Alegría*, which could further threatens the external validity of results in terms of religious belief.

4.2 Human Capital Variables

Several variables are proposed as proxies for human capital. All of them are expressed at the individual student level. The first measure is the score obtained in a cognitive reflection test (CRT), which students were required to complete as part of the survey. The use of this test is fairly common in the Behavioral and Experimental Economics literature and was originally introduced by Frederick (2005). The test presents respondents with various questions that involve two types of answers: one that is quick, automatic, and subconscious (System 1 thinking), and another which is slower and requires more cognitive effort (System 2 thinking).[2] The higher the score on the CRT, the more reflective the respondents are, bringing them closer to the neoclassical rationality of the *homo economicus*. This variable is not only relevant for its novelty in the literature on the topic of this thesis and its quality,[3] but also because it serves as a strong predictor of performance on other standardized analytical tests, such as the SAT, ACT or overall GPA (Brañas-Garza et al., 2019). Although this test has the virtue of, on the one hand, being fairly standardized and, on the other hand, being relatively easily applicable to different social contexts and feasible to include in a survey, many authors have criticized its simplistic approach to the complex reality of cognitive skills. For example, Campitelli and Gerrans (2014) claim that the standard version of the CRT may exclussively capture mathematical skills, leaving other cognitive dimensions uncovered. For these reasons, several scholars have proposed expansions and alternative versions of the test (see, for example, Toplak et al., 2014; Thomson and Oppenheimer, 2016).[4]

The second variable proposed is the score obtained in a test measuring $Financial$ $abilities$. In particular, this task focused on general financial mathematics questions related to interest compounding and probability. The test was administered also as part of the experiment and is arguably a precise measure of human capital due to its

[2] In this version of the CRT, three questions were presented:

- Emilia's father has 3 daughters. The first two are named April and May. What is the name of the third? (*fast* answer: June, correct answer: Emilia).
- In a library, every month the number of books doubles. If it takes 48 months to fill the library, how long would it take to fill half of it? (*fast* answer: 24, correct answer: 47).
- If you are running a race and you pass the person in second place, where do you stand? (*fast* answer: first place, correct answer: second place).

[3] The test was conducted in a classroom setting during the experiment, supervised by enumerators, making it a relatively reliable measure of students' cognitive abilities.

[4] Note that the version of the CRT that was applied in this case is a variant of the original test proposed by Frederick (2005).

strong connection with future and current economic and financial decision-making. Moreover, it may also be considered as a proxy for overall mathematics abilities. For all these reasons, this variable is key in the framework of this study as it represents, a priori, an aspect of human capital that could be considered of relatively high value.

The third set of variables are consistency in time preferences and risks attitudes tasks. In a time preferences task (multiple price list [MPL]), children were asked to choose between an impatient option with a lower payoff (e.g., \$10 today) and a patient option after a given amount of time (e.g., \$15 in one week). As the task progressed in several rounds, patient payoffs were increasing in value. Inconsistent behavior in time preferences was captured with a dummy variable taking value 1 when a child had chosen a patient option and, in any of the following rounds he or she switched back to an impatient option and 0 otherwise (the opposite is done for consistency). Similarly, in a risk attitudes task, children were asked to choose between two lotteries, one with a higher probability but a lower expected payoff (risk averse) and another one with a lower probability but a higher expected payoff (risk loving). As before, the expected payoff in the risky lottery was increasing in subsequent rounds. Inconsistent behavior in this risk attitudes task was measured with a dummy variable taking value 1 if the child had chosen the risky option and, in any of the following rounds he or she switched back to the risk averse lottery and 0 otherwise (the opposite is done for consistency). Consistency has been found to be a good predictor of educational performance and alternative measures of human capital (see Gonzales et al., 2024).

The fourth and last category is composed of two variables measuring the expectations (subjective probability) that each child reports for continuing their studies the next year or for going to university. Despite children not necessarily knowing them with great precision or even exaggerating attitudes towards the future of their studies, these probabilities are relevant as they are also a proxy for how motivated students are or how much they value education, thus providing a measure capable of capturing the future effort or investment that each child would expect to put into human capital.

4.3 Social Capital Variables

Social capital variables are constructed using network analysis. Every child was asked to report who they had conflicts with in their classroom (*Enemies*). If those who were reported by the child also report the latter as an enemy, then it is counted as a mutual (or confirmed) enemy. In this respect, the main conflict variable of interest in the proposed analysis is the average number of mutual enemies in each class. An alternative interpretation of the latter measure is that of mutual enemies per student in each class. All measures are calculated at the school class level.

It could be argued that, while the above measure captures conflict at the class level (i.e., *bad apples* as defined by Hoxby and Weingarth (2005)), it does not reflect overall social capital as well. For example, a class with many enemies but many friends at the same time should probably not be considered as having accumulated little or poor social capital. Therefore, my analysis considers an additional measure that does accurately account for the level of social capital by showing the difference between the average number of mutual enemies and the average number of mutual friends at the class level. This alternative proxy is closely related to the second dimension of social capital defined in Woolcock (1998), capturing the value of interpersonal links in a community. Note that increases in this variable imply worse (rather than better) levels of social capital in the classroom to keep a similar interpretation to the previous measure. This means that negative effects of the latter on human capital would reflect beneficial impacts that would be expected of social capital on academic performance.

Additionally, to add robustness to the analysis, two alternative measures or variations of the previous ones are also considered. First, one which, instead of using $Enemies$ and $Friends$, calculates the variables based on $Worst\ enemies$ and $Best\ friends$, respectively. Second, one which considers the network density of $Enemies$ and the difference of $Enemies$ density and $Friends$ density instead of the class average.[5]

Average measures at the class level are proposed rather than individual ones for two reasons: first, they probably capture better the general level of conflict and social capital of each child's social environment; second, they are most likely exogenous to the child's individual academic performance.[6]

Nevertheless, it is important to note that the measures of social capital used in this thesis capture only quantitative aspects (i.e., based on the quantity of enmity or friendship relationships), however there is a qualitative dimension that I have discussed in the previous section but that is not covered in the analysis (i.e., those aspects related to the quality of friendship and enmity relationships in the network, or like social capital that are given by the degree of trust between peers). A relevant example in El Salvador could be the one already pointed out by authors who find how peer effects could also induce criminality or other behaviors (Calvó-Armengol and Zenou, 2004; Ballester et al., 2010; Jackson et al., 2017; Gaviria and Raphael, 2001; Deming, 2011; Eren et al., 2022; Carrasco and González-González, 2024). In this sense, having a bond of enmity with a child whose behavior in class could be determined by his or her relationship (personal or through their family) with gangs may not necessarily be considered as *worse* social capital;[7] similarly, having friendship ties with this child should not be counted as a *better* level of social capital either. However, in my analysis, this distinction is not made and possible relationships of friendship and enmity as described above would be part of a *better* and *worse* social capital, respectively.[8] In fact, this is an old issue in the intellectual

[5] The density of a network is calculated as the number of mutual connections (friend/enemy relations) divided by the number of total maximum possible connections.

[6] This is the main reason why I do not have worry about computing averages excluding each individual child (i.e., leave-me-out average) or for considering class leave-me-out-average covariates in my analysis, as is suggested by Manski (1993). The reason is that, in Manski's terms, these are not "endogenous" peer effects.

[7] Although this specific case is debatable.

[8] Also note that this problem could be further aggravated if it was the case that problematic children may join in friendly relationships with others with similar behaviors and make enemies with more peaceful children as suggested by the homophily thesis, for which it has been shown

discussion as social capital has been often been criticized for not necessarily being the source of positive economic and social outcomes (e.g., social capital driving the rise of the Nazi Party in Germany through mass membership to local associations or clubs as was shown by Satyanath et al. (2017)). . Although this problem cannot be solved in the context of this study, it is appropriate to take it into account not only when describing the variables that I have defined as measuring social capital, but also when interpreting and discussing the results, particularly in those cases that might seem counter-intuitive.

4.4 Covariates

A set of covariates is proposed as control variables for the analysis. That is, sociodemographic variables such as age, gender and a self-reported proxy of family income. Furthermore, class size is controlled for as it might be correlated to the capacity of a given classroom to accumulate conflict or social capital and has been found to affect academic performance (Angrist and Lavy, 1999). Lastly, I control for municipality and school unobservable characteristics that might be correlated with both conflict and human capital.

4.5 Descriptive Statistics

Table 4.1 presents summary statistics for social capital and conflict measures at the class level, as well as human capital accumulation, and sociodemographic variables. The first four rows show that there is about one mutual enmity relationship for every five children and approximately one mutual pair of worst enemies for every twenty children, and that, on average, there are five mutual friendships and three reciprocal best friendships for every three and five students, respectively.

Table 4.1: Summary statistics

Variables	Obs.	Mean	St. Dev.	Min	Max
Enemies (class average)	2,589	0.180	0.135	0	0.675
Friends (class average)	2,589	1.680	0.749	0.278	3.875
Worst enemies (class average)	2,589	0.053	0.051	0	0.269
Best friends (class average)	2,589	0.608	0.264	0.056	1.155
Cognitive reflection test	2,580	0.433	0.191	0	1
Financial abilities	2,580	0.184	0.224	0	1
Consistency (time)	2,580	0.574	0.495	0	1
Consistency (risk)	2,581	0.435	0.496	0	1
Continue studies next year (probability)	2,572	0.819	0.248	0	1
Continue studies in university (probability)	2,572	0.705	0.284	0	1
Female	2,589	0.488	0.500	0	1
Age	2,588	14.891	1.630	11	21
Family income index	2,588	5.532	2.167	1	10
Class size	2,589	27.772	7.633	3	44
Rural	2,589	0.263	0.440	0	1

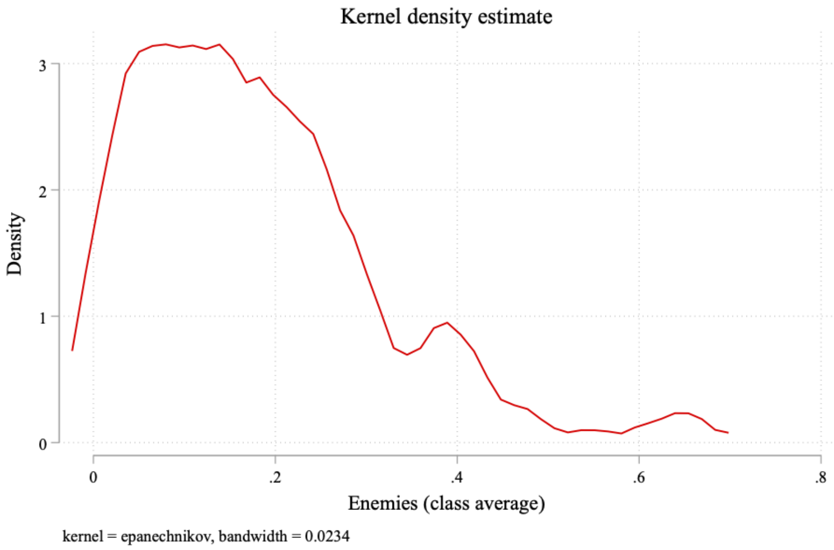
Source: Own elaboration based on data from COM-PHAS.

Note: Values referring to class level are calculated for 122 different classrooms in the sample.

that there is evidence supporting it (Jackson et al., 2017).

In addition, Figure 4.1 shows the distribution of average classroom reciprocal enemy relationships. The density graph presents a right-skewed distribution, suggesting that enmity across all classrooms seems to be concentrated at relatively low values, with many classes showing relatively few confirmed enemy relationships per student.

Figure 4.1: Distribution of average class enemies

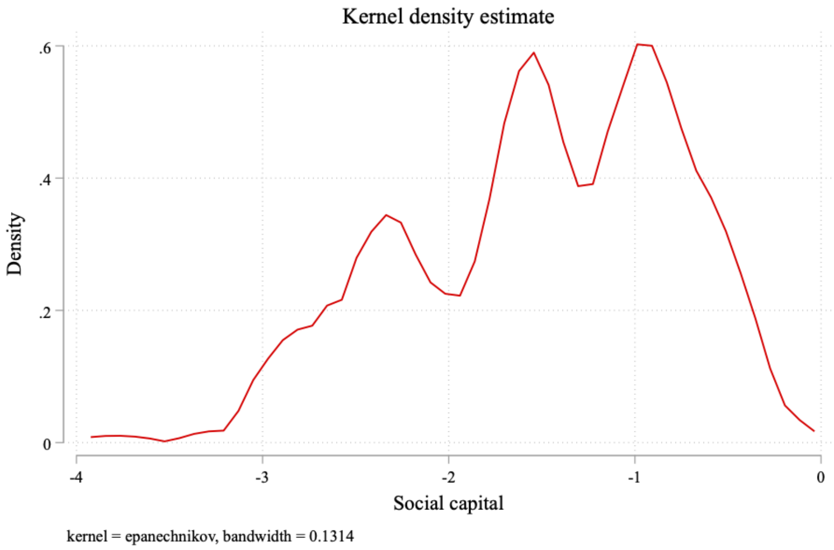


Source: Same as Table 4.1.

On the other hand, Figure 4.2 shows a somewhat different and less skewed pattern, with the difference between pairs of enemies and pairs of friends per student arranged in what appears to be a multimodal distribution with values clustering around three levels of class social capital. These three modes showing common values make it relatively easy to categorize most classrooms as high-, medium-, and low-social-capital, going from left to right along the density distribution.[9] Interestingly, medium- and low-social-capital classrooms tend to be more prevalent in the sample.

[9]Note that the zero value in the social capital measure defines classes where the number of mutual friendships is the same as the number of mutual enmities.

Figure 4.2: Distribution of class social capital



Source: Same as Table 4.1.

The difference between the two distributions above might already indicate the fact that using these two measures in the analysis could yield different results. The main reason for this would be, as I have discussed above, that both capture different things: while average class enemies is a proxy for conflict and disruptive behavior (i.e., *bad apples*), my measure of social capital rather captures the overall quality of student relationships within the classroom (i.e., relational quality or general interpersonal wellbeing).

Tables 4.2 and 4.3 show average academic performance for the different human capital measures across different levels of the class enemy and social capital distributions, respectively.

Table 4.2: Human capital variables by percentiles of class enmity

Variables	$< P25$	$P25 - P50$	$P50 - P75$	$> P75$
Cognitive reflection test	0.432	0.436	0.434	0.428
	(0.189)	(0.191)	(0.190)	(0.194)
Financial abilities	0.195	0.179	0.179	0.183
	(0.222)	(0.223)	(0.229)	(0.222)
Consistency (time)	0.603	0.579	0.570	0.538
	(0.490)	(0.494)	(0.495)	(0.499)
Consistency (risk)	0.489	0.429	0.399	0.421
	(0.500)	(0.495)	(0.490)	(0.494)
Continue studies next year	0.827	0.824	0.802	0.824
	(0.247)	(0.239)	(0.259)	(0.245)
Continue studies in university	0.708	0.692	0.696	0.723
	(0.281)	(0.288)	(0.295)	(0.272)
Number of classes	36	28	28	30

Source: Same as Table 4.1.
Note: Standard deviations in parentheses.

The first two rows of Table 4.2 present a general decrease of both cognitive and financial abilities with higher values of average enmity, with the former having its maximum average value between the bottom 25% and 50% and the latter showing a slight increase at the very top of the class enmity distribution. In the remaining rows regarding consistency and expectations to continue studies, only consistency in the time discounting task decreases consistently throughout the whole distribution, with the other three measures presenting what appears as a U-shaped pattern.

Table 4.3: Human capital variables by percentiles of social capital

Variables	$< P25$	$P25 - P50$	$P50 - P75$	$> P75$
CRT	0.425	0.425	0.453	0.429
	(0.192)	(0.194)	(0.185)	(0.193)
Financial abilities	0.178	0.162	0.220	0.176
	(0.226)	(0.216)	(0.238)	(0.212)
Consistency (time)	0.568	0.536	0.596	0.592
	(0.496)	(0.499)	(0.491)	(0.492)
Consistency (risk)	0.421	0.405	0.452	0.462
	(0.494)	(0.491)	(0.498)	(0.499)
Continue studies next year	0.815	0.801	0.822	0.837
	(0.251)	(0.252)	(0.261)	(0.227)
Continue studies in university	0.729	0.685	0.694	0.709
	(0.270)	(0.294)	(0.291)	(0.281)
Number of classes	27	32	28	35

Source: Same as Table 4.1.
Note: Standard deviations in parentheses.

In Table 4.3, however, different descriptive results are observed. First, neither CRT nor financial abilities seem to vary across different levels of social capital (if anything, children in classes with poorer levels of social capital might show a slightly better performance in cognitive abilities). Second, regarding consistency, performance in time and risk tasks is generally increasing in worse social capital levels (both presenting minimum average values at the second quartile). Third, expectations to continuing studies present a clear U-shape along the distribution.

The latter descriptive evidence also seems to suggest that the different patterns that are observed across different measures of both human and *bad apple* social capital could be in line with the heterogeneities and non-linearities that have already been reported by previous literature, as was discussed in the previous section. For this reason, non-linear results and their rationale are also considered and discussed in my analysis.

5

Methods

5.1 OLS Model

A first approach to measuring the association of social capital and educational outcomes could be through ordinary least squares (OLS) regressions. Formally, a human capital accumulation function could be estimated following Equation 5.1:

$$h_{ims} = \beta_0 + \beta_1 \overline{SC}_c + \beta_2 \overline{SC}_c \times Female_{ims} + \beta_3' X_{ims} + \alpha_m + \pi_s + \epsilon_{ims} \quad (5.1)$$

Where h_{ims} represents the different measures of human capital for child i, living in municipality m, and studying in school s; $\overline{SC}_c$ are social capital measures (mutual enemies or the difference between mutual enemies and mutual friends) averaged at the classroom level c; $Female_{ims}$ is a dummy taking value 1 if the child is a girl and 0 otherwise; X_{ims} is a vector of child-specific covariates including age, a proxy for family economic status, and class size; α_m and π_s are municipality and school fixed effects, respectively; and ϵ_{ims} is the error term. The interaction of social capital measures with the female dummy is mainly included to account for potential non-linearities and heterogeneous gendered effects.

The coefficients of interest are β_1, which captures the association between class social capital and individual educational outcomes for boys, and β_2, which measures any differential association observed among girls with respect to boys.[1] OLS will provide consistent coefficients as long as social capital measures are not correlated with the error term. In other words, estimates will measure causal effects as long as class *bad apple* social capital is exogenous to human capital accumulation. Because, my measures of social capital are aggregated at the classroom level, it is not unrealistic to think that classical endogeneity issues like omitted variable biases or inverse causality may not play a huge threat to the internal validity of this simple identification strategy.[2] Even so, potential endogeneity is considered and discussed below.

[1] Note that the overall association for girls can be calculated as $\beta_1 + \beta_2$ in cases where $\beta_2 \neq 0$. In cases where the interaction term with gender is statistically insignificant, β_1 can also be thought of as the association between class social capital and human capital for both boys and girls, as there would be no evidence supporting a gendered differential correlation.

[2] Measurement error is not considered as network variables capturing reciprocity are assumed to be precise (i.e., friend or enemy relationships of any two given students have mutual approval by both children).

5.2 Quantile Regression Model

Given its importance and prevalence in the literature, an additional strategy is to study the possible non-linear effect of social capital and peer effects at different levels of the distribution of human capital accumulation, which is possible by resorting to quantile regressions.

In particular, I build a continuous variable capturing expected future years of schooling which, following Borgen et al. (2021) and Borgen et al. (2023), seems to provide an appropriate case for using unconditional quantile treatment effects (QTE). Compared to average treatment effects (ATE) obtained through OLS, consistent QTE estimates can be interpreted as the treatment effect for any given quantile at the outcome distribution (Borgen et al., 2021).[3] Results obtained through this estimation method may be seen as a comparison between individuals belonging to the same quantile of human capital distributions for different levels of the independent variable (i.e., average classroom social capital). QTE are particularly useful when the research question focuses on studying the effects of a particular characteristic (e.g., *bad apple* social capital or peer effects at the class level) across the unconditional distribution of a given continuous dependent variable (e.g., expected years of schooling) (Borgen et al., 2023).[4]

5.3 IV Model

Although measures of social capital aggregated at the class level should be rather exogenous to individual academic performance and, moreover, given that I control for a comprehensive set of covariates, it is worth making certain observations about possible endogeneity problems. It would seem implausible that individual academic performance could affect the levels of social capital or enmity of the class as a whole, so it would be reasonable to think that reverse causality can be ruled out.[5] However, inconsistent OLS estimates could also come from omitted variable bias, which may be more problematic when trying to make a causal interpretation, for example, if classes of certain schools happened to be located in areas with higher rates of violence which might affect the level of conflict in the classroom and affect the academic performance of individual children. I consider the latter possibility in the *Interpretation and Potential Mechanisms* section of this study, but given that I control for municipality fixed effects, that source of endogeneity should also be accounted for.

[3] Note that a key assumption in QTEs is that of rank invariance, which means that individuals would maintain their expected position (ranks) in the outcome distributions for all levels of the independent variable (Borgen et al., 2021).

[4] In particular, Borgen et al. (2023) highlight that studies related to socioeconomic gradients, as is the case of this thesis when considering expected future years of education, should preferably use QTE as opposed to other types of quartile regression models.

[5] Were this to pose a potential credible threat to internal validity, controlling for different centrality measures of each child in the network could be a way of avoiding it since, as shown above, there is evidence that a child's position within the network could influence peer behavior (Jackson et al., 2017; Calvó-Armengol et al., 2009). I have performed the analysis I present in this thesis adding eigenvector centrality in friendship and enmity as controls and the results are virtually the same (results not provided), which adds yet more credence to the idea that reverse causality is not an endogeneity problem in this case.

Another possibility is that other unobservable characteristics at the class level such as, for example, difference in teachers' engagement, could be correlated with both social and human capital and, therefore, be driving part of the results. If some children were exposed to teachers who were less involved in providing a good classroom environment and ensuring that their students learn and acquire knowledge (e.g., because of poor work motivation), then some of the negative effect that such a teacher has on their students' grades would be erroneously attributed to the greater enmity or lower level of social capital in the class. Since the same teacher can teach in different classrooms and given that my data do not include specific characteristics of the teaching staff, problems of omitted variables such as the one mentioned above could lead to endogeneity problems.[6]

As discussed previously, a common approach that some authors use when estimating the causal effects of peer effects on human capital is to take advantage of exogenous movements of people such as migration inflows or even the random assignment of roommates in the case of university education (Castilla, 2024; Angrist and Lang, 2004; Imberman et al., 2012; Sacerdote, 2001; Zimmerman, 2003; Carrell et al., 2009). This type of identification strategies provides useful natural experiments by exploiting exogenous variations in the levels of social capital. The closest way to approximate the above with my data is through students who repeat school years (repeaters, hereafter). Given their poor academic performance, from one year to the next, repeaters are sent to a new classroom composed of children which used to be one school year below and have progressed academically. Thus, these classes receive an exogenous shock to their level of social capital with the arrival of new-coming repeaters. Assuming that the latter tend to be on average more troublesome and thus capable of generating more conflict, enmity, and worse social capital accumulation at the class level, the total number of repeaters as a proportion of the total number of students in the class is taken as an instrumental variable to estimate the effect of social capital and *bad apple* peer effects on students' human capital.[7]

A potential threat to the internal validity of this approach is given by the fact that class assignment for repeaters may not be necessarily random. In fact, that decision is often made by school directors or authorities, who might decide to spread problematic repeaters across different classrooms so as to minimize their joint disruption potential. However, this is not possible when only one classroom is available for the next year in a given course. In such cases, no strategic class allocation is possible and all repeaters would have to be pooled together with the new (and only) group of students. In order to prevent this director- or school-authorities-driven potential selection bias, not only is the percentage of repeaters in a classroom used as an instrument, but also its interaction with an indicator variable taking value 1 if the classroom they belong to is the only one available for their given school year in their institution and 0 otherwise.

[6] Carrasco and González-González (2024) find evidence consistent with the idea that teacher behavior could be an important driver of the effects of different socioeconomic determinants on human capital (those of obesity, in this specific case).

[7] Repeaters were identified as those students who were in the same school year for a given school during the first and second wave of data collection. The time difference between the two surveys was one year. About 6.4% of the sample were identified as repeaters.

I estimate Equation 5.1 through two-stage least squares (2SLS), where the measures of social capital are instrumented using the percentage of repeaters in the class and the latter interacted with a dummy indicating whether the child is in a school year for which there is only one class in his or her school in the first stage. Formally, the first stage is estimated following the peer effects specification in Roychowdhury (2019) as shown in Equation 5.2:

$$\overline{SC}_c = \gamma_0 + \gamma_1 \overline{Repeaters}_c + \gamma_2 \overline{Repeaters}_c \times I_c + \gamma_3 I_c + \gamma_4' X_{ims} + \lambda_m + \sigma_s + \mu_{ims} \quad (5.2)$$

Where $\overline{Repeaters}_c$ is the proportion of repeaters; I_c is the unique class dummy; λ_m and σ_s are municipality and school fixed effects, respectively; and μ_{ims} is the error term.

Two conditions must hold for the instruments to be valid. First, they must be relevant, or correlated to the endogenous variable. Second, they should not affect individual human capital accumulation other than through their effect on class social capital. While the first condition can be tested (i.e., if $\gamma_1 \neq 0$, $\gamma_2 \neq 0$, $\gamma_3 \neq 0$, or any linear combination of all of them), the second one can only be justified logically. As I argued above, the number of repeaters in a class would be expected to produce higher levels of conflict, especially in cases in which they could not be dispersed in different classes by the school management. This, in turn, would have an indirect effect on children's academic performance (only) through a worse environment and poorer class-level social capital. It is difficult to think of any other channel through which the proportion of repeaters in a class could affect the educational outcomes of individual students.

The coefficients estimated through 2SLS should be interpreted as local average treatment effects (LATE), which capture causal impacts only on compliers, that is, on those whose behavior may be affected by the instrument (children in classes for which the presence of repeaters changes overall classroom social capital and enmity) (Imbens and Angrist, 1994). Results also present Hausman tests for the exogeneity of class social capital measures under the validity of the instruments, as well as Sargan overidentification tests for the exogeneity of additional instruments under the validity of one of them (e.g., average repeaters in unique classrooms).

6

Empirical Analysis

6.1 OLS Results

The main regression results from the OLS estimates are presented in Tables 6.1 through 6.4. All tables present coefficients for enemies or social capital aggregated at the class level as well as the interaction of the latter with a gender dummy capturing differential effects for girls to account for potential heterogeneous effects. Full estimations are also provided in the Appendix A. Moreover, standard errors were estimated as heteroskedasticity-robust and are presented in parentheses.

Table 6.1: Enemies and cognitive abilities (OLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Enemies (class average)	0.024	0.007	-0.059	0.007	-0.218***	-0.191*	-0.230***	-0.217*
	(0.031)	(0.043)	(0.036)	(0.052)	(0.082)	(0.111)	(0.082)	(0.111)
Female × Enemies		0.034		-0.127**		-0.053		-0.025
		(0.056)		(0.061)		(0.142)		(0.143)
Female	-0.001	-0.008	-0.076***	-0.054***	-0.064***	-0.055*	-0.032	-0.027
	(0.007)	(0.012)	(0.008)	(0.014)	(0.019)	(0.032)	(0.019)	(0.032)
Age	0.004	0.004	0.012***	0.011***	0.006	0.006	0.010	0.010
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)	(0.007)
Family income	-0.004**	-0.004**	-0.007***	-0.007***	-0.002	-0.002	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Class size	-0.002***	-0.002***	-0.001	-0.001	-0.003*	-0.003*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.407***	0.408***	0.043	0.036	0.419***	0.416***	0.650***	0.649***
	(0.051)	(0.051)	(0.057)	(0.057)	(0.132)	(0.132)	(0.134)	(0.134)
Observations	2,579	2,579	2,579	2,579	2,579	2,579	2,579	2,579
R-squared	0.033	0.033	0.087	0.089	0.039	0.040	0.026	0.026
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

Table 6.1 presents interesting results. First, there is no statistically significant evidence that belonging to classes with higher number of mutual enemy relationships per student is associated with worse CRT scores, as reported in column (1). Despite CRT representing a standardized measure that is usually identified as a good predictor of academic performance and cognitive abilities, it does not seem to be associated in any way to classroom conflict. Regarding financial abilities, a correlation with average class enemies is only found among girls when the interaction term is included in the specification (column (4)), for which an increase of 1 mutual enmity relation per student in the classroom is associated with a decrease of 1.2 points out of 10 in the financial abilities test. This is equivalent to a reduction of 0.54 standard deviations. Lastly, columns (5) through (8) show that class conflict is negatively correlated with consistency in both the risk preferences and the time discounting tasks, with no difference found between boys and girls. The magnitude of these associations are relatively similar across specifications in both tasks, with coefficients ranging from -0.19 to -0.23, which correspond to decreases of around 20% on the probability of completing the tasks consistently for every additional enmity relationship per capita in the classroom. These results could be due to the fact that enmity in the classroom may be associated with poorer levels of concentration among students by creating a more conflictual environment that is less conducive to paying attention. This in turn could be reflected in greater inconsistency, which results from paying less attention during task performance.

Table 6.2: Enemies and expectations to continue studies (OLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Enemies (class average)	-0.053	-0.003	0.022	0.094
	(0.038)	(0.050)	(0.044)	(0.059)
Female × Enemies		-0.097		-0.138*
		(0.067)		(0.076)
Female	0.021**	0.038**	0.058***	0.083***
	(0.010)	(0.016)	(0.011)	(0.018)
Age	-0.018***	-0.018***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002***	-0.002***	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.079***	1.073***	0.853***	0.844***
	(0.070)	(0.069)	(0.075)	(0.075)
Observations	2,571	2,571	2,571	2,571
R-squared	0.048	0.049	0.058	0.059
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

Regarding subjective expectation of continuing studies, higher class enmity only seems to be associated with a lower probability of attending university in the case of girls. Introducing an additional relation of mutual enemies per student in a classroom correlates with a decrease of about 4% in the self reported probability of girls eventually enrolling in university studies. Note that, in the case of probability of going to university, there seems to be a positive correlation with class conflict in the case of boys which is perfectly offset by the differential association observed in girls before controlling for municipality fixed effects (see columns (1) through (3) of Table A.6 in Appendix A). This relationship that is only observed among boys without accounting for unobservable municipality characteristics suggests that there would seem to be something at this territorial level that would explain why children in more conflictive classes show a greater predisposition to study in the future. An interesting plausible explanation for these results is based on the theoretical insight that was previously discussed relating violent conflict, social capital, and human capital proposed by Justino (2011). Gang activity, which could be driving violent behavior of school children in municipalities were it is higher, might be altering returns to education, only making human capital investments attractive to those who could benefit the most from them (boys in this case). I further develop this possibility in the *Interpretation and Potential Mechanisms* section.

Table 6.3: Social capital and cognitive abilities (OLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Social capital ($\overline{E}_c - \overline{F}_c$)	0.001	-0.007	-0.006	-0.012	0.014	0.001	-0.000	0.004
	(0.006)	(0.008)	(0.007)	(0.010)	(0.016)	(0.021)	(0.016)	(0.020)
Female × Social capital		0.017*		0.012		0.025		-0.009
		(0.010)		(0.012)		(0.027)		(0.027)
Female	-0.001	0.024	-0.077***	-0.059***	-0.064***	-0.027	-0.032	-0.045
	(0.007)	(0.017)	(0.008)	(0.019)	(0.019)	(0.044)	(0.019)	(0.044)
Age	0.004	0.004	0.012***	0.012***	0.008	0.008	0.011*	0.011*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)	(0.007)
Family income	-0.004**	-0.004**	-0.007***	-0.007***	-0.002	-0.002	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Class size	-0.001**	-0.001**	-0.001	-0.001	-0.003*	-0.003*	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.409***	0.397***	0.038	0.029	0.398***	0.380***	0.629***	0.635***
	(0.050)	(0.051)	(0.057)	(0.057)	(0.131)	(0.133)	(0.134)	(0.135)
Observations	2,579	2,579	2,579	2,579	2,579	2,579	2,579	2,579
R-squared	0.032	0.033	0.087	0.087	0.037	0.037	0.023	0.023
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

Table 6.3 above presents OLS results for the relationship between social capital at the classroom level and different cognitive skills. Interestingly, the picture is very different to that shown in Table 6.1 when considering enmity. The reason for such different results might be, again, because both variables (class enemies and class social capital) do not measure quite the same thing. While conflictive and disruptive behaviors that may arise from enmity relationships could have stronger effects on aspects such as concentration or mathematical (financial) abilities for individual students, including the attenuating effect of friendship relationships seems to mitigate or alter them. Here, the only correlation between social and academic performance is positive and shows up exclusively for female students in CRT scores, suggesting that girls perform better in classrooms with worse social capital accumulation. Even so, the magnitude does not appear to be very large, as classes where the average difference between mutual enemies and mutual friends increases by 1 per student are associated with a 0.05 standard deviations increase in CRT for girls.[1] This could be because in classes with fewer opportunities to invest in social capital (due to the presence of less friendly and/or more hostile peers), the efforts that girls would have to put into socializing would be such that they would prefer to devote themselves to

[1] It is this small magnitude in the coefficient that could be related to the amplitude of its standard error, which only allows the estimate to be significant at the 10% confidence level. Given my sample size, statistical power limitations might not allow for further inference in such a small association.

improving aspects of their education that they would find more valuable or profitable in the future, such as those related to cognitive reflection.[2] In this sense, if this relationship is true, the previous result would be providing evidence that investments in social and human capital could become substitutes, which would be in line with the theoretical results in Glaeser et al. (2002). I will return to the difference in findings for boys and girls in more detail in the *Interpretation and Potential Mechanisms* section.

Table 6.4: Social capital and expectations to continue studies (OLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Social capital ($\overline{E}_c - \overline{F}_c$)	0.021***	0.006	-0.001	-0.010
	(0.008)	(0.010)	(0.008)	(0.011)
Female × Social capital		0.029**		0.016
		(0.013)		(0.015)
Female	0.021**	0.064***	0.058***	0.083***
	(0.010)	(0.021)	(0.011)	(0.024)
Age	-0.017***	-0.017***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002**	-0.002**	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.098***	1.076***	0.854***	0.841***
	(0.070)	(0.071)	(0.076)	(0.076)
Observations	2,571	2,571	2,571	2,571
R-squared	0.050	0.052	0.058	0.059
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

In the case of subjective probabilities of continuing studies, Table 6.4 shows again results that do not correspond to those discussed when considering enmity at the class level exclusively. In this case, children in classes with poorer levels of social capital show higher predisposition to continue studies the next year. However, this association seems to only be driven by girls, as including the interaction term with gender in the specification captures the bulk of this positive correlation. An additional increase in the difference between average enemies and friends in the classroom per student is associated with around a 2% higher chance that a girl will continue studies next year, as self reported by her. The explanation for this result follows the same logic regarding the trade-off between investing in social or human capital in the case of girls. The fact that this relationship is only statistically significant in the probability of staying in school an additional year suggests a potential short term effect, which could also be related to the relatively small magnitude observed in the association of social capital and CRT and provides an additional interesting insight: the dilemma between taking advantage of the social dynamics of the class or being more involved in the studies could be true but of relatively low importance for overall girls' human capital investment decisions.

[2]Note that this interpretation works both ways, with girls in classrooms where it is easier to socialize potentially willing to focus on investing in improving their network of relationships at the expense of neglecting their studies.

6.2 Quantile Regression Results

Given the previous somewhat heterogeneous associations between *bad apple* social capital peer effects and the subjective probabilities of continuing studies, it is interesting to study the possible effects of the former on the number of years of education that each child is expecting to complete given his or her current perceptions. As I have data on the current years of study of each child, their subjective probabilities, and the fact that university starts at the 12th year of education in the Salvadoran education system, a variable measuring expected future years of schooling can be calculated with the expression in Equation 6.1:

$$\mathbb{E}[y_i] = y_i + p_i^n(1) + p_i^u(11 - y_i) \tag{6.1}$$

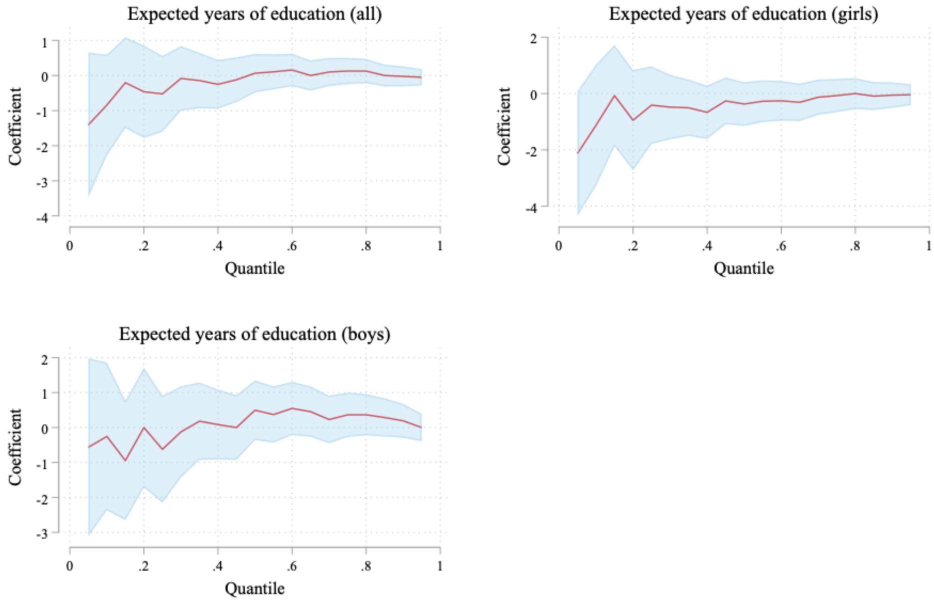
Where the value of current years of schooling y_i of child i is increased by an additional year multiplied by their subjective probability of continuing the next year p_i^n, plus how many years it would take them to start university at the 12th year of education given that the next year is completed $(12 - (y_i + 1)$, which is the same as $11 - y_i)$ times their subjective probability of going to university p_i^u. Note that only consistent respondents were considered, that is, those which showed monotonically decreasing perceptions of probabilities with time, $p_i^n > p_i^u$.[3] Here I take a conservative estimation by considering only the first year of college, as including additional years (e.g., 3 or 4 years of average length of a college degree) might give too unrealistic a view by not considering the probability of dropping out.

Results for the associations between class conflict and social capital and expected years of schooling are presented in QTE regressions to account for potential non-linearities in Figures 6.1 and 6.2, respectively.[4] Regressions are estimated for all children as well as for subsamples for boys and girls, separately.

[3]Also note that, for simplicity, expected years of education for students in their 11th year was calculated as $\mathbb{E}[y_i] = y_i + p_i^n(1)$, which would be exact for Equation 6.1 if $p_i^n = p_i^u$. Nevertheless, both probabilities were not found to be the same for children in their last years of high-school (the hypothesis $p_i^n = p_i^u$ is rejected at the 1% confidence level), potentially due to the fact that some students might decide to continue their studies somewhere other than college (such as technical high-school, as was presented in the *Context* section).

[4]QTE were also estimated for other non-binary human capital measures like CRT and financial abilities. However, as both are expressed only in a few discrete values, results across the distribution were not conclusive or relevant. For that reason, QTE results are only presented for expected years of education in this thesis.

Figure 6.1: Quantile regression estimates for enemies

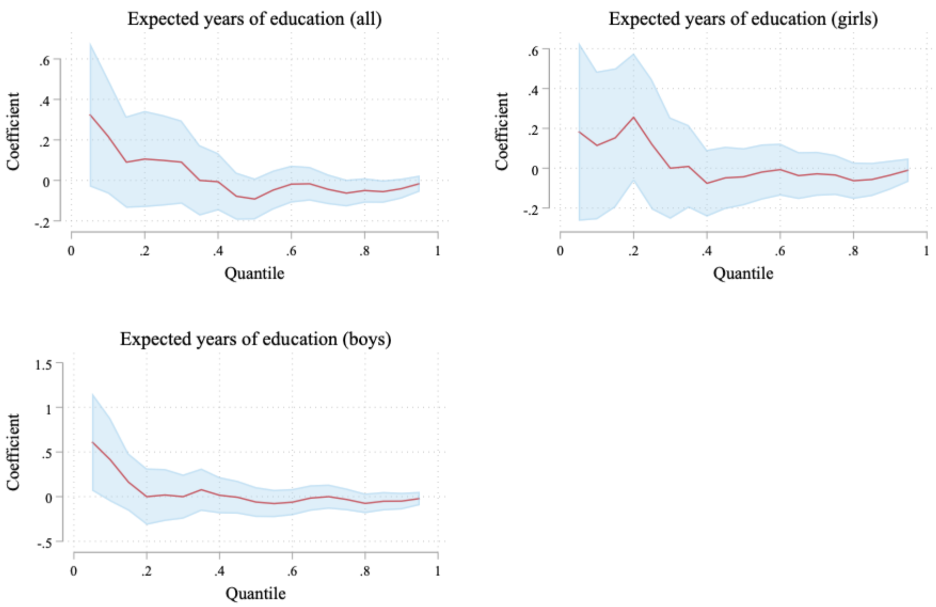


Source: Same as Table 4.1.
Note: Confidence intervals expressed at the 5% confidence level. All regressions control for gender, age, family income, classroom size, municipality, and school fixed effects.

With respect to average class enmity, all results in Figure 6.1 show no clear statistically significant relationship with subjective expected years of schooling at any point in the distribution, both for boys and girls included together as well as separately. Nevertheless, class-level conflict is associated with a lower willingness to invest in years of schooling for the 5% least likely to continue schooling among girls at a confidence level very close to 5% ($p \approx 0.06$). This part of the distribution corresponds to students who would expect to complete about 9 years of education (or finish after the third year of middle school). The results therefore show that, for these girls at the bottom of the human capital investment distribution, increasing the number of enmity relationships per student in the class by only 1 is associated with a disincentive of about 2 years of expected schooling. This means that, from this one additional enmity threshold, first-grade middle school girls with the worst projections about continuing their studies would probably be willing to drop out at the end of that same year.

Additionally, estimates seem to show increasing and concave-shaped relationships in all cases suggesting that, if anything, higher enmity would be correlated with academic discouragement for children with lower expectations. The gendered heterogeneous result as well as the shape of the QTE across the distribution are again consistent with the hypothesis of potential *bad apple* social capital effects outside the classroom like gang violence (with the potential to modify returns to education at the community level) mediating through class conflict and affecting mostly those students who would benefit less from investing in schooling.

Figure 6.2: Quantile regression estimates for social capital



Source: Same as Table 4.1.
Note: Confidence intervals expressed at the 5% confidence level. All regressions control for gender, age, family income, classroom size, municipality, and school fixed effects.

As was the case with OLS results, QTE estimates show different patterns depending on which measure of social capital is analyzed. Figure 6.2 shows a decreasing association along the distribution. A positive relationship between worse levels of social capital in the classroom and expected years of education is observed for all students at the bottom 5% of the distribution, mostly driven by boys (for which this association is positive at the 5% confidence level). In this sense, increasing by 3 units in the enemies-friends balance inside the class is correlated with a 1 year increase in expected year of education for those initially willing to stay less than 9 years in school. This might be evidence, again, of a potential trade-off between incentives to invest in social capital and continuing studies.

However, negative estimates are observed at the 10% confidence level for children at the middle of the distribution (corresponding to 11 years of expected schooling, or those willing to stay in education only until the end of high school), as well as those at the top 25% to 15% (corresponding to those very likely expecting to finish all secondary schooling and also mostly willing to go to university). These results are consistent with previous findings in the the literature regarding non-linear returns to education through the so-called "diploma" or "sheepskin" effect (see Card, 1999; Hungerford and Solon, 1987). The fact that these negative associations appear at the parts of the distribution that correspond to the end of secondary studies suggests a disincentive socialization effect at graduation, with classes having lower opportunities to invest in social capital (and, therefore, socialize and create a network of valuable relations) making it less attractive for children who could be initially considering university to actually enroll. This is reasonable as moving to college would imply a change of social capital levels (i.e., dealing with a completely different group of peers) for which, if there were few socialization opportunities during middle and high school, additional efforts would be required that these students may be less willing to undertake. In this sense, and contrary to what occurs at the bottom of the distribution, social capital and human capital are shown to be complementary investments, although it is important to note that the magnitudes of these relationships are significantly smaller. In conclusion, the result regarding non-linear relationships that is common in the peer effects literature also seems to be repeated in my analysis, especially when considering the latter measure of human capital.

6.3 IV Results

As discussed above, the previous results may not be interpreted causally as some considerations of endogeneity may be driving part of them. In order to obtain consistent estimates, Tables 6.5 through 6.8 present 2SLS estimates where class *bad apple* social capital is instrumented by the proportion of repeaters in each classroom as well as the latter interacted with a unique class dummy.

Table 6.5: Effects of enemies on cognitive abilities (2SLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (time)	(6) Consistency (time)	(7) Consistency (risk)	(8) Consistency (risk)
				Panel A: Two Stage Least Squares				
Enemies (class average)	0.422	0.491	0.909**	1.333***	0.973	1.584	1.167	1.155
	(0.330)	(0.370)	(0.424)	(0.455)	(0.853)	(0.979)	(0.845)	(0.951)
Female × Enemies		-0.152		-0.908*		-1.006		0.128
		(0.410)		(0.481)		(1.138)		(1.097)
Female	-0.002	0.026	-0.077***	0.087	-0.032	0.149	-0.065***	-0.088
	(0.008)	(0.074)	(0.010)	(0.087)	(0.020)	(0.206)	(0.020)	(0.198)
Age	0.005*	0.005*	0.015***	0.014***	0.015**	0.014*	0.012	0.012
	(0.003)	(0.003)	(0.004)	(0.004)	(0.008)	(0.008)	(0.007)	(0.008)
Family income	-0.004*	-0.004*	-0.007***	-0.007***	-0.012***	-0.013***	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Class size	-0.003**	-0.003**	-0.003**	-0.004**	-0.004	-0.005*	-0.007**	-0.007**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.440***	0.432***	0.061	0.007	0.462***	0.390**	0.420***	0.424***
	(0.056)	(0.060)	(0.072)	(0.076)	(0.151)	(0.164)	(0.150)	(0.162)
Observations	2,579	2,579	2,579	2,579	2,579	2,579	2,579	2,579
Hausman F-statistic	1.54	0.92	5.78**	5.00***	2.04	1.77	2.76*	1.48
Overidentification test χ^2	6.44**	10.66**	3.81	9.13*	3.73	9.52**	5.15*	5.34
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
				Panel B: First stage for enemies and enemies interacted with gender				
Repeaters (class average)	-0.024	-0.010	-0.024	-0.010	-0.024	-0.010	-0.024	-0.010
	(0.038)	(0.046)	(0.038)	(0.046)	(0.038)	(0.046)	(0.038)	(0.046)
Repeaters × Unique class	0.227**	0.179	0.227**	0.179	0.227**	0.179	0.227**	0.179
	(0.107)	(0.143)	(0.107)	(0.143)	(0.107)	(0.143)	(0.107)	(0.143)
Unique class	0.049***	0.050***	0.049***	0.050***	0.049***	0.050***	0.049***	0.050***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Female × Repeaters		0.110**		0.110**		0.110**		0.110**
		(0.050)		(0.050)		(0.050)		(0.050)
Female × Repeaters × Unique class		-0.649***		-0.649***		-0.649***		-0.649***
		(0.146)		(0.146)		(0.146)		(0.146)
Female × Unique class		-0.005		-0.005		-0.005		-0.005
		(0.010)		(0.010)		(0.010)		(0.010)
Female		0.177***		0.177***		0.177***		0.177***
		(0.006)		(0.006)		(0.006)		(0.006)
F-statistic	20.47***	15.97***	20.47***	15.97***	20.47***	15.97***	20.47***	15.97***

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

Source: Same as Table 4.1.
Note: F-statistics in the first stage for even-numbered columns refer to those regressing on enemies interacted with gender.

The first interesting findings that stand out in Table 6.5 come from the first stage. First, the instruments seem to be quite relevant (as indicated by the F-statistic values for the instruments in the last row), thus supporting the first criterion for the IV validity. Second, and most importantly, there seems to be evidence in favor of deliberate spread allocation of repeaters across different classrooms by the schools direction to avoid potential joint disruptive behavior. As is shown in the first two rows of Panel B in odd-numbered columns, while repeaters do not seem to have any effect on general enmity in classrooms that are not unique for a given course and school, a higher presence of them in groups where there is only one classroom for the school year increases average class conflict significantly. For instance, every increase in the presence of repeaters representing 10% of all students results in an average enmity per capita increase of 0.02 in classes that are unique to their school year. If the average classroom is made up of around 28 students, this would mean that, on average, a unique class which had no repeaters in a given year and receives 4 of them in the next, would see an increase of 1 enmity relationship due to the presence of the latter.

Although this result is more instrumental and secondary to the analysis in this thesis, it provides an important methodological insight for any work that intends to instrument peer effects on the number or presence of repeaters. There seems to be evidence that the assignment of repeaters to different classes may not be random, causing a possible selection bias in cases where there are several available classrooms for the same grade by school management and officials. Failure to take this into account in the analysis could yield invalid results.

2SLS results in Panel A show that, in general, most coefficients are not statistically significant. A priori, this could suggest the lack of causal effects of social capital on academic outcomes. Nevertheless, it is important to consider the results from the Hausman test which, if statistically insignificant, would reject the hypothesis of average class enmity being endogenous to human capital measures under the validity of the instruments. This would in turn provide evidence in favor of the consistency of OLS coefficients, which would be preferred to those obtained through 2SLS for their greater efficiency. However, for the instruments to be valid (and, therefore, any IV estimation result) attention should be paid to the Sargan overidentification test which checks for the validity of additional instruments given the previously assumed validity of one of them (for example, repeaters in unique classrooms) under the null hypothesis.

Estimates in columns (1) and (2) point no statistically significant effects of class conflict on CRT, both for all children, as well as for boys and girls separately. However, the overidentification test results show that, in this case, some instruments included in my specification might not be valid. If the percentage of repeaters in unique classrooms (the interaction term in Panel B) was really a valid instrument (which I have justified above) this result could be indicating that repeaters in non-unique classrooms may be endogenous and individually invalid as an instrument, which could be the case considering the potential selection bias associated to the intentional allocation of repeaters in different classes. Even if the relevant instrument in my identification strategy is the interaction term (since both the percentage of repeaters in non-unique classes and the unique class dummy are included to control for a possible selection bias effect), results that are not validated by the Sargan test will be disregarded for the sake of caution.[5] In the case of CRT, no arguments regarding causality can be made. Even if the instrument were to be valid, note that OLS results in Table 6.1 would also suggest no statistically significant effects on CRT.

Regarding financial abilities, 2SLS results in columns (3) and (4) show large positive effects of enemy relationships at the class level. In this case, the overidentification test seems to validate the instruments and the Hausman test suggests the endogeneity of average class enemies. The positive impacts are only observed among boys, with girls presenting a negative differential effect that compensates for that of their male counterparts.[6] Even so, these effects are overly large, with an increase of 1 additional mutual enemy relation per student in the classroom increasing scores in the financial abilities task by a magnitude that exceeds the maximum possible value by 1/3 (equivalent to more than 5 standard deviations). However, despite the skepticism that this result may arouse, it would be reasonable to think that, at the very least, it would suggest a positive sign in the estimation of this impact. This, together with the heterogeneous effects observed between boys and girls, could have a similar explanation to that provided in previous findings. The fact that it only seems to occur in financial abilities may be because of how closely related these are to (practical and applied) mathematical skills, which could be perceived by boys as a specially highly valuable, high-return human capital investment.[7]

For consistency measures, columns (7) and (8) show that, despite coefficients being statistically insignificant when estimated through 2SLS, the Hausman test points to the exogeneity of enemies per student in this case, with OLS estimates likely being consistent.[8] With this in mind, an unit increase in this measure of conflict could cause around a 20% decrease in the probability of answering risk and time discounting tasks consistently, both for boys and girls. This validates the detrimental effects that enmity at the classroom level seem to have on concentration.

[5] An alternative option for the analysis would have been restricting the sample only to students in unique classroom for a given school year in each school. This, however, would have caused problems of power as only 389 students in the sample belong to such classes. An additional problem in this alternative approach would be that of the external validity of the results, that is, how representative they would be for all students, including those in schools and courses for which there is more than one classroom.

[6] A joint test is not able to reject the null hypothesis that the linear combination of the enemies and its interaction with the female dummy is equal to 0 in this specification ($p = 0.42$).

[7] Similar findings were observed by Carrasco and González-González (2024), where they show that obesity could increase mathematics scores for Spanish school children given a trade-off between improving body weight and investing in their studies. The fact that this is only the case in mathematics is argued by the authors to be due to this aspect of human capital being considered as highly valuable by the children.

[8] This Hausman test result is reasonable, since, as discussed in the previous section, social capital peer effects measures aggregated at the class level have very little room to fall into endogeneity with respect to individual human capital measures.

Table 6.6: Effects of enemies on expectations to continue studies (2SLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Panel A: Two Stage Least Squares				
Enemies (class average)	-0.224	-0.061	0.729	1.007*
	(0.460)	(0.515)	(0.489)	(0.549)
Female × Enemies		-0.327		-0.594
		(0.554)		(0.629)
Female	0.021**	0.080	0.058***	0.165
	(0.010)	(0.100)	(0.011)	(0.114)
Age	-0.019***	-0.019***	-0.012***	-0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002	-0.002	-0.003**	-0.003**
	(0.001)	(0.001)	(0.002)	(0.002)
Constant	1.192***	1.171***	0.831***	0.795***
	(0.077)	(0.082)	(0.085)	(0.091)
Observations	2,571	2,571	2,571	2,571
R-squared	0.042	0.038		
Hausman F-statistic	0.14	0.14	2.20	1.47
Overidentification test χ^2	5.37*	6.97	1.72	5.41
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Panel B: First stage for enemies and enemies interacted with gender				
Repeaters (class average)	-0.026	-0.015	-0.026	-0.015
	(0.038)	(0.046)	(0.038)	(0.046)
Repeaters × Unique class	0.230**	0.184	0.230**	0.184
	(0.107)	(0.143)	(0.107)	(0.143)
Unique class	0.049***	0.050***	0.049***	0.050***
	(0.008)	(0.009)	(0.008)	(0.009)
Female × Repeaters		0.110**		0.110**
		(0.050)		(0.050)
Female × Repeaters × Unique class		-0.648***		-0.648***
		(0.146)		(0.146)
Female × Unique class		-0.005		-0.005
		(0.010)		(0.010)
Female		0.177***		0.177***
		(0.006)		(0.006)
F-statistic	20.44***	15.80***	20.44***	15.80***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on enemies interacted with gender.

Results for the impacts on expectations to continue studies in Table 6.6 show similar results as those observed in consistency measures. Despite coefficients not being statistically significant, the Sargan test confirms the validity of the instruments and the Hausman test provides evidence in favor of OLS estimates being consistent. Therefore, it can be concluded that class enmity only reduces the self-perceived likelihood of going to university among girls.

Note that the latter results also validates the exogeneity of average class mutual enemies in QTE regressions when considering expected subjective future years of schooling, as this variable was built using the self-reported probabilities of continuing studies as was shown in Equation 6.1. Thus, the associations found in this part of the analysis may also be interpreted as causal.

Table 6.7: *Effects of social capital on cognitive abilities (2SLS)*

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Panel A: Two Stage Least Squares								
Social capital ($\overline{E}_c - \overline{F}_c$)	0.045	0.043	0.042	0.018	0.127	0.090	0.102	-0.052
	(0.028)	(0.037)	(0.033)	(0.044)	(0.080)	(0.104)	(0.081)	(0.107)
Female × Social capital		-0.012		0.024		0.059		0.296***
		(0.041)		(0.043)		(0.103)		(0.111)
Female	-0.001	-0.018	-0.076***	-0.041	-0.063***	0.025	-0.031	0.409**
	(0.008)	(0.061)	(0.009)	(0.065)	(0.019)	(0.155)	(0.020)	(0.166)
Age	0.005**	0.005*	0.013***	0.013***	0.012*	0.012	0.015**	0.015*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.008)
Family income	-0.004**	-0.004**	-0.007***	-0.007***	-0.002	-0.002	-0.013***	-0.012**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Class size	-0.000	-0.001	0.000	-0.000	-0.000	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.484***	0.491***	0.143**	0.123*	0.541***	0.496***	0.562***	0.345**
	(0.050)	(0.060)	(0.059)	(0.067)	(0.135)	(0.157)	(0.133)	(0.160)
Observations	2,579	2,579	2,579	2,579	2,579	2,579	2,579	2,579
R-squared	0.013	0.018	0.070	0.077	0.018	0.020	0.007	
Hausman F-statistic	2.49	0.96	2.17	0.78	2.14	1.15	1.68	6.46***
Overidentification test χ^2	6.97**	13.06**	7.97**	20.25***	5.09*	4.97	3.76	2.36
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: First stage for social capital and social capital interacted with gender								
Repeaters (class average)	-0.958***	-0.650***	-0.958***	-0.650***	-0.958***	-0.650***	-0.958***	-0.650***
	(0.181)	(0.216)	(0.181)	(0.216)	(0.181)	(0.216)	(0.181)	(0.216)
Repeaters × Unique class	8.581***	8.454***	8.581***	8.454***	8.581***	8.454***	8.581***	8.454***
	(0.945)	(1.112)	(0.945)	(1.112)	(0.945)	(1.112)	(0.945)	(1.112)
Unique class	0.034	0.065	0.034	0.065	0.034	0.065	0.034	0.065
	(0.072)	(0.089)	(0.072)	(0.089)	(0.072)	(0.089)	(0.072)	(0.089)
Female × Repeaters		-2.845***		-2.845***		-2.845***		-2.845***
		(0.290)		(0.290)		(0.290)		(0.290)
Female × Repeaters × Unique class		5.789***		5.789***		5.789***		5.789***
		(1.019)		(1.019)		(1.019)		(1.019)
Female × Unique class		-0.325***		-0.325***		-0.325***		-0.325***
		(0.080)		(0.080)		(0.080)		(0.080)
Female		-1.299***		-1.299***		-1.299***		-1.299***
		(0.028)		(0.028)		(0.028)		(0.028)
F-statistic	35.25***	23.07***	35.25***	23.07***	35.25***	23.07***	35.25***	23.07***

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

Source: Same as Table 4.1.
Note: F-statistics in the first stage for even-numbered columns refer to those regressing on social capital interacted with gender.

When considering the alternative *bad apple* social capital measure, results in Table 6.7 present findings that differ from those when using class enemies. In the first place, Panel B shows further evidence of repeaters only worsening levels of social capital in classrooms that are unique for that course year for a given school. In this case, these impacts are much stronger both in terms of magnitude and statistical significance, with increases of the number of repeaters in the classroom equivalent to 10% of all students leading to an increase of almost 1 unit in the number of enmity relations after deduction of mutual friendships. However, it is also worth noting that repeaters in classrooms that are not unique to their school year do seem to improve the general level of coexistence. This could be because, when they are distributed in different classes, the arrival of new repeater students who find themselves without sufficient opportunity or incentive to create a bad environment because they are not likely to be accompanied by other disruptive repeaters, could in fact increase the incentives of them socializing and creating new valuable networks of relationships (probably through new friendships, as it was shown that repeaters in these classrooms do not increase enmity in Panels B of Tables 6.5 and 6.6).

In this case, almost no statistically significant coefficients are obtained for different cognitive abilities variables from 2SLS estimation and the instruments do not seem to be jointly valid except for consistency measures. The only exception is found in time consistency among girls, for which a unit increase in the *bad apple* social capital measure at the classroom level causes girls to be about 24% more likely to finish the time discounting task consistently. This effect is quite considerable both in magnitude and in statistical significance. In this case, the Hausman test provides statistically significant evidence supporting the endogeneity of social capital as a regressor, thus making 2SLS estimates preferable. Despite the Hausman test pointing to the consistency of OLS estimates for the rest of consistency variables, none of them were found to be associated with social capital in Table 6.3.

Table 6.8: Effects of social capital on expectations to continue studies (2SLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Panel A: Two Stage Least Squares				
Social capital ($\overline{E}_c - \overline{F}_c$)	0.036	0.023	-0.006	-0.033
	(0.040)	(0.052)	(0.043)	(0.056)
Female × Social capital		0.012		0.046
		(0.051)		(0.058)
Female	0.021**	0.039	0.058***	0.126
	(0.010)	(0.076)	(0.011)	(0.086)
Age	-0.017***	-0.017***	-0.015***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.001	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.181***	1.171***	0.887***	0.853***
	(0.067)	(0.078)	(0.074)	(0.086)
Observations	2,571	2,571	2,571	2,571
R-squared	0.049	0.051	0.058	0.057
Hausman F-statistic	0.16	0.07	0.01	0.14
Overidentification test χ^2	4.54	6.77	4.11	8.85*
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Panel B: First stage for social capital and social capital interacted with gender				
Repeaters (class average)	-0.971***	-0.665***	-0.971***	-0.665***
	(0.183)	(0.219)	(0.183)	(0.219)
Repeaters × Unique class	8.594***	8.468***	8.594***	8.468***
	(0.945)	(1.112)	(0.945)	(1.112)
Unique class	0.033	0.064	0.033	0.064
	(0.072)	(0.089)	(0.072)	(0.089)
Female × Repeaters		-2.842***		-2.842***
		(0.290)		(0.290)
Female × Repeaters × Unique class		5.789***		5.789***
		(1.019)		(1.019)
Female × Unique class		-0.325***		-0.325***
		(0.080)		(0.080)
Female		-1.300***		-1.300***
		(0.028)		(0.028)
F-statistic	35.31***	22.89***	35.31***	22.89***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on social capital interacted with gender.

Lastly, similar to the results in Table 6.6, no statistically significant coefficients are estimated for the effects of class social capital on expectations to continue studies, as is shown in Table 6.8. However, the Sargan overidentification test supports the validity of all additional instruments in these cases, and the Hausman test confirms the exogeneity of average social capital, making OLS estimates consistent. As was the case with class enemies, OLS results for the probabilities of continuing studies as well as QTE regressions for expected years of schooling may be interpreted as causal.

6.4 Robustness Checks

In order to check for robustness, I perform the same analysis as was shown above with alternative measures of average class social capital. First, OLS, QTE and 2SLS coefficients are estimated using average worst enemies per student at the classroom level as well as the difference between the latter and average best friends per student. Second, estimates are presented using the network density of enemies in the classroom as well as the difference between the latter and the network density of friends using the same estimation methods. Due to limited space, results are presented in the Appendix A. Only the main insights will be discussed in this section.

When using average class worst and best friends as independent variables, the findings are practically equivalent to those in the previous section in the direction and statistical significance of the correlations and effects on human capital measures as shown in Tables A.13 through A.20. The same is true for QTE results when considering subjective expected years of schooling (see Figures A.1 and A.2). The main difference in this case is given by the magnitude of the estimates, which are significantly larger than those previously presented. This suggests a reasonable interpretation: the effects of *bad apple* social capital when using worst enemies and best friends are larger and more pronounced than when considering enemies and friends, meaning that a higher presence of the former is a stronger determinant to human capital than the latter.

Nevertheless, the robustness of my previous results does not hold as well when using network density measures as it can be inferred from Tables A.21 through A.28. Associations and effects of enemy and social capital density are only relatively comparable to those obtained with average classroom measures in expectations to continue studies, QTE in expected subjective years of education (see Figures A.3 and A.4), and financial abilities. The reason for this difference in results may be due to the fact that network average and density measures may not be capturing the same things. While the former refers to the number of mutual connections per node (student) in the network (how *extensive* social capital is), the latter captures the number of mutual connections as a proportion of all possible connections in the network (how *full* is the maximum capacity of social capital stock in a particular class, or how *intensive* it is).[9] The latter may explain why results do not seem to be too robust to changes in the measures of network distribution. Additionally, note that the first stage when estimating the effects of *bad apple* social capital density through IV shows that repeaters in unique classrooms improve these proxies of social

[9] As a consequence, the variance of both types of measures differ significantly in the sample, with enemy density showing a smaller coefficient of variation (CV) than average class enmity, and social capital density having a larger CV than its average class counterpart. This difference in the variation of the two types of variables could also affect which effects are being captured.

capital intensity (see Panel B in Tables A.25 through A.28). The reason for this could be that additional repeaters in classrooms that are unique to their school year could significantly increase the number of students relative to the previous year to a greater extent than in non-unique classrooms (where school officials could distribute them more freely), thus increasing the number of maximum possible network connections (i.e., the denominator in the network density calculation). If the marginal increase of these repeaters on the actual mutual enmity or poor social capital links in the network is not enough to compensate the marginal increase in number of possible links, then the effect on overall density will come up with a negative sign, as it seems to be the case. As an externality to my results, this inconsistency or lack of robustness ends up providing support for the validity of my instruments and for the need to include the interaction term between number of repeaters and the single class dummy to avoid what seems evidently a selection bias when assigning repeaters voluntarily in different classrooms.

6.5 Interpretation and Potential Mechanisms

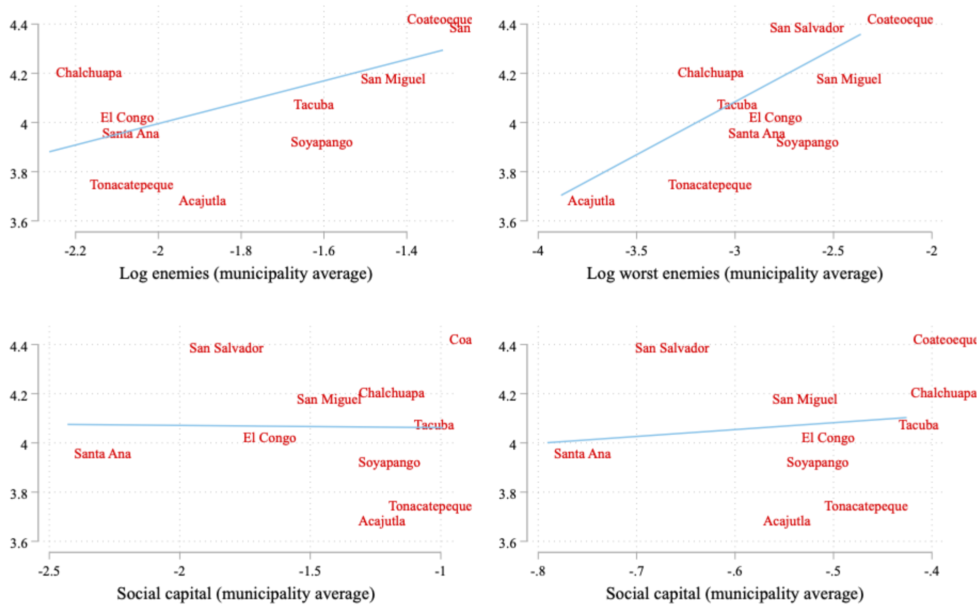
This section explores two potential determinants and mechanisms of social capital that could be explaining the results previously discussed: gang violence and bullying by classroom peers. Both allow for plausible interpretations of the results presented above and are able to explain the heterogeneity (both in terms of gender and for different aspects of human capital) as well as the non-linearities in the results.

6.5.1 Gang Violence

Considering the general development of gangs and violence in El Salvador presented in the *Context* section above, I propose that the conflict at the classroom level that is observed in my data and has been found to affect different educational outcomes could be influenced by gang violence. In order to test this potential interpretation, I collect official data from homicide rates (total number of homicides per 10,000 inhabitants) across different municipalities during 2020.[10] Figure 6.3 shows the correlation between homicide rates and average mutual enemy relationships, average worst enemy relationships, and social capital measures (difference between enemies and friends and difference between worst enemies and best friends) by municipalities.

[10] The data is publicly available at `https://flo.uri.sh/visualisation/6005450/embed?auto=1`.

Figure 6.3: Gang violence and school social capital (municipality average)



Source: Own elaboration based on data from COM-PHAS, *Instituto de Medicina Legal* (IML), *Fiscalía General de la República* (FGR), and *Policía Nacional Civil* (PNC).
Note: Vertical axis in all figures represents log homicide rate per 10,000 inhabitants.

Children attending school in municipalities with higher levels criminal violence show more mutual enmity relationships in their classrooms, on average. However, the same is not true for *bad apple* social capital measures, for which there seems to be no correlation with homicide rates. Nevertheless, Figure 6.3 only shows scatter plots with aggregated measures for the 10 municipalities, making any inference difficult due to the small number of observations. A more elaborated analysis is presented in Table 6.9, which shows OLS results measuring the associations between the log of homicide rate at the municipal level and the different class-average social capital measures. I control for population in each municipality to discard any potential scale effects, as it could be that more populated municipalities may present greater opportunities or incentives for criminal acts by gangs, as well as being associated with a greater number of students in the classroom, leading to a greater investment in social capital (either disruptive or friendship) for students.[11]

[11]This approach is equivalent to controlling for class size when considering the effects of social capital aggregated at the class level on individual academic outcomes presented previously.

Table 6.9: *Gang violence and school social capital (OLS)*

VARIABLES	(1) Enemies (class average)	(2) Worst enemies (class average)	(3) Social capital ($\overline{E}_c - \overline{F}_c$)	(4) Social capital ($\overline{WE}_c - \overline{BF}_c$)
Log homicide rate	0.222***	0.066**	-0.162	0.019
	(0.064)	(0.026)	(0.257)	(0.105)
Population	0.000	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.732***	-0.214**	-0.465	-0.501
	(0.253)	(0.100)	(1.027)	(0.426)
Observations	122	122	122	122
R-squared	0.138	0.074	0.121	0.093

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

Source: Own elaboration based on data from COM-PHAS, FGR, IML, PNC, and *Oficina Nacional de Estadísiticas y Censos*

The results here are quite similar to those in Figure 6.3. Municipality homicide rates are positively correlated with both class enemies and class worst enemies per student, even after controlling for potential population effects. The estimates are stronger in average mutual enmity relationships, for which a 4.5% increase in municipal homicide rates is associated with 1 additional mutual enemy relationship per student. Taking into account that the average classroom has about 28 students in my sample, this would be equivalent to saying that a 1% increase in homicide rates is correlated with an increase of more than 6 mutual enemy relationships (i.e., a total of 12 children who would be in conflict with each other) per classroom, on average. The estimate is smaller when considering average class worst enemies, with a 1% increase in homicide rates being associated with around a 0.07 increase in the number of worst enemies per student at the classroom level, or, in other words, just under 2 additional worst enemy relationships (4 students, in total) per classroom, on average. Interestingly, there seems to be no relationship between municipal criminal violence and overall classroom social capital levels.

The above findings have interesting implications for my analysis. Higher gang activity may be only correlated with class enmity because of its ability to induce children's conflictive behavior inside the classroom. In the case of social capital, this correlation may not exist as conflictive children (even those whose behavior could have been influenced by gangs) would also probably make friends with other peers.[12] This makes gang violence a determinant of class-level conflict which could explain its effects on different measures of human capital, as well as its non-linearities and differences between boys and girls. It is important to clarify that at no time do I

[12]Here it is important to note what I mentioned above about social capital quality not being captured by the variables in the analysis. This is a clear example where such appreciation could be problematic as *being friends* with children that might have been influenced by gang activity could have very undesirable implications given findings by previous peer effects literature (Calvó-Armengol and Zenou, 2004; Ballester et al., 2010; Jackson et al., 2017; Gaviria and Raphael, 2001; Deming, 2011; Eren et al., 2022). Even so, *being enemies* with them may certainly not be considered *a good thing* (quite the contrary), meaning that my measure of average enemies per student is still a good proxy for overall conflict or a negative aspect of social capital (i.e., *bad apples*).

claim that the children (or even that any child) in my sample belong directly to a gang, although it cannot be ruled out either. Rather, I state that, even without necessarily belonging to these organizations, the children could show conflictive behaviors influenced by the presence and activity of these gangs, either because they assimilate it in their family and social context (transmitting that social capital coming from the community level), or because they have more direct contact with gang members. All these explanations are in line with the positive correlations that are observed.

Returning to Justino's (2011) observation about the potential of violent conflict to alter returns to education and the consequences this has on the incentives to invest in human capital of different individuals, the latter is shown to provide a very plausible interpretation to explain why classes with higher levels of enmity reduce the self-reported probability of going to college among girls by 4%; the number of years of education expected by girls in the bottom 5% of the human capital distribution by about 2 years (those who would least expect to benefit from educational investment among girls, already penalized); and increase mathematics and financial skills only among boys. If part of the enmity that is observed inside the classroom is due to conflict which is brought by children who might be contextually influenced by gangs outside the classroom (as it seem to be the case), then it might specially trigger lower academic involvement by girls and, in particular, those with the lowest expectations about their future education. On the other hand, positive effects could be observed among boys if they had the prospect of benefiting from the labor market failures created by gang violence (which would be reflected in increased enmity relations in the classroom), particularly in aspects or dimensions of human capital that they might consider especially valuable, such as financial mathematics skills. An alternative explanation to why girls' expectations to continue studies are negatively affected by conflict that may be channeled through gang violence could be that the latter might increase their likelihood of migrating as is shown by Sviatschi (2022).

6.5.2 Bullying

A mechanism that could be driving the effects of *bad apple* social capital on human capital accumulation could be peer discrimination or bullying in the classroom. Bullying has been found to impact negatively different economic outcomes, with human capital and future returns to education being the most relevant ones (Brown and Taylor, 2008; Sarzosa and Urzúa, 2021). Moreover, as Vasco Ruiz (2022) shows, social capital in both friendship and enmity networks predicts propensity to being bullied quite well. If poorer social capital at the classroom level is responsible for triggering bullying to specific children, they could be penalized in their academic performance relative to their non-bullied peers, as a result of decreased motivation to go to school and concentrate in their studies.

I exploit variables measuring bullying in my dataset which, like measures of friendship or enmity, are obtained from network analysis. A total of four bullying variables are presented: (1) bullying that the children themselves claim they do or do not suffer (self reported); (2) bullying that any other classmate reports for a given child (others report); (3) the bullying that is self-reported by any child *and* by any other class peer (intersection);[13] and (4) the bullying that is self-reported by any child *or* by any other class peer (union). Tables 6.10 and 6.11 present marginal effects results (estimated at the average value of the independent variables) obtained from probit regressions capturing the relationship between social capital variables at the classroom level and the different measures of bullying.

Table 6.10: Bullying and enemies (probit marginal effects)

VARIABLES	(1) Self reported	(2) Others report	(3) Intersection	(4) Union
Enemies (class average)	0.014	-0.012	-0.005	0.007
	(0.042)	(0.101)	(0.031)	(0.103)
Female × Enemies	-0.056	0.013	-0.043	-0.000
	(0.058)	(0.130)	(0.040)	(0.132)
Female	-0.002	-0.159***	0.001	-0.162***
	(0.013)	(0.029)	(0.009)	(0.030)
Observations	2,587	2,587	2,587	2,587
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: Same as Table 4.1.
Note: Controls include age, a family income index, and classroom size.

Table 6.10 reports no statistically significant association between class average enmity and any of the four bullying variables, both when considering boys and girls together as well as separately. This means that the amount and intensity of conflict there is in a classroom does not necessarily determine discrimination to specific students.

Table 6.11: Bullying and social capital (probit marginal effects)

VARIABLES	(1) Self reported	(2) Others report	(3) Intersection	(4) Union
Social capital ($\overline{E}_c - \overline{F}_c$)	0.007	-0.024	0.015**	-0.031
	(0.008)	(0.019)	(0.006)	(0.019)
Female × Social capital	-0.017	-0.034	-0.017**	-0.036
	(0.011)	(0.025)	(0.007)	(0.025)
Female	-0.037**	-0.208***	-0.030**	-0.218***
	(0.018)	(0.041)	(0.012)	(0.042)
Observations	2,587	2,587	2,587	2,587
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: Same as Table 4.1.
Note: Controls include age, a family income index, and classroom size.

Nonetheless, results in Table 6.11 only show statistically significant coefficients for

[13]This could be considered as "confirmed bullying", as it is validated not just by each child, but also by peers in the classroom that recognized discrimination towards the former.

bullying that is both self-reported and reported by other classmates when considering average *bad apple* social capital. Despite being the only conclusive result out of all the four bullying variables, this finding is quite relevant as that which is measured by intersection may reasonably be considered as the most exact or precise one. A 1 unit increase in the difference between average class enemies and friends at the average of this social capital measure is associated with approximately a 2% higher probability of a boy in that classroom to suffer bullying. The same is not true, however, in the case of girls, for which a differential correlation is found that exactly offsets the negative relationship observed among boys. It could be reasonable to think that less cohesive classrooms with poorer levels of relational quality may be more conducive environments for bullying to occur, partly because the it is less conducive to socialization, and partly because there would be a greater detachment of students from their peers, making it more unlikely that bullying behaviors would be judged or rejected (Sarzosa and Urzúa, 2021). The fact that this association is only observed among boys could be related to the reason why girls seem to be less bullied than boys, on average (see third row in Tables 6.10 and 6.11). Since boys are usually the main perpetrators of bullying in the classroom, they may have a preference for other male peers when choosing their victims (see Vasco Ruiz, 2022; Sarzosa and Urzúa, 2021).

The previous finding helps explain the heterogeneous effects by gender observed in human capital accumulation when considering the overall levels of social capital in the classroom. The fact that it is only girls who, faced with poorer levels of social capital in their school environment, show a positive association with CRT scores; a positive effect on the self-perceived probability of continuing their studies the following year; and a positive impact on the probability of consistently taking the time-counting test, could be due to the fact that it is only them who face the dilemma that could exist between investing in social or human capital. Being more prone to bullying in those classes, boys may not encounter such a trade-off as socialization may be, on average, more difficult to achieve for them (i.e., the costs of investing in individual social capital are higher for boys than for girls).

7

Conclusion

Building on previous literature and social capital theoretical insights, this thesis investigates the effect of conflict and *bad apple* social capital on different human capital outcomes in El Salvador. The study considers, on the one hand, the possibility of finding heterogeneous effects by gender and, on the other hand, that the results obtained are not necessarily linear. In addition, gang violence at the municipal level and discrimination by classmates or bullying are analyzed as possible mechanisms to explain the different findings.

Using data from Salvadoran students from middle school and high school in 12 schools located in different socially and economically disadvantaged areas of the country, I exploit exogenous variation in the proportion of repeater students in different classrooms and obtain consistent estimates capturing the impacts of class-level enmity and a variable of social capital on several educational outcomes measuring different cognitive skills as well as subjective expectations to continue studies. The main findings can be summarized as follows: (1) Class conflict mediated by mutual enemy relationships reduces consistency in a two different tasks during the completion of the survey in a similar magnitude for boys an girls equally, the self-reported likelihood that girls will enroll in university, the expected future years of schooling for girls at the bottom 5% of the human capital distribution, and increases financial abilities only in boys. (2) A worse quality of social capital accumulation at the classroom level is associated with a higher CRT performance among girls, improves consistency in a time discounting task for girls, increases the probability of girls continuing studies the following year, and increases the expected years of schooling at the bottom of the human capital distribution for both boys and girls but reduces it for students initially considering completing secondary school and potentially going to university. (3) Gang activity might be driving part of the enmity effects by altering returns to education and reducing human capital investments in girls and students who might benefit less from education, with municipalities where gang violence is more prevalent showing higher average mutual enemy relationships among students. (4) Bullying, on the other hand, helps explain why it is only girls who might perceive investments in social and human capital as substitutes, as boys, being more prone to be victims of bullying in classes with poorer levels of social capital, could find it significantly harder to socialize in socially hostile classrooms.

The results are robust to the inclusion of worst enemies and best friends as the variables of analysis for social capital. However, the same is not true when considering alternative measures of network distribution such as enemy and social capital density at the classroom level. The main reason for this might be that the latter should be interpreted as a proxy for the *intensity* of social capital, as opposed to *extensive* social capital, which would be captured by average class measures of mutual links.

With respect to the initial hypotheses, the findings of this study provide interesting conclusions. On the one hand, the hypothesis that poorer levels of social capital worsen students' academic performance is rejected, insofar as this is not necessarily the case for all the dimensions of human capital considered here (although it is true for some). Nevertheless, part of the reason for the latter confirms the existence of heterogeneities and non-linearities, both at the gender level and along the distribution of expected human capital accumulation. Finally, it is confirmed that both gang activity and bullying represent important factors explaining the results, the former as a determinant of human capital capable of giving a realistic interpretation for gender effects in the case of enmity, and the latter providing a plausible mechanism when considering the measure of *bad apple* social capital.

These findings have relevant implications for policy-making. First, despite the seemingly positive effects that worse levels of social capital could have on some educational outcomes, public interventions aimed at improving overall relational quality in Salvadoran schools through awareness-raising programs or extracurricular activities would most likely generate a double welfare effect by facilitating better social and human capital investments. Initiatives like these would be appropriate not only to improve most dimensions of human capital, but also to ensure greater educational equality between boys and girls. This, in turn, would lead to greater equality of opportunities in the later stages of the economic life of these students, which would mean significant improvements in their level of economic development in a country as unequal as El Salvador. Even so, policies should bear in mind the potential trade-offs that children might face when deciding whether to invest more time and effort on socialization with peers or on improving academic achievement.

The analysis of different mechanisms also provide useful insights for public policy. First, besides the evident benefits that fighting gang violence might have for the economy (including education), spillover effects should be expected by reducing school conflictive behavior which might be induced by gangs in children and adolescents, thus improving general social capital accumulation in the classroom, further increasing human capital investments, and potentially solving gender inequalities that could arise from the presence of higher violent conflict. Second, reducing bullying practices through different specialized programs might also have externality effects on both better socialization and educational performance and motivation. In this case, a special focus should be mostly put on boys.

Future research should continue to focus on the study of the interaction between social and human capital in the developing world. Attention should be paid to methodological issues, with experimental and quasi-experimental designs providing more relevant and consistent results. If the presence of repeaters is used as an instrument for class-level conflict, researchers should be cautious when considering the possible selection bias due to the non-randomization of the assignment of repeaters to different classes. Lastly, studies focused on the impact assessment of different social-capital-improving interventions could be helpful to measure their efficiency not only in improving children's relational quality, but also in enhancing human capital accumulation through potential spillovers.

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Appendix A

Appendix

Table A.1: Enemiees and CRT (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Enemies (class avg.)	0.019	0.009	0.007	0.007	0.022	0.007
	(0.028)	(0.033)	(0.041)	(0.041)	(0.042)	(0.043)
Female × Enemies		0.019	0.030	0.030	0.031	0.034
		(0.034)	(0.056)	(0.056)	(0.056)	(0.056)
Female			-0.003	-0.003	-0.007	-0.008
			(0.013)	(0.013)	(0.012)	(0.012)
Age			0.005**	0.005*	0.004	0.004
			(0.002)	(0.003)	(0.003)	(0.003)
Family income			-0.003*	-0.003*	-0.004**	-0.004**
			(0.002)	(0.002)	(0.002)	(0.002)
Class size				-0.000	-0.002***	-0.002***
				(0.001)	(0.001)	(0.001)
Constant	0.429***	0.429***	0.373***	0.383***	0.409***	0.408***
	(0.006)	(0.006)	(0.038)	(0.046)	(0.051)	(0.051)
Observations	2,580	2,580	2,579	2,579	2,579	2,579
R-squared	0.000	0.000	0.004	0.004	0.032	0.033
Municipality FE	No	No	No	No	Yes	Yes
School FE	No	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.2: Enemies and financial abilities (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Enemies (class avg.)	-0.000	0.077	0.078	0.064	0.007
	(0.032)	(0.048)	(0.048)	(0.050)	(0.052)
Female × Enemies		-0.139**	-0.140**	-0.137**	-0.127**
		(0.062)	(0.062)	(0.061)	(0.061)
Female		-0.046***	-0.046***	-0.050***	-0.054***
		(0.014)	(0.014)	(0.014)	(0.014)
Age		0.014***	0.013***	0.012***	0.011***
		(0.003)	(0.003)	(0.003)	(0.003)
Family income		-0.007***	-0.007***	-0.008***	-0.007***
		(0.002)	(0.002)	(0.002)	(0.002)
Class size			-0.000	-0.001*	-0.001
			(0.001)	(0.001)	(0.001)
Constant	0.184***	0.037	0.055	0.036	0.036
	(0.007)	(0.045)	(0.056)	(0.057)	(0.057)
Observations	2,580	2,579	2,579	2,579	2,579
R-squared	0.000	0.044	0.044	0.079	0.089
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.3: Enemies and consistency (time) (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Enemies (class avg.)	-0.158**	-0.135	-0.135	-0.167	-0.217*
	(0.072)	(0.101)	(0.101)	(0.107)	(0.111)
Female × Enemies		-0.028	-0.028	-0.032	-0.025
		(0.143)	(0.143)	(0.143)	(0.143)
Female		-0.022	-0.022	-0.024	-0.027
		(0.032)	(0.032)	(0.032)	(0.032)
Age		0.015**	0.015**	0.011*	0.010
		(0.006)	(0.006)	(0.007)	(0.007)
Family income		-0.014***	-0.014***	-0.013***	-0.013***
		(0.005)	(0.005)	(0.005)	(0.005)
Class size			0.000	-0.001	-0.001
			(0.001)	(0.002)	(0.002)
Constant	0.602***	0.461***	0.455***	0.642***	0.649***
	(0.016)	(0.099)	(0.123)	(0.134)	(0.134)
Observations	2,580	2,579	2,579	2,579	2,579
R-squared	0.002	0.009	0.009	0.022	0.026
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.4: Enemies and consistency (risk) (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Enemies (class avg.)	-0.128*	-0.089	-0.086	-0.109	-0.193*
	(0.072)	(0.103)	(0.103)	(0.108)	(0.111)
Female × Enemies		-0.064	-0.067	-0.065	-0.051
		(0.144)	(0.144)	(0.143)	(0.142)
Female		-0.042	-0.042	-0.050	-0.055*
		(0.033)	(0.033)	(0.032)	(0.032)
Age		0.013**	0.011*	0.007	0.006
		(0.006)	(0.007)	(0.006)	(0.006)
Family income		-0.002	-0.002	-0.002	-0.002
		(0.004)	(0.004)	(0.004)	(0.004)
Class size			-0.001	-0.004**	-0.003*
			(0.001)	(0.002)	(0.002)
Constant	0.459***	0.299***	0.345***	0.362***	0.371***
	(0.016)	(0.098)	(0.123)	(0.129)	(0.129)
Observations	2,581	2,580	2,580	2,580	2,580
R-squared	0.001	0.006	0.006	0.035	0.040
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.5: Enemies and study next year (probability) (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Enemies (class avg.)	-0.006	0.036	0.039	0.033	-0.003
	(0.034)	(0.047)	(0.047)	(0.049)	(0.050)
Female × Enemies		-0.100	-0.104	-0.104	-0.097
		(0.068)	(0.068)	(0.067)	(0.067)
Female		0.044***	0.044***	0.040**	0.038**
		(0.016)	(0.016)	(0.015)	(0.016)
Age		-0.015***	-0.018***	-0.018***	-0.018***
		(0.003)	(0.004)	(0.003)	(0.003)
Family income		0.001	0.001	0.001	0.001
		(0.002)	(0.003)	(0.002)	(0.002)
Class size			-0.001*	-0.003***	-0.002***
			(0.001)	(0.001)	(0.001)
Constant	0.820***	1.025***	1.091***	1.074***	1.073***
	(0.008)	(0.051)	(0.064)	(0.069)	(0.069)
Observations	2,572	2,571	2,571	2,571	2,571
R-squared	0.000	0.014	0.015	0.046	0.049
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.6: Enemies and study in university (probability) (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Enemies (class avg.)	0.075*	0.142**	0.143**	0.088	0.094
	(0.039)	(0.056)	(0.056)	(0.057)	(0.059)
Female × Enemies		-0.144*	-0.145*	-0.136*	-0.138*
		(0.076)	(0.076)	(0.076)	(0.076)
Female		0.088***	0.088***	0.083***	0.083***
		(0.018)	(0.018)	(0.018)	(0.018)
Age		-0.012***	-0.013***	-0.015***	-0.015***
		(0.003)	(0.004)	(0.004)	(0.004)
Family income		0.013***	0.013***	0.013***	0.013***
		(0.003)	(0.003)	(0.003)	(0.003)
Class size			-0.001	-0.001*	-0.002*
			(0.001)	(0.001)	(0.001)
Constant	0.691***	0.764***	0.791***	0.842***	0.844***
	(0.009)	(0.056)	(0.071)	(0.075)	(0.075)
Observations	2,572	2,571	2,571	2,571	2,571
R-squared	0.001	0.030	0.030	0.059	0.059
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.7: Social capital and CRT (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Social capital ($\overline{E}_c - \overline{F}_c$)	0.005	0.004	-0.005	-0.005	-0.007	-0.007
	(0.005)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Female × Social capital		0.002	0.019*	0.019*	0.017	0.017*
		(0.005)	(0.010)	(0.010)	(0.010)	(0.010)
Female			0.031*	0.031*	0.024	0.024
			(0.017)	(0.017)	(0.017)	(0.017)
Age			0.005**	0.005*	0.004	0.004
			(0.002)	(0.003)	(0.003)	(0.003)
Family income			-0.003*	-0.003*	-0.004**	-0.004**
			(0.002)	(0.002)	(0.002)	(0.002)
Class size				-0.000	-0.002***	-0.001**
				(0.001)	(0.001)	(0.001)
Constant	0.440***	0.440***	0.370***	0.374***	0.400***	0.397***
	(0.009)	(0.009)	(0.039)	(0.046)	(0.051)	(0.051)
Observations	2,580	2,580	2,579	2,579	2,579	2,579
R-squared	0.000	0.000	0.005	0.005	0.032	0.033
Municipality FE	No	No	No	No	Yes	Yes
School FE	No	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.8: Social capital and financial abilities (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Social capital ($\overline{E}_c - \overline{F}_c$)	0.002	-0.006	-0.007	-0.012	-0.012
	(0.006)	(0.009)	(0.009)	(0.010)	(0.010)
Female × Social capital		0.013	0.013	0.011	0.012
		(0.012)	(0.012)	(0.012)	(0.012)
Female		-0.051***	-0.051***	-0.059***	-0.059***
		(0.020)	(0.020)	(0.019)	(0.019)
Age		0.014***	0.014***	0.012***	0.012***
		(0.003)	(0.003)	(0.003)	(0.003)
Family income		-0.007***	-0.007***	-0.008***	-0.007***
		(0.002)	(0.002)	(0.002)	(0.002)
Class size			-0.000	-0.002**	-0.001
			(0.001)	(0.001)	(0.001)
Constant	0.188***	0.040	0.055	0.035	0.029
	(0.010)	(0.046)	(0.056)	(0.058)	(0.057)
Observations	2,580	2,579	2,579	2,579	2,579
R-squared	0.000	0.043	0.043	0.078	0.087
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.9: Social capital and consistency (time) (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Social capital ($\overline{E}_c - \overline{F}_c$)	0.007	0.007	0.008	0.001	0.004
	(0.013)	(0.019)	(0.019)	(0.020)	(0.020)
Female × Social capital		-0.006	-0.006	-0.009	-0.009
		(0.027)	(0.027)	(0.027)	(0.027)
Female		-0.036	-0.036	-0.044	-0.045
		(0.044)	(0.044)	(0.044)	(0.044)
Age		0.016***	0.016**	0.011*	0.011*
		(0.006)	(0.006)	(0.007)	(0.007)
Family income		-0.013***	-0.014***	-0.013***	-0.013***
		(0.005)	(0.005)	(0.005)	(0.005)
Class size			0.000	-0.002	-0.002
			(0.001)	(0.002)	(0.002)
Constant	0.584***	0.437***	0.429***	0.630***	0.635***
	(0.022)	(0.101)	(0.123)	(0.135)	(0.135)
Observations	2,580	2,579	2,579	2,579	2,579
R-squared	0.000	0.008	0.008	0.020	0.023
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.10: Social capital and consistency (risk) (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Social capital ($\overline{E}_c - \overline{F}_c$)	0.018	0.001	0.000	-0.001	0.002
	(0.014)	(0.019)	(0.020)	(0.021)	(0.021)
Female × Social capital		0.030	0.030	0.024	0.025
		(0.027)	(0.027)	(0.027)	(0.027)
Female		-0.008	-0.009	-0.026	-0.027
		(0.045)	(0.045)	(0.044)	(0.044)
Age		0.013**	0.012*	0.008	0.008
		(0.006)	(0.007)	(0.007)	(0.006)
Family income		-0.002	-0.002	-0.002	-0.002
		(0.004)	(0.004)	(0.004)	(0.004)
Class size			-0.001	-0.004**	-0.003*
			(0.001)	(0.002)	(0.002)
Constant	0.463***	0.281***	0.308**	0.342***	0.345***
	(0.022)	(0.102)	(0.124)	(0.131)	(0.132)
Observations	2,581	2,580	2,580	2,580	2,580
R-squared	0.001	0.006	0.006	0.034	0.037
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.11: Social capital and study next year (probability) (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Social capital ($\overline{E}_c - \overline{F}_c$)	0.014**	0.001	-0.001	0.008	0.006
	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
Female × Social capital		0.031**	0.031**	0.028**	0.029**
		(0.014)	(0.014)	(0.013)	(0.013)
Female		0.072***	0.072***	0.063***	0.064***
		(0.022)	(0.022)	(0.021)	(0.021)
Age		-0.016***	-0.017***	-0.017***	-0.017***
		(0.003)	(0.004)	(0.003)	(0.003)
Family income		0.001	0.001	0.001	0.001
		(0.002)	(0.003)	(0.002)	(0.002)
Class size			-0.001	-0.002***	-0.002**
			(0.001)	(0.001)	(0.001)
Constant	0.840***	1.036***	1.079***	1.082***	1.076***
	(0.011)	(0.053)	(0.065)	(0.071)	(0.071)
Observations	2,572	2,571	2,571	2,571	2,571
R-squared	0.002	0.017	0.018	0.049	0.052
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.12: Social capital and study in university (probability) (OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Social capital ($\overline{E}_c - \overline{F}_c$)	-0.008	-0.016	-0.017	-0.011	-0.010
	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
Female × Social capital		0.021	0.021	0.016	0.016
		(0.015)	(0.015)	(0.015)	(0.015)
Female		0.092***	0.092***	0.083***	0.083***
		(0.025)	(0.025)	(0.024)	(0.024)
Age		-0.013***	-0.014***	-0.015***	-0.015***
		(0.003)	(0.004)	(0.004)	(0.004)
Family income		0.013***	0.013***	0.013***	0.013***
		(0.003)	(0.003)	(0.003)	(0.003)
Class size			-0.001	-0.001*	-0.002*
			(0.001)	(0.001)	(0.001)
Constant	0.693***	0.767***	0.797***	0.838***	0.841***
	(0.013)	(0.057)	(0.072)	(0.076)	(0.076)
Observations	2,572	2,571	2,571	2,571	2,571
R-squared	0.000	0.028	0.029	0.058	0.059
Municipality FE	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes

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

Source: Same as Table 4.1.

Table A.13: Worst enemies and cognitive abilities (OLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Worst enemies (class average)	0.118	0.146	-0.090	0.091	-0.354*	-0.508*	-0.439**	-0.394
	(0.076)	(0.109)	(0.088)	(0.130)	(0.200)	(0.276)	(0.201)	(0.279)
Female × Worst enemies		-0.057		-0.357**		0.302		-0.088
		(0.144)		(0.163)		(0.376)		(0.379)
Female	-0.001	0.002	-0.077***	-0.058***	-0.065***	-0.081***	-0.033*	-0.028
	(0.007)	(0.011)	(0.008)	(0.012)	(0.019)	(0.028)	(0.019)	(0.028)
Age	0.004	0.004	0.012***	0.011***	0.006	0.007	0.010	0.010
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)	(0.007)
Family income	-0.004**	-0.004**	-0.007***	-0.007***	-0.002	-0.002	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Class size	-0.002***	-0.002***	-0.001	-0.001	-0.003**	-0.003**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.403***	0.402***	0.042	0.036	0.370***	0.376***	0.651***	0.650***
	(0.051)	(0.051)	(0.057)	(0.057)	(0.129)	(0.129)	(0.134)	(0.135)
Observations	2,579	2,579	2,579	2,579	2,580	2,580	2,579	2,579
R-squared	0.033	0.033	0.087	0.089	0.038	0.038	0.024	0.024
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

Table A.14: Worst enemies and expectations to continue studies (OLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Worst enemies (class average)	-0.152	-0.018	-0.012	0.243
	(0.094)	(0.134)	(0.110)	(0.158)
Female × Worst enemies		-0.263		-0.500**
		(0.180)		(0.206)
Female	0.020**	0.034**	0.058***	0.085***
	(0.010)	(0.013)	(0.011)	(0.016)
Age	-0.018***	-0.019***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002***	-0.002***	-0.001*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.082***	1.077***	0.857***	0.847***
	(0.070)	(0.070)	(0.075)	(0.075)
Observations	2,571	2,571	2,571	2,571
R-squared	0.048	0.049	0.058	0.060
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

Table A.15: Social capital ($\overline{WE}_c - \overline{BF}_c$) and cognitive abilities (OLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Social capital ($\overline{WE}_c - \overline{BF}_c$)	0.001	-0.023	-0.014	-0.033	0.007	-0.008	-0.007	-0.012
	(0.016)	(0.022)	(0.018)	(0.026)	(0.042)	(0.057)	(0.042)	(0.055)
Female × Social capital		0.049*		0.038		0.031		0.010
		(0.028)		(0.032)		(0.074)		(0.074)
Female	-0.001	0.026	-0.077***	-0.056***	-0.064***	-0.047	-0.032*	-0.026
	(0.007)	(0.017)	(0.009)	(0.019)	(0.019)	(0.045)	(0.019)	(0.045)
Age	0.004	0.004	0.011***	0.011***	0.007	0.007	0.011*	0.011*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Family income	-0.004**	-0.004**	-0.007***	-0.007***	-0.002	-0.002	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Class size	-0.002**	-0.002**	-0.001	-0.001	-0.003**	-0.003**	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.409***	0.397***	0.041	0.032	0.348***	0.340***	0.630***	0.628***
	(0.051)	(0.051)	(0.057)	(0.057)	(0.129)	(0.130)	(0.135)	(0.136)
Observations	2,579	2,579	2,579	2,579	2,580	2,580	2,579	2,579
R-squared	0.032	0.033	0.087	0.087	0.037	0.037	0.023	0.023
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

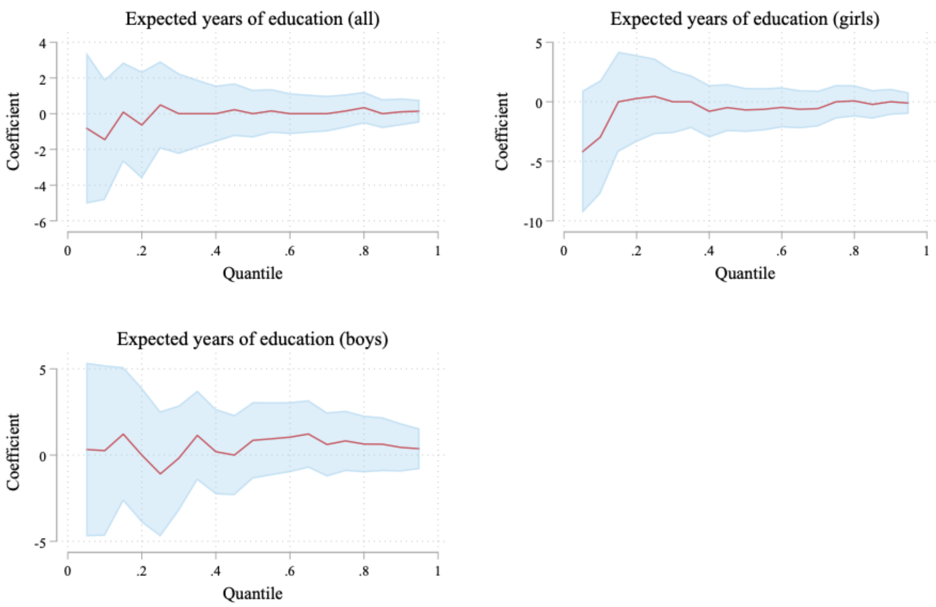
Table A.16: Social capital ($\overline{WE}_c - \overline{BF}_c$) and expectations to continue studies (OLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Social capital ($\overline{WE}_c - \overline{BF}_c$)	0.040*	0.018	0.004	-0.007
	(0.021)	(0.028)	(0.023)	(0.032)
Female × Social capital		0.045		0.023
		(0.036)		(0.041)
Female	0.021**	0.046**	0.058***	0.071***
	(0.010)	(0.022)	(0.011)	(0.026)
Age	-0.017***	-0.017***	-0.015***	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002**	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.080***	1.069***	0.857***	0.851***
	(0.069)	(0.070)	(0.075)	(0.076)
Observations	2,571	2,571	2,571	2,571
R-squared	0.049	0.049	0.058	0.058
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

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

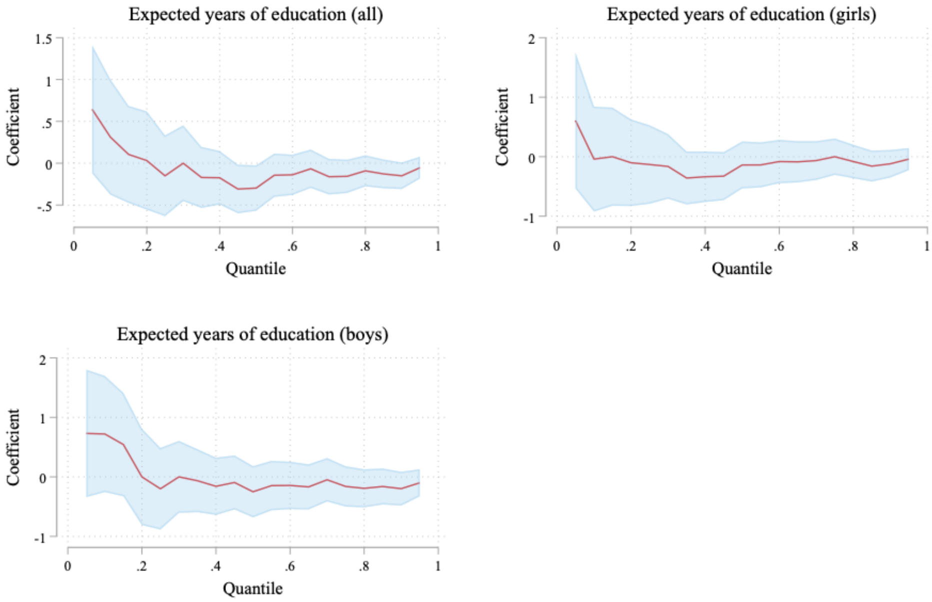
Source: Same as Table 4.1.

Figure A.1: Quantile regression estimates for worst enemies



Source: Same as Table 4.1.
Note: Confidence intervals expressed at the 5% confidence level. All regressions control for gender, age, family income, classroom size, municipality, and school fixed effects.

Figure A.2: Quantile regression estimates for social capital $\overline{WE}_c - \overline{BF}_c$



Source: Same as Table 4.1.

Note: Confidence intervals expressed at the 5% confidence level. All regressions control for gender, age, family income, classroom size, municipality, and school fixed effects.

Table A.17: Effects of worst enemy on cognitive abilities (2SLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (time)	(6) Consistency (time)	(7) Consistency (risk)	(8) Consistency (risk)
Panel A: Two Stage Least Squares								
Worst enemies (class average)	0.124	-0.573	0.967	0.749	0.457	3.362*	0.598	0.141
	(0.507)	(0.759)	(0.660)	(0.863)	(1.318)	(2.014)	(1.315)	(1.912)
Female × Worst enemies		1.340		0.471		-5.305*		1.056
		(1.094)		(1.177)		(2.855)		(2.756)
Female	-0.001	-0.072	-0.075***	-0.099	-0.031	0.251	-0.063***	-0.119
	(0.008)	(0.059)	(0.009)	(0.063)	(0.020)	(0.153)	(0.020)	(0.148)
Age	0.004	0.004	0.013***	0.014***	0.012*	0.011	0.008	0.009
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Family income	-0.004**	-0.004**	-0.007***	-0.007***	-0.013***	-0.013***	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)
Class size	-0.002**	-0.001**	-0.002*	-0.001*	-0.002	-0.002	-0.004**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.467***	0.494***	0.075	0.083	0.511***	0.393**	0.479***	0.495***
	(0.058)	(0.063)	(0.073)	(0.076)	(0.155)	(0.170)	(0.153)	(0.162)
Observations	2,579	2,579	2,579	2,579	2,579	2,579	2,580	2,580
R-squared	0.033		0.035	0.026	0.017		0.029	0.027
Hausman F-statistic	0.00	0.87	2.88*	1.79	0.47	2.22	0.54	0.36
Overidentification test χ^2	8.32**	12.61**	7.44**	19.95***	5.22*	9.11*	7.42**	7.86*
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: First stage for enemies and enemies interacted with gender								
Repeaters (class average)	0.031*	0.038*	0.031*	0.038*	0.030*	0.038*	0.031*	0.038*
	(0.018)	(0.022)	(0.018)	(0.022)	(0.018)	(0.022)	(0.018)	(0.022)
Repeaters × Unique class	0.094**	0.098*	0.094**	0.098*	0.094**	0.099*	0.094**	0.098*
	(0.041)	(0.059)	(0.041)	(0.059)	(0.041)	(0.059)	(0.041)	(0.059)
Unique class	0.033***	0.032***	0.033***	0.032***	0.033***	0.031***	0.033***	0.032***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Female × Repeaters		0.076***		0.076***		0.077***		0.076***
		(0.020)		(0.020)		(0.020)		(0.020)
Female × Repeaters × Unique class		-0.252***		-0.252***		-0.252***		-0.252***
		(0.067)		(0.067)		(0.067)		(0.067)
Female × Unique class		0.015***		0.015***		0.015***		0.015***
		(0.005)		(0.005)		(0.005)		(0.005)
Female		0.046***		0.046***		0.046***		0.046***
		(0.002)		(0.002)		(0.002)		(0.002)
F-statistic	24.68***	13.55***	24.68***	13.55***	24.55***	13.57***	24.68***	13.55***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on enemies interacted with gender.

Table A.18: Effects of worst enemy on expectations to continue studies (2SLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Panel A: Two Stage Least Squares				
Worst enemies (class average)	-0.861	-1.058	1.420*	2.279*
	(0.723)	(1.008)	(0.789)	(1.225)
Female × Worst enemies		0.413		-1.863
		(1.407)		(1.693)
Female	0.019*	-0.003	0.061***	0.159*
	(0.010)	(0.074)	(0.011)	(0.090)
Age	-0.020***	-0.020***	-0.013***	-0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.226***	1.233***	0.802***	0.771***
	(0.080)	(0.084)	(0.089)	(0.096)
Observations	2,571	2,571	2,571	2,571
R-squared	0.029	0.026		
Hausman F-statistic	1.00	0.62	3.77*	1.96
Overidentification test χ^2	3.82	5.91	0.63	4.66
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Panel B: First stage for enemies and enemies interacted with gender				
Repeaters (class average)	0.028	0.035	0.028	0.035
	(0.018)	(0.022)	(0.018)	(0.022)
Repeaters × Unique class	0.096**	0.102*	0.096**	0.102*
	(0.041)	(0.059)	(0.041)	(0.059)
Unique class	0.033***	0.031***	0.033***	0.031***
	(0.005)	(0.005)	(0.005)	(0.005)
Female × Repeaters		0.077***		0.077***
		(0.020)		(0.020)
Female × Repeaters × Unique class		-0.252***		-0.252***
		(0.067)		(0.067)
Female × Unique class		0.015***		0.015***
		(0.005)		(0.005)
Female		0.046***		0.046***
		(0.002)		(0.002)
F-statistic	24.62***	13.50***	24.62***	13.50***

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on enemies interacted with gender.

Table A.19: *Effects of social capital ($\overline{WE}_c - \overline{BF}_c$) on cognitive abilities (2SLS)*

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Panel A: Two Stage Least Squares								
Social capital ($\overline{WE}_c - \overline{BF}_c$)	0.262*	0.272	0.389**	0.303	0.700*	0.557	0.578	-0.024
	(0.136)	(0.176)	(0.168)	(0.212)	(0.364)	(0.465)	(0.361)	(0.478)
Female × Social capital		-0.050		0.115		0.250		1.144**
		(0.184)		(0.201)		(0.470)		(0.519)
Female	0.003	-0.025	-0.069***	-0.006	-0.051**	0.087	-0.021	0.610**
	(0.008)	(0.102)	(0.010)	(0.111)	(0.022)	(0.260)	(0.021)	(0.287)
Age	0.009**	0.009**	0.020***	0.019***	0.022**	0.021**	0.024**	0.021*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)	(0.011)
Family income	-0.004*	-0.004**	-0.007***	-0.007***	-0.002	-0.002	-0.013***	-0.012**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Class size	0.002	0.002	0.004*	0.004	0.006	0.005	0.006	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.413***	0.429***	0.043	0.021	0.351**	0.293	0.404**	0.127
	(0.061)	(0.073)	(0.076)	(0.085)	(0.163)	(0.192)	(0.160)	(0.207)
Observations	2,579	2,579	2,579	2,579	2,580	2,580	2,579	2,579
Hausman F-statistic	4.12**	1.86	6.67***	3.35**	4.17**	2.31*	2.89*	5.29***
Overidentification test χ^2	4.76*	10.38**	3.41	14.47***	3.19	3.09	2.41	2.72
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: First stage for enemies and enemies interacted with gender								
Repeaters (class average)	-0.205**	-0.156	-0.205**	-0.156	-0.205**	-0.155	-0.205**	-0.156
	(0.080)	(0.101)	(0.080)	(0.101)	(0.080)	(0.100)	(0.080)	(0.101)
Repeaters × Unique class	1.150***	1.126***	1.150***	1.126***	1.149***	1.125***	1.150***	1.126***
	(0.298)	(0.352)	(0.298)	(0.352)	(0.298)	(0.352)	(0.298)	(0.352)
Unique class	0.085***	0.085***	0.085***	0.085***	0.085***	0.086***	0.085***	0.085***
	(0.020)	(0.025)	(0.020)	(0.025)	(0.020)	(0.025)	(0.020)	(0.025)
Female × Repeaters		-0.620***		-0.620***		-0.620***		-0.620***
		(0.116)		(0.116)		(0.116)		(0.116)
Female × Repeaters × Unique class		1.009***		1.009***		1.010***		1.009***
		(0.358)		(0.358)		(0.358)		(0.358)
Female × Unique class		-0.019		-0.019		-0.019		-0.019
		(0.025)		(0.025)		(0.025)		(0.025)
Female		-0.527***		-0.527***		-0.527***		-0.527***
		(0.010)		(0.010)		(0.010)		(0.010)
F-statistic	13.91***	9.345***	13.91***	9.345***	13.94***	9.369***	13.91***	9.345***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on social capital interacted with gender.

Table A.20: Effects of social capital ($\overline{WE}_c - \overline{BF}_c$) on expectations to continue studies (2SLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Panel A: Two Stage Least Squares				
Social capital ($\overline{WE}_c - \overline{BF}_c$)	0.062	0.023	0.160	0.106
	(0.179)	(0.224)	(0.195)	(0.249)
Female × Social capital		0.054		0.082
		(0.222)		(0.254)
Female	0.022**	0.051	0.061***	0.106
	(0.010)	(0.122)	(0.012)	(0.140)
Age	-0.017***	-0.017***	-0.012**	-0.012**
	(0.005)	(0.005)	(0.006)	(0.006)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002	-0.002	0.001	0.000
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	1.159***	1.148***	0.851***	0.834***
	(0.079)	(0.093)	(0.087)	(0.102)
Observations	2,571	2,571	2,571	2,571
R-squared	0.048	0.049	0.042	0.044
Hausman F-statistic	0.02	0.00	0.66	0.34
Overidentification test χ^2	5.16*	7.17	3.40	8.72*
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Panel B: First stage for enemies and enemies interacted with gender				
Repeaters (class average)	-0.220***	-0.177*	-0.220***	-0.177*
	(0.081)	(0.102)	(0.081)	(0.102)
Repeaters × Unique class	1.164***	1.148***	1.164***	1.148***
	(0.299)	(0.352)	(0.299)	(0.352)
Unique class	0.084***	0.084***	0.084***	0.084***
	(0.020)	(0.025)	(0.020)	(0.025)
Female × Repeaters	-0.618***	-0.618***		
	(0.116)	(0.116)		
Female × Repeaters × Unique class		1.008***		1.008***
		(0.358)		(0.358)
Female × Unique class		-0.019		-0.019
		(0.025)		(0.025)
Female		-0.527***		-0.527***
		(0.010)		(0.010)
F-statistic	14.15***	9.197***	14.15***	9.197***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on social capital interacted with gender.

Table A.21: Enemy density and cognitive abilities (OLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Enemies (density)	0.233	0.201	0.085	0.117	-0.384	-0.349	-0.026	-0.128
	(0.186)	(0.229)	(0.217)	(0.281)	(0.470)	(0.590)	(0.469)	(0.583)
Female × Enemies		0.064		-0.066		-0.071		0.209
		(0.279)		(0.337)		(0.713)		(0.709)
Female	-0.002	-0.005	-0.076***	-0.073***	-0.064***	-0.061	-0.032	-0.042
	(0.007)	(0.015)	(0.008)	(0.017)	(0.019)	(0.039)	(0.019)	(0.038)
Age	0.003	0.003	0.012***	0.012***	0.007	0.007	0.011*	0.011*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)	(0.007)
Family income	-0.004**	-0.004**	-0.007***	-0.007***	-0.002	-0.002	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Class size	-0.002**	-0.002**	-0.001	-0.001	-0.004**	-0.004**	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.396***	0.398***	0.033	0.031	0.371***	0.369***	0.630***	0.637***
	(0.052)	(0.053)	(0.059)	(0.060)	(0.132)	(0.133)	(0.137)	(0.139)
Observations	2,579	2,579	2,579	2,579	2,580	2,580	2,579	2,579
R-squared	0.033	0.033	0.087	0.087	0.037	0.037	0.023	0.023
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

Table A.22: Enemy density and expectations to continue studies (OLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Enemies (density)	-0.407*	-0.681**	-0.328	-0.527
	(0.242)	(0.300)	(0.271)	(0.355)
Female × Enemies		0.557		0.405
		(0.352)		(0.414)
Female	0.021**	-0.005	0.058***	0.039*
	(0.010)	(0.019)	(0.011)	(0.022)
Age	-0.018***	-0.018***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002***	-0.002***	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.098***	1.113***	0.876***	0.887***
	(0.072)	(0.073)	(0.077)	(0.077)
Observations	2,571	2,571	2,571	2,571
R-squared	0.049	0.050	0.059	0.059
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

Table A.23: Social capital density and cognitive abilities (OLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Social capital (density)	-0.119**	-0.158**	-0.194***	-0.327***	-0.141	-0.254	0.085	-0.004
	(0.052)	(0.070)	(0.069)	(0.095)	(0.152)	(0.203)	(0.148)	(0.195)
Female × Social capital		0.064		0.220**		0.187		0.147
		(0.081)		(0.106)		(0.236)		(0.229)
Female	-0.002	0.004	-0.077***	-0.056***	-0.065***	-0.047	-0.032	-0.018
	(0.007)	(0.011)	(0.008)	(0.013)	(0.019)	(0.030)	(0.019)	(0.029)
Age	0.002	0.002	0.010***	0.009***	0.005	0.005	0.012*	0.012*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Family income	-0.003*	-0.003*	-0.007***	-0.007***	-0.002	-0.002	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Class size	-0.001**	-0.001**	-0.001	-0.001	-0.003**	-0.003**	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.397***	0.393***	0.019	0.004	0.335***	0.326**	0.637***	0.627***
	(0.051)	(0.051)	(0.057)	(0.058)	(0.128)	(0.128)	(0.135)	(0.136)
Observations	2,579	2,579	2,579	2,579	2,580	2,580	2,579	2,579
R-squared	0.034	0.034	0.090	0.091	0.037	0.037	0.023	0.023
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Source: Same as Table 4.1.

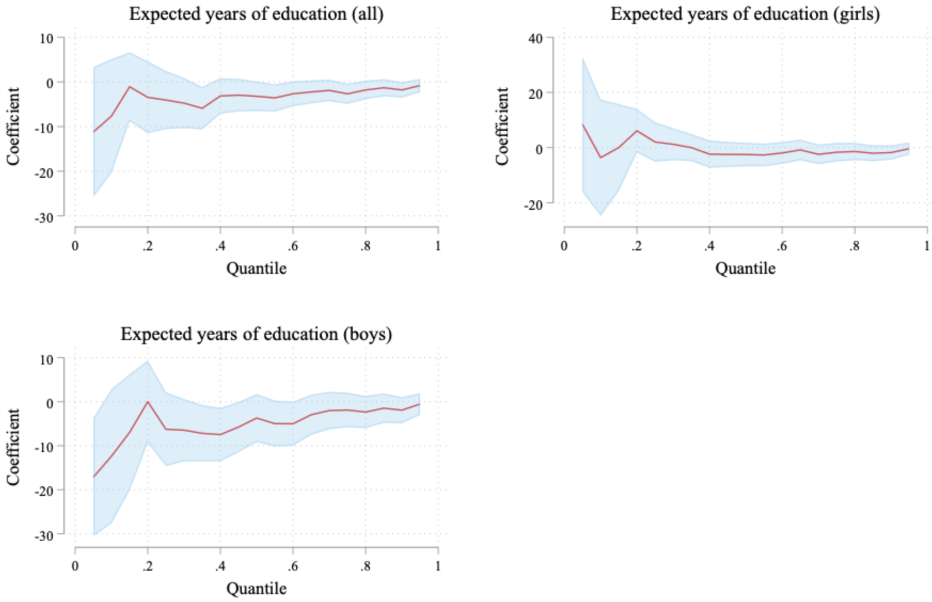
Table A.24: Social capital density and expectations to continue studies (OLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Social capital (density)	0.137*	0.175*	-0.123	-0.146
	(0.081)	(0.102)	(0.078)	(0.111)
Female × Social capital		-0.062		0.037
		(0.124)		(0.127)
Female	0.021**	0.015	0.058***	0.061***
	(0.010)	(0.015)	(0.011)	(0.017)
Age	-0.017***	-0.017***	-0.017***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.003***	-0.003***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.083***	1.087***	0.846***	0.844***
	(0.070)	(0.070)	(0.075)	(0.075)
Observations	2,571	2,571	2,571	2,571
R-squared	0.049	0.049	0.059	0.059
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

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

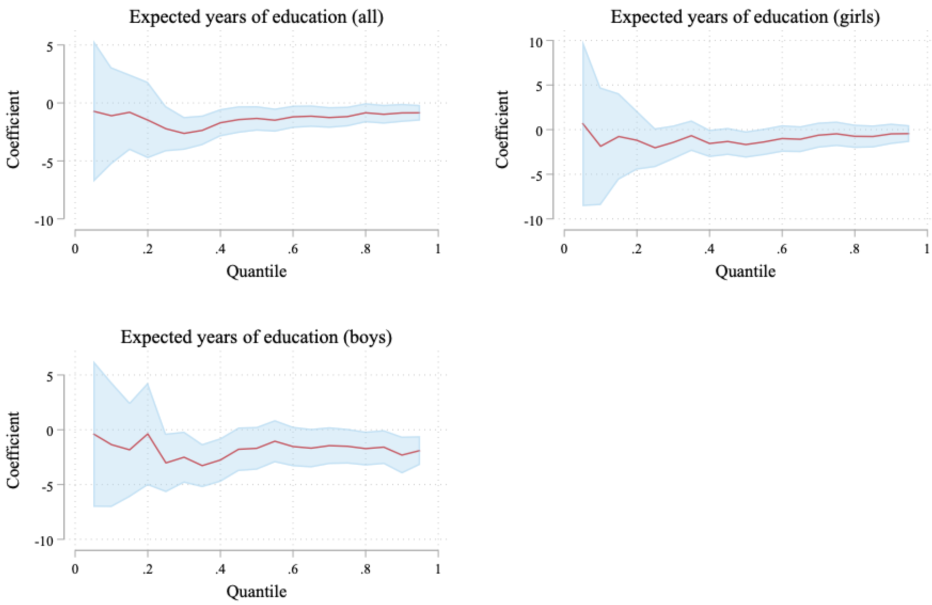
Source: Same as Table 4.1.

Figure A.3: Quantile regression estimates for enemy density



Source: Same as Table 4.1.
Note: Confidence intervals expressed at the 5% confidence level. All regressions control for gender, age, family income, classroom size, municipality, and school fixed effects.

Figure A.4: Quantile regression estimates for social capital density



Source: Same as Table 4.1.
Note: Confidence intervals expressed at the 5% confidence level. All regressions control for gender, age, family income, classroom size, municipality, and school fixed effects.

Table A.25: Effects of enemy density on cognitive abilities (2SLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (time)	(6) Consistency (time)	(7) Consistency (risk)	(8) Consistency (risk)
Panel A: Two Stage Least Squares								
Enemies (density)	0.855*	0.802	1.407**	1.172	1.687	1.466	1.930	1.513
	(0.457)	(0.574)	(0.567)	(0.722)	(1.197)	(1.483)	(1.201)	(1.478)
Female × Enemies		0.010		0.315		0.534		0.849
		(0.710)		(0.844)		(1.852)		(1.831)
Female	-0.002	-0.002	-0.077***	-0.092**	-0.032*	-0.057	-0.065***	-0.105
	(0.007)	(0.034)	(0.009)	(0.040)	(0.019)	(0.089)	(0.019)	(0.088)
Age	0.003	0.003	0.011***	0.011***	0.010	0.010	0.006	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Family income	-0.004**	-0.004**	-0.007***	-0.007***	-0.013***	-0.012***	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)
Class size	-0.002***	-0.002***	-0.001	-0.001	-0.002	-0.002	-0.004**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.470***	0.471***	0.127**	0.137**	0.531***	0.547***	0.507***	0.531***
	(0.049)	(0.054)	(0.059)	(0.064)	(0.131)	(0.141)	(0.131)	(0.140)
Observations	2,579	2,579	2,579	2,579	2,579	2,579	2,580	2,580
R-squared	0.028	0.029	0.072	0.073	0.018	0.017	0.028	0.027
Hausman F-statistic	2.45	1.04	6.92***	3.32**	2.40	1.26	4.42**	2.32*
Overidentification test χ^2	5.54*	10.67**	3.09	16.46***	3.41	11.09**	5.10*	5.26
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: First stage for enemies and enemies interacted with gender								
Repeaters (class average)	-0.050***	-0.048***	-0.050***	-0.048***	-0.050***	-0.048***	-0.050***	-0.048***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Repeaters × Unique class	-0.307***	-0.288***	-0.307***	-0.288***	-0.307***	-0.288***	-0.307***	-0.288***
	(0.023)	(0.037)	(0.023)	(0.037)	(0.023)	(0.037)	(0.023)	(0.037)
Unique class	0.027***	0.027***	0.027***	0.027***	0.027***	0.027***	0.027***	0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Female × Repeaters		-0.050***		-0.050***		-0.050***		-0.050***
		(0.006)		(0.006)		(0.006)		(0.006)
Female × Repeaters × Unique class		-0.228***		-0.228***		-0.228***		-0.228***
		(0.047)		(0.047)		(0.047)		(0.047)
Female × Unique class		0.031***		0.031***		0.031***		0.031***
		(0.004)		(0.004)		(0.004)		(0.004)
Female		0.046***		0.046***		0.046***		0.046***
		(0.001)		(0.001)		(0.001)		(0.001)
F-statistic	120.7***	45.30***	120.7***	45.30***	120.6***	45.30***	120.7***	45.30***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on enemies interacted with gender.

Table A.26: Effects of enemy density on expectations to continue studies (2SLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Panel A: Two Stage Least Squares				
Enemies (density)	0.062	0.012	0.595	1.201
	(0.621)	(0.777)	(0.674)	(0.879)
Female × Enemies		0.025		-1.335
		(0.987)		(1.062)
Female	0.021**	0.020	0.058***	0.120**
	(0.010)	(0.047)	(0.011)	(0.051)
Age	-0.018***	-0.018***	-0.016***	-0.015***
	(0.003)	(0.003)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.012***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.002***	-0.002***	-0.002*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.173***	1.174***	0.886***	0.848***
	(0.067)	(0.072)	(0.074)	(0.080)
Observations	2,571	2,571	2,571	2,571
R-squared	0.047	0.047	0.054	0.048
Hausman F-statistic	0.68	0.48	2.30	2.71
Overidentification test χ^2	5.43*	7.50	3.33	6.61
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Panel B: First stage for enemies and enemies interacted with gender				
Repeaters (class average)	-0.051***	-0.049***	-0.051***	-0.049***
	(0.005)	(0.006)	(0.005)	(0.006)
Repeaters × Unique class	-0.306***	-0.287***	-0.306***	-0.287***
	(0.023)	(0.037)	(0.023)	(0.037)
Unique class	0.027***	0.027***	0.027***	0.027***
	(0.004)	(0.004)	(0.004)	(0.004)
Female × Repeaters		-0.050***		-0.050***
		(0.006)		(0.006)
Female × Repeaters × Unique class		-0.228***		-0.228***
		(0.047)		(0.047)
Female × Unique class		0.031***		0.031***
		(0.004)		(0.004)
Female		0.046***		0.046***
		(0.001)		(0.001)
F-statistic	121***	45.46***	121***	45.46***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on enemies interacted with gender.

Table A.27: Effects of social capital density on cognitive abilities (2SLS)

VARIABLES	(1) Cognitive reflection test	(2) Cognitive reflection test	(3) Financial abilities	(4) Financial abilities	(5) Consistency (risk)	(6) Consistency (risk)	(7) Consistency (time)	(8) Consistency (time)
Panel A: Two Stage Least Squares								
Social capital (density)	-0.095	-0.033	-0.240**	-0.074	-0.285	-0.254	-0.232	-0.220
	(0.095)	(0.121)	(0.121)	(0.156)	(0.251)	(0.324)	(0.255)	(0.327)
Female × Social capital		-0.108		-0.281*		-0.051		0.045
		(0.132)		(0.158)		(0.353)		(0.361)
Female	-0.002	-0.012	-0.077***	-0.104***	-0.065***	-0.070*	-0.033*	-0.028
	(0.007)	(0.015)	(0.008)	(0.017)	(0.019)	(0.039)	(0.019)	(0.040)
Age	0.003	0.003	0.009***	0.009***	0.004	0.004	0.008	0.009
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Family income	-0.004*	-0.004*	-0.007***	-0.007***	-0.001	-0.001	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Class size	-0.001**	-0.001**	-0.001	-0.001	-0.003*	-0.003*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.478***	0.483***	0.144**	0.156***	0.527***	0.530***	0.549***	0.545***
	(0.049)	(0.050)	(0.058)	(0.059)	(0.130)	(0.131)	(0.131)	(0.132)
Observations	2,579	2,579	2,579	2,579	2,580	2,580	2,579	2,579
R-squared	0.034	0.033	0.090	0.083	0.037	0.037	0.021	0.021
Hausman F-statistic	0.09	1.40	0.23	9.25***	0.51	0.64	2.37	0.99
Overidentification test χ^2	7.53**	11.75**	6.19**	13.78***	6.42**	6.90	4.52	12.41**
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: First stage for social capital and social capital interacted with gender								
Repeaters (class average)	0.011	0.026	0.011	0.026	0.011	0.025	0.011	0.026
	(0.018)	(0.020)	(0.018)	(0.020)	(0.018)	(0.020)	(0.018)	(0.020)
Repeaters × Unique class	-0.946***	-1.057***	-0.946***	-1.057***	-0.946***	-1.057***	-0.946***	-1.057***
	(0.140)	(0.192)	(0.140)	(0.192)	(0.140)	(0.192)	(0.140)	(0.192)
Unique class	-0.163***	-0.150***	-0.163***	-0.150***	-0.163***	-0.150***	-0.163***	-0.150***
	(0.013)	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)
Female × Repeaters		0.106***		0.106***		0.106***		0.106***
		(0.014)		(0.014)		(0.014)		(0.014)
Female × Repeaters × Unique class		-0.338		-0.338		-0.338		-0.338
		(0.218)		(0.218)		(0.218)		(0.218)
Female × Unique class		-0.143***		-0.143***		-0.143***		-0.143***
		(0.014)		(0.014)		(0.014)		(0.014)
Female		-0.080***		-0.080***		-0.080***		-0.080***
		(0.002)		(0.002)		(0.002)		(0.002)
F-statistic	122.4***	66.99***	122.4***	66.99***	122.4***	67.03***	122.4***	66.99***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on social capital interacted with gender.

Table A.28: Effects of social capital density on expectations to continue studies (2SLS)

VARIABLES	(1) Additional year	(2) Additional year	(3) Universiy	(4) Universiy
Panel A: Two Stage Least Squares				
Social capital (density)	0.097	0.164	-0.233	-0.254
	(0.138)	(0.172)	(0.142)	(0.185)
Female × Social capital		-0.114		0.075
		(0.189)		(0.203)
Female	0.021**	0.010	0.057***	0.065***
	(0.010)	(0.020)	(0.011)	(0.022)
Age	-0.017***	-0.017***	-0.018***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.004)
Family income	0.001	0.001	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Class size	-0.003***	-0.003***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.170***	1.175***	0.898***	0.894***
	(0.067)	(0.067)	(0.074)	(0.075)
Observations	2,571	2,571	2,571	2,571
R-squared	0.049	0.049	0.058	0.059
Hausman F-statistic	0.12	0.12	0.86	0.30
Overidentification test χ^2	5.16*	6.70	1.58	7.49
Municipality FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Panel B: First stage for social capital and social capital interacted with gender				
Repeaters (class average)	0.010	0.024	0.010	0.024
	(0.018)	(0.020)	(0.018)	(0.020)
Repeaters × Unique class	-0.945***	-1.056***	-0.945***	-1.056***
	(0.140)	(0.192)	(0.140)	(0.192)
Unique class	-0.163***	-0.150***	-0.163***	-0.150***
	(0.013)	(0.011)	(0.013)	(0.011)
Female × Repeaters		0.106***		0.106***
		(0.015)		(0.015)
Female × Repeaters × Unique class		-0.338		-0.338
		(0.218)		(0.218)
Female × Unique class		-0.143***		-0.143***
		(0.014)		(0.014)
Female		-0.080***		-0.080***
		(0.002)		(0.002)
F-statistic	121.7***	67.04***	121.7***	67.04***

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

Source: Same as Table 4.1.

Note: F-statistics in the first stage for even-numbered columns refer to those regressing on social capital interacted with gender.