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I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality as a dissertation for the degree of Doctor of Philosophy.

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Preface

This dissertation is composed of three chapters. All three deal with topics in development economics. The first chapter examines the effects on village institutions of introducing formal financial institution options into the village. The second addresses the effects of government policy on educational investment and crime. The third tests the explanatory power of various explanations of the gender gap in math test scores.

The first chapter examines the effects of a transition from a "traditional" economy based on an uncertain source of income, with risk fully insured away by one's neighbors in a social network through costly network ties, to a "modern" economy in which some agents have access to partial insurance at a lower cost. A theoretical model is used to show that village social networks can break down as some members of the village no longer need the insurance the social network provides, producing a reduction in welfare (if the costs of reducing moral hazard are not too high) for at least some individuals and possibly the village as a whole. This loss of welfare can occur even when networks provide other benefits to those belonging to them and is likely to be heterogeneous, depending on the opportunities and networks available to individuals. This paper tests these predictions using Indonesian data to examine the effect of a change in the banking institutions available to a community on the strength of social networks (measured by community participation) and welfare (measured by household expenditure and by child health). The analysis finds that changing financial institution availability in general does not influence community participation or welfare, but that financial institutions that primarily serve certain groups do relatively reduce the welfare of households not in those groups, which is consistent with the hypotheses generated by the model.

Crime is an important feature of economic life in many countries, especially in the developing world. Crime distorts many economic decisions because it acts like an unpredictable tax on earnings. In particular, the threat of crime may influence people's willingness to invest in schooling or physical capital. The second chapter explores the questions "What influence do crime rates and levels of investment have on one another?" and "How do government policies affect the relationship between investment and crime?" by creating a simple structural model of crime and educational investment and attempting to fit this model to Mexican data. A method of simulated moments procedure is used to estimate parameters of the model and the estimated parameters are then used to carry out policy simulations. The simulations show that increasing spending on police or increasing the severity of punishment reduces crime but has little effect on educational investment. Increased educational subsidies increase educational investment but reduce crime only slightly. Thus, one type of policy is insufficient to accomplish the goals of both reducing crime and increasing education.

The third chapter is joint work with Prashant Bharadwaj, Giacomo De Giorgi, and Christopher Neilson. Boys tend to have better performances than girls in mathematical testing; in particular, there are significantly more boys than girls among high achievers and the score distribution appears to have a longer right tail for boys. We confirm such results on several low- and middle-income countries. In particular we find that the gender gap is already present by age 10 and substantially increases by age 14 and 15. We propose and try to test a series of explanations for such a gap: (i) parental investment, (ii) ability, (iii) school resources, (iv) individual investment and effort (not tested directly), (v) competitive environment, and (vi) cultural norms.

We conclude that none of our proposed explanations can account for a substantial portion of the gap.

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Chapter 1

Broken Links: The Effects of Credit Market Transition away from a Network Basis

1.1 Introduction

Most lower-income countries seek to develop and modernize by establishing institutions that foster exchange and allow for more developed markets in credit, insurance, labor, and products. Despite the undeniable benefits of these new institutions, however, many in these countries lament the impersonal nature of society that they say follows in the wake of these changes and the weakened traditions and loss of community spirit this produces. This process can also produce losing sectors or groups that seem not to participate fully in the benefits of modernization.

To examine these issues, I create a model of insurance on a simple preexisting social network, characterize the stable configurations of this network, and examine the effects of the exogenous introduction of an alternative credit scheme to some agents. I show that the introduction of such an outside source of credit may actually result in a loss of overall welfare, even if additional network benefits induce the agents in the new insurance scheme to remain in the network without participating in network insurance.

I then test some of the implications of this model using data on the spread of microfinance, and banking services more generally, in Indonesia between 1997 and 2000. Though I find that an increase in financial institutions generally has little effect on community participation or welfare, specific types of financial institutions can have a negative effect on the sectors of society that they do not serve extensively.

One area of current research motivating this study involves the transition from a traditional to a modern economy and the determinants of when (or whether) such a transition occurs and what its effects will be. Traditional economies are characterized by transactions based on interpersonal ties such as kinship, lack of institutionalized contract enforcement, and low costs of information within a social group, among other attributes. In contrast, modern economies rely much more heavily on interactions between individuals or corporate entities who need not know each other, transactions that are made possible by the existence of contract enforcement institutions. Greif (2006) addresses this transition in the context of the movement from economic interaction based on kin relations and close-knit social groups to more impersonal forms of interaction through the development of formal institutions that reduce transactions costs.

A wide variety of social groups may facilitate insurance on a social network. For example, Chen (2010) uses the Indonesian economic decline caused by the Asian financial crisis of 1997 to examine the change in religious participation caused by economic distress. This is of great use for this paper, since I am interested in a similar question in the same country and time period. Chen finds that households that experienced more economic distress in the wake of the financial crisis were more likely to increase their religious observance and to send their children to religious (Islamic) schools in order to have access to the credit networks and other help that religious institutions provided. However, "the effect of economic distress on religious intensity essentially disappears in places where credit is available in the form of banks, microfinance institutions, or Bank Rakyat Indonesia (BRI) loan products" (p. 303), which essentially encapsulates the relationship between social network participation and financial institutions that I wish to explore, though I use participation in community projects and organizations instead of religious participation. The potential competition between religious institutions and other institutions in society in providing economic help has been the subject of a large literature (Dehejia et al., 2007; Gruber and Hungerman, 2005, 2008).

Family networks may also facilitate credit provision and risk sharing. For example, Angelucci et al. (2011) find, using PROGRESA data from rural Mexico, that extended family networks serve as an important form of insurance in this setting by smoothing consumption and providing higher levels of consumption, capital, and income for their participants. Kinnan and Townsend (2011) show that kin networks can also serve as collateral for their participants, allowing them to get larger loans from formal financial institutions, which shows a potential role that family networks may serve as complements to financial institutions. This paper will attempt to take these family networks into account by controlling for siblings that do not live in the same household as survey respondents.

Tradeoffs between the traditional and modern modes of economic interaction may often produce suboptimal outcomes for segments of society, especially in the short run transition period. These tradeoffs may also explain why modernization often occurs slowly, if at all. For example, Banerjee and Newman (1998) model an economy with a traditional sector that has low productivity but also low asymmetry of information and a modern sector with high productivity and high information asymmetries. They use this model to show that modernization may not be optimal in the short run and may fail to extend to the entire economy even in the long run.

Abramitzky (2008) frames a similar institutional issue in terms of the tradeoff between redistribution and incentives in the context of the Israeli kibbutz. He examines the influence of individual productivity, kibbutz wealth, and the strength of socialist ideology on the persistence of kibbutzim. He finds, in particular, that high ability individuals are more likely to leave the kibbutz. Since one of the main functions of a kibbutz is as a risk-sharing network, this has strong implications for this paper, especially in terms of the implications for individuals with a high outside option.

Another motivation for this paper is the importance of social networks in developing countries particularly. In the absence of formal institutions, such as those involved in contract enforcement, insurance, credit, and information transmission, these functions are often exercised by networks of individuals founded upon repeated economic interaction or non-economic interactions in other spheres of society. The use of social networks may be particularly appropriate for modeling the traditional sector, as I intend to do in this paper. In their study of microcredit institution design in the Philippines, Giné and Karlan (2008) use social network variables as a dependent variable, as I intend to do in this paper. Udry and Conley (2005) examine economic and social networks in rural Ghana, including a model of network formation, and find that networks are important in many different types of transactions and in the process of economic development.

Social networks may also be very important in the informal economy, which composes a large portion of the economic activity in many developing countries and underdeveloped regions. For example, a study by Venkatesh (2006) of the informal economy in inner-city Chicago points out the importance of social ties in allocating the use of public space, providing public safety, and engaging in business transactions. Corominas-Bosch (2004) provides a social network model of relations between buyers and sellers that captures many aspects of the informal economy. Beyond these aspects, a network analysis may also allow for greater understanding and measurement of social capital, a notoriously difficult concept to measure (Durlauf and Fafchamps, 2005; Glaeser et al., 1999; Narayan and Pritchett, 1999). In this case, I will think of social capital as the efficiency enhancement allowed by the trust among households that is embodied in the social network.

One difficulty of working with networks is the possibly massive multiplicity of equilibria under some solution concepts, particularly if pairwise stability is used (Jackson, 2003, 2006). This paper will avoid many of these problems by allowing only deviations that destroy all of an agent's network links at once, thus removing deviating agents from the network entirely, and by beginning with a stable status quo and then introducing a destabilizing element. Considering only those deviations involving the severing of all network ties can be a reasonable assumption in the context I am considering, in which formal ties to other agents may be regulated by family and village norms, rather than being completely subject to individual choice.

Several papers have addressed topics relating to insurance and credit through a social network, as I intend to do. A very applicable paper for my analysis is Bloch et al. (2007), which addresses the difficult multiplicity of equilibria inherent in network models by introducing transfer norms describing the bilateral transfers between any two linked individuals that should occur given a set of income realizations. They are able to characterize the stability of a given transfer norm to deviations by individual agents, based on modeling the enforcement ability of other agents. They also briefly consider the stability of an insurance network to the exogenous breaking of some links in the network. I will also consider the effects of an outside disruption to a transfer scheme, but I will do so in terms of a new insurance option not relying on the network, rather than a change to the network structure. I have chosen to examine a very simple transfer norm in order to be able to focus effectively on the influence of introducing a specific alternative insurance scheme to some agents. Mobius and Szeidl (2007) also deal with questions of transfers along a network, in their case in the context of informal credit. They examine which loans will be repaid in this context, finding that the key constraint on lending along a path is the value of the lowest valued link on the path. This allows them to quantify trust as the maximum one agent would be willing to lend another, providing a useful measure for social capital inherent in a network. They are thus able to characterize network structures as having greater or lesser ability to sustain transfers. In a very limited way, I am also examining the value of a network and its ability to sustain transfers, though, as mentioned before, I am focusing on the effects of the introduction of an alternative insurance scheme in this context.

Dixit (2003) examines trading relationships in a network and how these can be sustained over time in the absence of formal enforcement mechanisms. This paper complements Dixit's work by looking at the power of informal enforcement norms and when informal institutions using existing social networks might be welfare-enhancing compared to more impersonal, though more efficient, formal institutions.

Fafchamps and Lund (2003) attempt to model the amount of friction present in insurance provision in a social network. They provide evidence from the rural Philippines that social networks may indeed be empirically important in providing insurance and credit in rural contexts to aid households in responding to risk. They show that transfers in response to shocks tend to occur among family and friends in a social network, rather than in village-level risk sharing markets.

In Section 2 of the paper, I elaborate a theoretical model and its testable implications, including an extension of the model to include incentives to remain in the social network apart from the main insurance aspect. In Section 3, I discuss the estimation strategy I have chosen, the data I use to implement it, and the results of this estimation. Section 4 concludes.

1.2 Theoretical Model

1.2.1 Network Model

In this model, agents are infinitely lived and belong to one of three groups of equal size N, which receive random income allocations (y_M, $y_H = y_M + m$,or $y_L = y_M - m$) that are perfectly coordinated over different states of the world, as shown in Table 1.1 below. This assumption, that there is no aggregate village-level risk, allows me to focus on the type of risk that is amenable to village-level insurance. Though some of the earlier literature on this topic uses only two groups of agents, I have chosen to use three in order to better understand the dynamics among remaining groups in a village if one group decides to leave the network. Agents have identical von

Neumann-Morgenstern utility functions

$$U_i = (1-\beta)\sum_{t=0}^{\infty}\beta^t(u(y_{it}) - .5\lambda * l_i), \tag{1.1}$$

where l_i is the number of links to other agents by agent i and $\lambda < 0$. Thus, links are costly, which reflects the costs of monitoring and of maintaining good relations with one's village connections. The state utility function, $u(.)$, is concave.

Consider an insurance scheme (I will call it the "traditional" or "network" insurance scheme) on a social network in which each agent is linked bilaterally to two agents of each of the other two types (four in total). In the scheme, each agent with a realization of y_H pays 0.5m to each of the agents with a realization of y_L connected to her, resulting in a constant income of y_M for each agent in all states of the world.

That full insurance will occur in this case is a reasonable assumption, since insurance is provided through a social network and the period utility function is concave, so that, by Jensen's inequality, a more stable income is preferred. A study by Townsend (1994) of three villages in India finds that "credit markets and gifts seem to smooth much of the fluctuations in income" across households (p. 587), though they do not achieve perfect insurance. The ties between the agents insuring one another can lower monitoring and enforcement costs, thus reducing moral hazard and allowing the assumption that risk is fully smoothed across linked individuals. However, it may be quite costly to carry out the monitoring needed to eliminate moral hazard. This is not fully embodied in my model, though monitoring against moral hazard could be modeled as part of the costs of maintaining network ties. The fact that the model does not incorporate monitoring decisions means that the welfare implications of the model may be overstated if monitoring costs are substantial.

Another possible hindrance to perfect insurance in an informal institutional setting is the problem of limited commitment ability (Ligon et al., 2002; Coate and Ravallion, 1993; Hendel and Lizzeri, 2003; Iannaccone, 1992; Kandel et al., 1992). The model follows the assumption that this is a problem for the outside insurance scheme but not for the village scheme. This is certainly a simplification but does attempt to capture the fact that informal social networks often have more knowledge of defaults and better enforcement power than formal institutions do.

This network will be stable to agents dropping out of the network completely if

$$(1-\beta)u(y_H) + \beta\overline{u} < u(y_M) - 2\lambda, \tag{1.2}$$

where $\overline{u} = \frac{1}{3}(u(y_M) + u(y_H) + u(y_L))$ is the outcome under no insurance.

Now assume that agents of type A (and only agents of type A) have the option to enter an outside insurance (or credit functioning as insurance) scheme that is not provided through the social network (I will call it the "modern" scheme because of its greater resemblance to formal insurance and credit institutions found in developed countries). This scheme provides a form of insurance because it allows agents to smooth consumption across states of the world. The assumption that only certain agents have access to the modern scheme reflects the fact that many financial institutions, including many microfinance institutions seek to achieve profitability or sustainability by only loaning to certain groups, in particular those who are able to take out and pay back larger loans (Morduch, 1999). Because of imperfect monitoring of moral hazard risks, these agents will receive a payment $x < m$ when $y = y_L$,and pay x when $y = y_H$. If and only if

$$(1-\beta)u(y_H - x) + \beta\hat{u} > u(y_M) - 2\lambda, \tag{1.3}$$

where $\hat{u} = \frac{1}{3}(u(y_M) + u(y_H - x) + u(y_L + x))$, agents of type A will choose to desert the traditional insurance scheme to receive the higher payoff available in the new arrangement. If the type A agents do this, agents of types B and C must decide whether to continue with the existing traditional insurance scheme, to renegotiate among themselves to a better insurance scheme, or to drop out of the social network completely. The existing traditional insurance scheme will break down, since nonzero insurance payments would occur only in state 2 and these would always be from agents of type C to agents of type B. If no new insurance scheme tailored to the new situation is introduced, overall welfare will be $((1-\beta)u_1 + \beta(\hat{u} + 2\overline{u}))N$, where $u_1 = u(y_H - x) + u(y_M) + u(y_L)$, the sum of utilities for the three types of players in the period when type A chooses to defect, producing a decrease in welfare from the original situation as long as

$$(1-\beta)u_1 + \beta(\hat{u} + 2\overline{u}) < 3u(y_M) - 6\lambda. \tag{1.4}$$

If λ is small, this condition will be satisfied.

Now, however, if payments can be renegotiated, the new scheme laid out in Table 1.2 will prevail so long as $\tilde{u} - \lambda > \overline{u}$, where $\tilde{u} = \frac{1}{3}(u(y_M - 0.5m) + u(y_M) + u(y_M + 0.5m))$, the ex ante outcome for types B and C under the renegotiated insurance scheme.

Introduction of this new insurance scheme only to agents in Group A will actually decrease overall welfare (which I measure as the sum of individual utilities) if

$$(1-\beta)u_1 + \beta(\hat{u} + 2\tilde{u}) - 2\lambda < 3u(y_M) - 6\lambda. \tag{1.5}$$

Thus, defection of Group A agents from the original insurance scheme will occur and will be welfare reducing if

$$\frac{(1-\beta)u_1 + \beta(\hat{u} + 2\tilde{u}) - 3u(y_M)}{4} > \lambda > \frac{(1-\beta)u(y_H - x) + \beta\hat{u} - u(y_M)}{2}. \tag{1.6}$$

It should be mentioned again here that this welfare loss is dependent on monitoring for moral hazard being relatively cheap in the traditional network scheme.

In this model, then, increased presence of formal financial institutions is predicted to lead to less participation in community networks, especially by those individuals who are more likely to be eligible for credit from these institutions (probably the agents with relatively higher incomes). The model also predicts that welfare will decrease in certain circumstances, especially for those with less ability to participate in formal financial institutions.

1.2.2 Network Size Effect

Now, include a network size effect $f_i(M, P_i)$ in the individual's utility function such that

$$U_i = (1-\beta)\sum_{t=0}^{\infty}\beta^t(u(y_{it}) - \frac{1}{2}\lambda l_i + f_i(M_i, P_i)) \tag{1.7}$$

where M is the number of agents in the network and P_i is an indicator for whether agent i participates in the traditional insurance scheme. Let $f(.,.)$ be increasing in M, with $f(0,.) = 0$ (that is, those who are not part of the network receive none of these benefits) and assume $f(M, 1) \leq f(M, 0)$ for a given value of M.

The network effect function f attempts to capture various additional benefits of network membership that are independent of the identity of one's network neighbors. Many possible justifications exist for the inclusion of this term and for its increasing in M. These benefits could be the result of costless information transfer over network links, such as about weather, crop infestations, or village events. They could also be the result of a network externality in consumption or production, such as communal production on village lands with increasing returns to scale, reduction of agricultural pests on one's own plots from the efforts of others to do so on their own plots, or participation in village social and religious life. Higher values of f for those who continue to participate in the network without participating in the associated insurance represent increased value of village membership for these individuals. I include this increased value because it allows me to examine the effects of the modern insurance scheme if individuals entering the modern scheme desire to remain in the social network in other ways. This might be the case, for example, if the network is able to substitute for benefits that previously arose as part of the network insurance relationship, such as pleasant social interactions with other village members. These effects also reflect a view that leaving the network may be quite a drastic action, entailing something like a physical move to another location. Empirical research such as that of Fafchamps and Lund (2003) shows that individuals still choose village life, implying they find it valuable, even though insurance is provided by family and friends rather than by the village as a whole. Finally, it is important to note that the inclusion of network effects apart from the benefits of network insurance implies that those who choose to leave a mutual insurance scheme cannot or will not be excluded from other aspects of village life by disgruntled former insurance partners.

The original configuration will be stable to agents leaving the network and insurance scheme if and only if $u(y_M) + f(3N,1) - 2\lambda > \overline{u}$, which will be true as long as overall network effects, $f(3N,1) - 2\lambda$, are not too negative. Since belonging to the network now has some intrinsic benefit associated with it, we must also consider whether agents might desert the insurance scheme but remain in the network. A necessary condition for this to occur is that $u(y_M) < \overline{u} + \Delta f(3N)$ (where $\Delta f(M) = f(M,0) - f(M,1)$), so I will assume $u(y_M) - \overline{u} > \Delta f(3N)$ to ensure initial stability. Given this specification, however, agents in Group A may now have as a best response deserting the traditional insurance scheme but remaining within the social network, once the modern insurance scheme is introduced. If agents must choose to retain all existing ties or desert the entire network, type A agents will stay in the network but take the payout from the modern rather than the traditional insurance scheme if $(1-\beta)u(y_H - x) + \beta\hat{u} > u(y_M) - \Delta f(3N)$ and $2\lambda < f(3N,0)$. That is, agents stay in the network without insurance if overall network effects (for $P_i = 0$)

are positive but the outside income source provides higher utility than the insurance scheme. In the rest of this analysis, I will consider only the case in which type A agents choose to remain in the network but leave the insurance scheme, since the case in which they leave the network was considered above.

Given that type A agents leave the traditional insurance scheme while remaining in the network, types B and C will not want to drop out if and only if $\overline{u} < \tilde{u} + f(3N,1) - 2\lambda$. This will be true as long as $\Delta f(3N)$ is not too large, since $\overline{u} < \tilde{u}$ and $2\lambda < f(3N,0)$. Types B and C will never choose to remain in the network without insurance, as type A might, because $\overline{u} < \tilde{u}$.

Given that type B and type C agents remain in the revised network insurance scheme, total welfare will be

$$N((1-\beta)(u(y_H-x)+u(y_M)+u(y_L))+\beta(\hat{u}+2\tilde{u})+2f(3N,1)+f(3N,0)-6\lambda), \quad (1.8)$$

leading to a change in welfare of

$$N((1-\beta)u_1+\beta(2\tilde{u}+\hat{u})-3u(y_M)+\Delta f(3N)). \quad (1.9)$$

If $\Delta f(3N)$ is not too big, net welfare will decrease.

If type B and type C agents drop out, which will occur, as discussed above, when $\Delta f(3N)$ is relatively large, the network will collapse and total welfare will be $((1-\beta)u_1+\beta(\hat{u}+2\overline{u}))N$, leading to a change in welfare of

$$((1-\beta)u_1+\beta(\hat{u}+2\overline{u})-3u(y_M)-3(f(3n,1)-2\lambda))N. \quad (1.10)$$

Since full insurance provides higher utility than no insurance or the modern scheme, welfare will decrease if $2\lambda - f(3N,1)$ is sufficiently small.

1.3 Empirical Analysis

1.3.1 Data

I use data from the Indonesian Family Life Surveys (IFLS) to test the predictions of this model. This survey was carried out in three waves in 1993, 1997, and 2000 among a sample of 7,224 households in 13 of the 26 Indonesian provinces (a 2007 wave was also performed, but I have not yet incorporated this data in my analysis) (Frankenberg and Karoly, 1995; Frankenberg and Thomas, 2000; Strauss et al., 2004). The IFLS data contains community-level variables for number and type of financial institutions and household-level data on expenditure, child health, participation in community activities, and credit availability through the family network. This study also includes data on community-level control variables that measure economic integration, village size, and economic development. Given the linguistic diversity of Indonesia, I also use a set of 18 language dummy variables (one for each language used in conducting surveys).

My financial institution variable is constructed for 1997 and 2000 as how many of seven different types of financial institutions are available for a village. This variable provides a simple first pass at understanding the effects of having more financial options. This version will work best if financial institutions are relatively constant and homogeneous in the effect of adding one more option. Because this may not always be the case, I also examine the effects of each one individually later on in the paper. The seven types of financial institutions are Bank Rakyat Indonesia (BRI), a large, government-owned (at the time) bank specializing in microfinance; People's Credit Banks (BPR), small, rural, private banks; Village Credit Institutions (LKD), very small banks supervised by BRI; Village Credit Fund Institutions (LDKP), regional non-bank entities that carry out microfinance; Village Unit Cooperatives (KUD);

other formal cooperatives; and private banks. Conroy (2000) provides helpful explanations of the function of most of these financial institutions.

I use per capita household expenditure as a measure of welfare, where values are adjusted for inflation. Community participation is measured as how many of eight different community building activities were participated in by members of the household, dividing by the number of household members to obtain a per capita measure. These activities include community meetings, cooperatives, voluntary labor projects, programs to improve the village or neighborhood, neighborhood security organizations, projects to create a system for garbage disposal, women's association activities, and projects to create community weighing posts for weighing and caring for the health of children. Days sick is computed as a per-child average for the past month for children 15 and under by asking parents, guardians, or the children themselves (for children over 11 years old).

The variables I will use are summarized in Table 1.3.

1.3.2 Empirical Strategy

To reiterate, the model explained in the previous section produces several testable implications:

1. An increase in the availability of credit will reduce participation in social networks, especially among households that receive the most access to credit as a result.

2. This reduction in social network participation will reduce the welfare of participants in the network, especially for those households with the least access to credit.

3. Financial institutions with a stronger profit motive will be less likely to lend to the poor, so that welfare will decrease more for the poor as the result of the introduction of a financial institution with a stronger profit motive.

4. Community activities that are more closely related to the economic network in a village will be more likely to be disrupted by the introduction of a financial institution than activities are more purely social in nature.

In order to test these hypotheses, I use Indonesian data that includes information on different village financial institutions to see how changes in availability of these institutions between 1997 and 2000 affect participation in various community organizations and projects. The main regression specification I use is

$$\Delta y = \alpha + \beta(\Delta FI) + \gamma(1993Exp.) + \delta(\Delta FI) * (1993Exp.) + X'\theta + \epsilon, \qquad (1.11)$$

where Δy is the change in an outcome variable, such as community participation, average days a household's children were sick in the past month, or log per capita expenditure. ΔFI is the change in the financial institutions index described above, and $1993Exp.$ is 1993 log per capita expenditure. X is a set of village and household controls, as described above. Observations are at the household level. The regression is in differences in order to focus on the effects of *changes* in financial institution availability on outcome variables, though a roughly equivalent regression could also be run using levels of these variables and interactions with the year that observations are from.

If implication 1 above is true, the coefficient on the financial institutions index in the regression with the change in community participation as the dependent variable should be negative, and the coefficient on the interaction with 1993 expenditure should also be negative; if implication 4 is true, these effects should be stronger when the change in participation in a community activity that is more economic in nature is involved. If implication 2 is true, the coefficient on the financial institutions index in the regression with the change in expenditure as the dependent variable could be positive or negative, and the coefficient on the interaction with 1993 expenditure should be negative. If implication 3 is true, then, when we split the financial institutions index into the individual types of institutions involved and look at the effect of each separately, financial institutions with a stronger profit motive will see a larger coefficient on the interaction term in the direction indicated for the other implications.

One important requirement for this identification strategy to be valid is that changes in the availability of financial institutions should be plausibly exogenous to the relationships investigated in this paper. For example, exogeneity could be violated if financial institutions are more likely to establish a presence in places that have weak social networks or more poor people. Several circumstances provide arguments in favor of exogeneity in this case. First, between 1997 and 2000, Indonesia underwent a severe financial crisis, which put severe stress on many financial institutions, especially banks and other for-profit organizations. These problems were likely to be the first-order consideration for these institutions in deciding to expand or retract their operations, not local conditions. Second, one might worry that non-profit organizations, such as microfinance-oriented NGOs, might be more likely to establish operations in poorer locations. However, unlike in many developing countries, even in Southeast Asia, NGOs play only a very small role in microfinance in Indonesia. Instead, the main player in this field in Indonesia during this time was Bank Rakyat Indonesia (BRI), which was owned by the Indonesian government during the period under study and which came largely unscathed through the 1997 financial crisis, in large part because of the success of its microfinance division (Conroy, 2000). Because BRI was a government enterprise, its practices relating to the expansion of its business may be expected to be more even-handed in seeking to extend credit access. Third, one might be concerned about unobserved village characteristics influencing both financial institutions' decisions and social cohesion within a village. Therefore, I am controlling for several village characteristics, including village size, the distance from the village to provincial headquarters, and the percent of households in the village that have electricity. Some households may have access to other social networks aside from the village that also provide insurance, especially within kin relationships, so I am also controlling for the number of siblings that the household head has outside the village.

Accounts of the history of financial institutions in Indonesia also provide information about the ways and reasons that different types of institutions spread. According to Robinson (2002), government requirements were important in some sectors. For example, "[i]n 1999 new regulations increased capital requirements for opening new BPRs or branches by 10 times, to 500 million rupiah. Adjusting for inflation, the new capital requirement was more than three times the previous requirement" (p. 102). Starting in the early 1990s, the Indonesian government also required banks to use a certain percentage of their credit volume or profits to support small enterprises or microfinance. Bank Indonesia, the central bank, also participated indirectly in microfinance at during the 1990s by providing credit subsidies to village cooperatives (KUD), as well as through the branches of BRI. Another important feature is the large increase in the early 1990s of BPRs, which can be either public or private, and public LKDPs and the troubles that these faced during the financial crisis, when 45% of these institutions were reported to not be in full health (p. 113). In addition to this, an array of other, village-level institutions exist that provide additional financial options, but almost all are public, receive government assistance, or both. Therefore, they are heavily tied to the national government's goals of furthering credit access for the poor through microfinance products. Unfortunately, many of the government programs designed for this purpose fail to achieve it, particularly credit subsidies, and these programs are likely to fail quickly as the government loses interest.

As an additional way to see what financial institutions are basing their location decisions on, I run a household-level regression of the change in financial institution presence on the 1997 values of the major dependent and independent variables in my main regressions, which are described above. The results of this exercise are in Table 1.4. The regression in the first column of the table has as its dependent variable the change in an index of financial institution availability that includes seven different types of financial institutions, which are described above. None of the explanatory variables are statistically significant in this column, and their substantive significance is also quite low, with most of the variables having less than a 0.1 financial institution effect for a one standard deviation change in the variable. When I perform this exercise separately for each type of financial institution, shown in columns two through eight, no clear patterns emerge, though a few variables have statistically significant effects for one financial institution or another. The results of this exercise thus provide evidence that financial institutions are not using the variables included here to decide whether to add or remove their presence in an area. As an additional exercise to understand the decisions of specific kinds of institutions, in Table 1.5 I show the marginal effects at the mean of probits with the same independent variables and a dependent variable of whether there was any addition of a financial institution, in column (1), and whether each type of financial institution was added, in columns (2) through (8). Table 1.6 does the same for the loss of financial institutions. Households with higher income were less likely to see new types of financial institutions, especially "other formal cooperatives," LDKPs, and private banks, arrive in their village, but were also less likely to see financial institutions leave the village, especially "other formal cooperatives" and LKDs. Having siblings living outside the household also made a household more likely to see financial institutions arrive in or leave their village. Financial institutions were more likely to arrive in, but not to leave, villages with a higher percentage of households having electricity. These probits were at the household level of observation, but running them at the village level provided similar results, but with a lower level of statistical significance[1].

Table 1.7 has information about the proportion of households in the sample that had access to each type of financial institution in 1997 and 2000, as well as the number of households that lost or gained each different type of financial institution. As this table shows, most financial institution types had a high degree of turnover, with large numbers of most types entering some villages and exiting others. Most types of financial institutions had some closures on net between 1997 and 2000, most likely due to the financial crisis, but Village Credit Institutions (LKDs) and Village Unit Cooperatives (KUDs) were hit especially hard. "Other formal cooperatives" were the only institutions to exhibit an increased presence over the period.

A check of the validity of the strategy used in this paper is to see if having access to more financial institutions actually increases the use of financial products. Though I do not have data on specific financial products in the IFLS, the 1997 wave does have a set of questions about the amount of debt that households have, including the current amount of debt as well as the amount of new debts in the past year and the amount of debts paid off in that period. Debt is not a perfect proxy for financial product access, but seeing movement in these variables does indicate that different financial institutions change the financial landscape for households. Reductions in debt may indicate improved saving technologies that are introduced, for example. I regress the various debt variables, measured in millions of rupiahs, on different measures of financial institution availability, including the index that combines the various types of financial institution and the set of disaggregated institution types, along with the set of controls used in the main regression specification (to be described hereafter). Because one prediction of the model is that making lending more available

[1]Available upon request from the author

only to certain groups, such as the rich, will have very different effects than broad-based lending, I also perform a specification in which I interact expenditure with each type of institution. The results of these regressions are in Table 1.8. Columns one, four, and seven have the combined financial institution variable's effect on current debt, new debt, and paid-off debt, respectively. Though the main coefficient is not statistically significant in these regressions, a change of one standard deviation in financial institution availability increases current debt by 128,000 rupiahs, new debt by 222,000 rupiahs, and paid debt by 249,000 rupiahs. These magnitudes are fairly large given that average current debt in this year was 1.24 million rupiahs and the exchange rate was around 2400 rupiahs per US dollar (Chen, 2010). Columns two, five, and eight look at the effect of each type of financial institution individually, and columns three, six, and nine add interactions of these types with 1997 log household expenditure. BPR branches and private banks have a strong positive effect on levels of debt as well as changes in debt (both new and paid), while LDKPs, BRI branches, and LKDs have fairly strong, though not always significant, negative effects on debt and changes in debt (except that BRI increases debt paid off). These negative effects are consistent with the fact that BRI offers an array of savings products that are an important part of its business (Robinson, 2002). The two categories of cooperatives considered produce reductions in debt overall because debt paid off is greater than new debt, though both are positively affected. The interactions with log expenditure show that many of these financial institutions have quite different effects on high-expenditure households than on low-expenditure households, as is required for the assumptions to hold that underlie the estimations in this paper.

Another useful check of how well this strategy will test the predictions of the model is to look at financial institutions' lending standards and practices to see who they say they target or actually lend to. Robinson (2002) has an extensive discussion of these standards and practices for different institutions and finds a wide variety. She finds, for example, that BPRs vary significantly in how much they loan to the poor; in one chapter, she says she will discuss several BPRs that "are sustainable financial intermediaries that serve both poor and non-poor clients," but that another BPR "provides a classic example of how corruption, politicization, and lack of accountability can prevent profitable commercial microfinance while putting poor savers' money at risk" (pp. 84-85). This last bank mentioned is an example of an institution that would be a good test of the theory in this paper. The credit subsidies provided by the Indonesian government during this time were often thought to benefit primarily a narrow crony network, rather than all potential borrowers (p. 107).

Community participation will serve as a proxy for the strength of traditional village networks in this approach. This is an imperfect measure in several ways. First, it does not actually allow us to observe the structure of the village network: who is connected to whom and in what ways they are connected. This means some implications of a theoretical model that is based on these networks will be harder to test. Second, community participation may reflect other modes of interaction within the village apart from the economic network, such as religious or purely social ties. This could cause the effects on the economically oriented network to be understated or overstated if some of the activities that make up the index of community participation are really not related to this network (depending on these activities' response to the changes in independent variables. Looking at these different activities separately will help me to eliminate this source of potential bias. Third, outside intervention, such as government funding, could affect participation levels in some community activities by making them easier to fund. As long as this government funding is uncorrelated with the change in financial institutions or pre-period expenditure, it should not affect the results of my regressions. Despite these drawbacks, community participation does reflect the ties that individuals and households have to others in their community that make them willing to contribute to public goods, which are likely to be the same ties that allow them to borrow from and lend to one another without fearing a lack of reciprocity.

Attrition is another potential source of bias in these results if those who attrit are different than those who remain in the sample in fundamental ways. Thomas et al. (2010) address the ways that the survey design of the IFLS seeks to reduce attrition in successive waves by seeking information that will allow them to follow and re-contact survey respondents in future waves. Thomas et al. (2010) find that attrition among adults is associated with education, age, and baseline location, as well as other observed and unobserved characteristics. It is unclear what characteristics of the baseline location are associated with attrition, but attrition could be a special concern if it is correlated with financial institution presence or overall community participation levels. Nevertheless, the 1997 and 2000 waves of the IFLS were successful at interviewing over 90% of the originally selected, eligible target households, which helps reduce these concerns about attrition somewhat.

I am focusing on credit in the empirical analysis because it can function as insurance (though it also has other functions, of course) so that it is relevant to the model just presented and because good data is available regarding the presence of different financial institutions in Indonesia that provide credit products.

1.3.3 Results

Column (1) of Table 1.9 shows the results of regressing the change in per capita household participation between 1997 and 2000 on the change in the number of available financial institution types, per capita household expenditure in 1993, and the interaction of these variables. In all regressions, errors are clustered at the village level. The 1993 per capita expenditure variable is meant to serve as a predetermined measure of how well-off a household is, which will allow me to test prediction 1, that the effects of introducing financial institutions may differ with variation in the resources to which a household has access. Column (2) adds the village controls, the set of language dummies, and the measure of change in outside networks. Columns (3) and (4) have the same respective sets of independent variables, with change in log per capita household expenditure as the dependent variable. Columns (5) and (6) have the same independent variables again with the change in child illness on the left hand side.

The model would predict that the coefficients in columns (1) and (2) of Table 1.9 on the variables for the change in the number of kinds of financial institutions and its interaction with 1993 log per capita expenditure would be negative if all types of financial institutions have the same effect in reducing participation and have a greater effect on richer households. However, once the regression is actually run, the coefficient on the interaction proves to be positive, though very small and not significant, and the financial institution coefficient is statistically insignificant and quite small (only a reduction of 0.071 in the change of activities participated in for one more financial institution added for a household two standard deviation below the mean in 1993 log per capita expenditure and a reduction of 0.024 activities for a household two standard deviations above the mean[2]), though negative.

In columns (3) and (4), once again, the coefficients on the financial institutions variable and its interaction with the variable for 1993 log per capita expenditure are insignificant, though they are negative and positive, respectively, as one would predict if financial institutions help mostly higher-expenditure individuals while weakening social networks for all[3], as prediction 2 says. The effect of increasing financial institutions by one on a household with 1993 log per capita expenditure two standard deviations below the mean would be a 7.4% reduction in the change in expenditure

[2]Based on column (1)

[3]As long as moral hazard conditions do not make network participation too costly

between 1997 and 2000, while a household two standard deviations above the mean would see a 4.0% reduction[4].

Since child sickness is a measure of lower welfare, the coefficient on the change in financial institutions variable is predicted to be positive and the coefficient on the interaction with 1993 expenditure is predicted to be negative, but these predictions are not borne out in columns (5) and (6), though the coefficients are statistically indistinguishable from zero. A household with 1993 log per capita expenditure two standard deviations below the mean is predicted to have a change of 0.020 fewer sick days in the past month as a result of adding one more financial institution, while a household two standard deviations above the mean is predicted to have a change of 0.026 fewer sick days.[5] Adding the set of control variables in columns (2), (4), and (6) does not materially change the results.

Table 1.10 examines the effects on specific community-building activities instead of the broader community participation variable, which allows a test of hypothesis 4. These effects are also somewhat easier to explain and interpret. Though the coefficient on the change in the number of kinds of financial institutions has the correct (negative) sign in all but one regression, this is never statistically significant. The interaction term has a negative sign for its coefficient in all but one of these regressions, which is the opposite of the prediction, but none of these is statistically significant. The largest effect, for example, was for neighborhood improvement programs, which saw a decrease of 0.045 in the change in participation for households two standard deviations below the mean in 1993 log per capita expenditure and a decrease of 0.011 for households two standard deviations above the mean. Thus, introduction of a new financial institution does not seem to have a significant effect on these community participation measures individually either.

[4]Based on column (3)

[5]Based on column (5)

Table 1.11 looks separately at the effects of introduction or removal of the seven different types of financial institutions discussed above, along with interactions with log 1993 per capita household expenditure, to test prediction 3 above. The dependent variables and control variables are the same as the respective columns in Table 1.9. None of these types of financial institutions has a statistically significant effect on the change in participation or children's number of sick days. Only BRI and the LDKPs had a significant effect on the change in expenditure in column (4): BRI had a negative effect on expenditure change for households with low expenditure in 1993 and a less negative effect on households with high expenditure[6], as the model predicts for institutions that tend to lend to high earners, and the LDKPs had the reverse effect, as would be predicted for institutions that tend to lend to poor households[7]. Private banks have a significant effect on the change in expenditure in column (3) that is similar in direction to the effect of the LDKPs, raising the difference in expenditure for households with more 1993 expenditure and raising it even more for households with low 1993 expenditure, though the relationship weakens when controls are added.

Because the community participation difference variable may not be a linear measure of the strength of a social network, I also employ an ordinal logit, in which the dependent variable is the decile of the distribution of changes in participation, to provide a different way of getting at the effects of changes in financial institution availability. Table 1.12 displays the results of this ordinal logit. For a easier interpretation of these results, Table 1.13 gives the probability that an household that faces the given change in financial institutions will find itself in each of the sample deciles. Since the underlying data is fairly granular, the deciles do not contain exactly 10 percent; in particular, there is a large group of households that had no change in

[6] In column (4), negative 97% for a household two standard deviations below the mean for 1993 log per capita expenditure and negative 32% for a household two deviations above

[7] In column (4), positive 272% for a household two standard deviations below the mean for 1993 log per capita expenditure and positive 52% for a household two deviations above

participation and end up in the 6th decile, so that no 7th decile exists. These tables paint a similar picture to the results in Table 1.9, with a reduction or increase in financial institutions making little difference in levels of participation in community activities. Indeed, going from a +1 increase in financial institutions to a +2 increase had no influence at all on any of the probabilities of being in a given decile.

1.4 Conclusion

This paper's model has shown that modernization can be a mixed blessing under some circumstances and, indeed, has the potential to reduce overall welfare, particularly when the gains of modernization are unevenly distributed. When this uneven distribution of gains occurs, existing traditional social institutions that were based on the old market structure (or lack thereof) may weaken or disintegrate, creating a welfare reduction for those with little access to the modern institutions that are supposed to act as substitutes. Even when those with access to modern institutions retain some network affiliation, overall welfare can decrease.

The ideas in this paper may be especially salient for those seeking to extend modern institutions of credit, insurance, communication, and so on to the poor. If program coverage is uneven, such as if microcredit is offered only to the relatively less poor or the more entrepreneurial in a village, the program may have unforeseen and unintended adverse consequences on nonparticipants, especially if programs disrupt traditional social ties. Morduch (1999) discusses further the tradeoffs regarding cost and overall program effect involved in determining the proper scope of microcredit and possibilities for sustainability. One particular concern is that a drive for sustainability may lead microcredit providers to target a relatively prosperous subset of a village's population so as to be able to make bigger loans and thus reduce relative monitoring costs, while leaving out poorer potential borrowers.

This paper has used a model which begins with a stable network configuration, then introduces an exogenous change to the setup to examine its effects on network structure and agent welfare. This shows the potential usefulness of network models in explaining both the stable configurations of economic networks and the changes induced in these networks when the "rules of the game" change. By using this idea and by restricting agent actions in a natural way so that agents must drop out of the network rather than deleting links to individual nodes, I have reduced the multiplicity of possible equilibria that is often involved in models of network formation, particularly when pairwise stability is the equilibrium concept used.

This paper performed empirical tests, using Indonesian household survey data, of the model's prediction that introduction of formal financial institutions will reduce participation in social networks, especially for those with the most access to formal credit, and may reduce welfare, especially for those with the least access to formal credit. These tests had mixed results at best when carried out with all financial institutions aggregated, but the predictions were mostly borne out for three individual types of formal financial institutions.

The empirical part of this paper has not worked with the actual underlying social networks of individuals linked to one another in the Indonesian case studied, because this data does not exist in the data set used. Further research on this subject should seek to collect this type of data to try to understand the details of these social networks, especially as they relate to economic structures within a village, and how these are mediated by and shape community institutions.

1.5 Figures and Tables

Table 1.1: Agent Payoffs in each State of the World

State	Probability	Received by Agents in Group A	Received by Agents in Group B	Received by Agents in Group C
1	1/3	y_H	y_M	y_L
2	1/3	y_M	y_L	y_H
3	1/3	y_L	y_H	y_M

Table 1.2: Insurance Payments under New Scheme

		Income realization of linked agent		
		y_H	y_M	y_L
Agent's income realization	y_H	0	$0.25m$	$0.5m$
	y_M	$-0.25m$	0	$0.25m$
	y_L	$-0.5m$	$-0.25m$	0

Table 1.3: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Total siblings outside HH: 1997	7.23	4.33	0	37
Total siblings outside HH: 2000	7.37	5	0	77
Total financial institutions: 1997	3.06	1.45	0	7
Total financial institutions: 2000	2.76	1.29	0	7
Distance to regency headquarters	21.4	29.3	0	198
Percentage of HHs with electricity: 1997	78.3	28.3	0	100
Number HHs in village	1909	4392	38	90554
Community participation: 1997	1.02	0.862	0	5
Community participation: 2000	0.739	0.750	0	4.5
Number days children sick: 1997	1.07	2.13	0	28
Number days children sick: 2000	1.24	2.43	0	30
Log household expenditure: 1993	14.60	1.66	8.23	21.33
Log household expenditure: 1997	15.86	0.88	11.88	20.22
Log household expenditure: 2000	15.85	0.82	11.78	19.81

Table 1.4: Influence of 1997 Levels of Major Dependent and Independent Variables on 1997-2000 Change in Financial Institutions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	ΔFIs	ΔBRI	ΔBPR	ΔLKD	ΔLDKP	ΔKUD	ΔOther Coop.	ΔPrivate bank
1997 Participation	0.00387	0.000526	-0.00310	0.00137	0.00640	-0.000883	-0.00627	0.00582
	(0.020)	(0.0014)	(0.0073)	(0.0065)	(0.0042)	(0.0066)	(0.0087)	(0.0066)
1997 Log Expenditure	-0.0791	-0.00343	-0.0226	0.0180	-0.0214	-0.00952	-0.00550	-0.0346
	(0.060)	(0.0082)	(0.019)	(0.022)	(0.017)	(0.022)	(0.025)	(0.023)
1997 Days Sick Per Child	0.00875	-0.00358*	0.00348	-0.00406	0.00767*	0.00323	-0.00307	0.00507
	(0.013)	(0.0020)	(0.0046)	(0.0058)	(0.0046)	(0.0049)	(0.0061)	(0.0054)
Outside Siblings	-0.00478	-0.00202**	-0.000462	-0.00310	-0.000533	-0.000319	0.00394	-0.00228
	(0.0073)	(0.0010)	(0.0023)	(0.0024)	(0.0015)	(0.0024)	(0.0033)	(0.0028)
Distance to HQ	-0.00270	-0.00112	-0.00160	0.000881	0.000220	-0.000959	0.000984	-0.00110
	(0.0031)	(0.0012)	(0.0012)	(0.0012)	(0.00053)	(0.0016)	(0.0013)	(0.0013)
% with Electricity	0.00408	0.000416	-0.000237	0.000209	0.000146	0.000426	0.000752	0.00237
	(0.0040)	(0.00070)	(0.0012)	(0.0011)	(0.00086)	(0.0016)	(0.0013)	(0.0015)
Number Households	-0.00000256	-0.000000345	0.00000238	-0.00000782***	-0.000000343	0.00000194	-0.00000118	0.00000281
	(0.0000093)	(0.00000073)	(0.0000026)	(0.0000028)	(0.0000016)	(0.0000026)	(0.0000033)	(0.0000042)
Constant	0.801	0.0715	0.373	-0.385	0.272	-0.0249	0.0700	0.424
	(0.93)	(0.16)	(0.30)	(0.34)	(0.25)	(0.37)	(0.40)	(0.38)
Language Dummies?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5003	5003	5003	5003	5003	5003	5003	5003
R-squared	0.08	0.15	0.04	0.04	0.04	0.05	0.04	0.06

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

Table 1.5: Influence of 1997 Levels of Major Dependent and Independent Variables on 1997-2000 Addition of Financial Institutions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	Any New	BRI	BPR	LKD	LDKP	KUD	Other Formal Coop.	Private bank
Participation Index	0.000476	-0.0270	0.00793	0.0234	0.0315*	0.00967	0.0184	-0.00372
	(0.013)	(0.017)	(0.020)	(0.021)	(0.019)	(0.017)	(0.016)	(0.017)
Log HH Expend.	-0.137***	-0.0248	-0.0760	-0.0110	-0.141	-0.00589	-0.128**	-0.140**
	(0.048)	(0.083)	(0.063)	(0.071)	(0.10)	(0.045)	(0.060)	(0.058)
Child Days Sick	0.0114	-0.0523	-0.00429	-0.00482	0.0406*	0.00367	-0.000605	0.0103
	(0.011)	(0.039)	(0.014)	(0.014)	(0.023)	(0.017)	(0.015)	(0.013)
Outside Siblings	0.0263***	-0.00438	0.00371	-0.000507	0.0184**	0.0223***	0.0228***	0.0125**
	(0.0058)	(0.0058)	(0.0075)	(0.0077)	(0.0090)	(0.0060)	(0.0075)	(0.0058)
Distance to HQ	-0.00354	0.00634	-0.0122	0.00215	-0.0154	-0.00164	0.00174	-0.00368
	(0.0031)	(0.0049)	(0.0075)	(0.0055)	(0.012)	(0.0045)	(0.0039)	(0.0045)
% with Electricity	0.00603*	-0.00121	0.00232	0.00713*	0.00296	0.000811	0.00938**	0.00761*
	(0.0031)	(0.0030)	(0.0041)	(0.0040)	(0.0047)	(0.0060)	(0.0047)	(0.0043)
Number Households	-0.0000456	0.00000365	-0.0000787	-0.000147**	-0.000130*	-0.0000623	-0.00000869	-0.0000104
	(0.000034)	(0.0000078)	(0.000051)	(0.000066)	(0.000075)	(0.000071)	(0.000014)	(0.000015)
Constant	1.400*	-1.497	-0.188	-1.914*	0.399	-1.645*	0.0564	0.578
	(0.77)	(1.55)	(1.05)	(1.15)	(1.72)	(0.86)	(1.01)	(0.91)
Language Dummies?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6123	5119	5745	5831	5624	5705	5999	6005

Robust standard errors in parentheses, household level observations, marginal effects from probit
*** p<0.01, ** p<0.05, * p<0.1

Table 1.6: Influence of 1997 Levels of Major Dependent and Independent Variables on 1997-2000 Loss of Financial Institutions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	Any Lost	BRI	BPR	LKD	LDKP	KUD	Other Formal Coop.	Private bank
Participation Index	0.0124	-0.0659**	0.0168	0.00646	-0.0242	0.00686	0.0428**	-0.0238
	(0.012)	(0.029)	(0.018)	(0.015)	(0.022)	(0.015)	(0.017)	(0.016)
Log HH Expend.	-0.123***	0.129	0.0358	-0.120**	0.0279	-0.0190	-0.0962*	0.0235
	(0.046)	(0.083)	(0.052)	(0.060)	(0.065)	(0.056)	(0.057)	(0.058)
Child Days Sick	0.00115	0.0339*	-0.0118	0.0116	-0.0244	-0.00489	0.00996	-0.0117
	(0.011)	(0.018)	(0.014)	(0.016)	(0.021)	(0.011)	(0.012)	(0.014)
Outside Siblings	0.0314***	0.0484***	0.0113*	0.0207***	0.0204***	0.0242***	0.00699	0.0212***
	(0.0058)	(0.0065)	(0.0060)	(0.0064)	(0.0073)	(0.0059)	(0.0074)	(0.0075)
Distance to HQ	0.00549**	0.00671*	0.00166	-0.00217	-0.00715	0.00253	-0.00287	0.000443
	(0.0023)	(0.0038)	(0.0033)	(0.0032)	(0.0049)	(0.0034)	(0.0052)	(0.0035)
% with Electricity	0.00413	-0.0126*	0.00310	0.00255	0.00119	-0.000350	0.00810**	-0.00140
	(0.0029)	(0.0068)	(0.0039)	(0.0040)	(0.0064)	(0.0034)	(0.0039)	(0.0041)
Number Households	-0.00000111	-0.0000543	-0.000105*	0.0000119	-0.0000315	-0.0000350	-0.00000495	-0.000135*
	(0.000011)	(0.000095)	(0.000061)	(0.0000094)	(0.000044)	(0.000037)	(0.000012)	(0.000071)
Constant	1.159	-3.747**	-2.068**	0.433	-1.948**	-0.771	-0.483	-1.359
	(0.74)	(1.56)	(0.86)	(0.95)	(0.92)	(0.91)	(0.97)	(0.97)
Language Dummies?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6143	5008	6084	6110	5763	6129	6044	6030

Robust standard errors in parentheses, household level observations, marginal effects from probit
*** p<0.01, ** p<0.05, * p<0.1

Table 1.7: Financial Institution Presence in Surveyed Households: 1997 and 2000

Financial Institution	Proportion: 1997	Proportion: 2000	Became Available	Became Unavailable
Bank Rakyat Indonesia (BRI)	0.964279	0.960413	160	195
People's Credit Bank (BPR)	0.343881	0.303825	1020	1393
Village Credit Institution (LKD)	0.296219	0.195507	639	1474
Village Credit Fund Institution (LDKP)	0.08607	0.053673	357	608
Village Unit Cooperative (KUD)	0.570945	0.412386	625	1977
Other Formal Cooperative	0.269254	0.319004	1619	1159
Private bank	0.538806	0.525683	1305	1354

Table 1.8: Effect of Financial Institutions on Current Debt, New Debt from Past Year, and Debt Paid off in Past Year: 1997 Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
COEFFICIENT	currentdbt97	currentdbt97	currentdbt97	newdbt97	newdbt97	newdbt97	paiddbt97	paiddbt97	paiddbt97
Number Fin. Inst. Types: 1997	0.0885			0.153			0.172		
	(0.072)			(0.11)			(0.11)		
1997 Log Expenditure			-1.321			-0.762			0.0171
			(1.00)			(0.63)			(0.23)
Bank BRI		-1.348	-38.65**		-1.005	-26.93**		0.147	-1.934
		(1.06)	(16.6)		(0.92)	(11.3)		(0.16)	(5.28)
(BRI)x(1997 Expend.)			2.350**			1.643**			0.137
			(0.99)			(0.67)			(0.33)
People's Credit Bank (BPR)		0.859	-18.62		0.965*	-27.01		0.678*	-15.96
		(0.53)	(16.3)		(0.56)	(18.2)		(0.41)	(12.0)
(BPR)x(1997 Expend.)			1.210			1.759			1.038
			(1.05)			(1.18)			(0.78)
Village Credit Institution (LKD)		-0.164	-1.395		-0.431	11.08		-0.446	13.10
		(0.40)	(11.4)		(0.52)	(13.6)		(0.41)	(10.5)
(LKD)x(1997 Expend.)			0.0780			-0.727			-0.847
			(0.73)			(0.88)			(0.68)
Village Credit Fund Institution (LDKP)		-0.713*	14.08		-0.896**	18.12		-0.607*	9.624
		(0.40)	(9.91)		(0.43)	(12.4)		(0.32)	(8.62)
(LDKP)x(1997 Expend.)			-0.915			-1.187			-0.632
			(0.64)			(0.79)			(0.55)
Village Unit Cooperative (KUD)		-0.200	6.435		0.0213	1.808		0.162	-7.583
		(0.43)	(11.6)		(0.41)	(12.1)		(0.23)	(6.38)
(KUD)x(1997 Expend.)			-0.395			-0.104			0.488
			(0.74)			(0.77)			(0.40)
Other Formal Cooperative		-0.0455	2.249		0.180	-10.76		0.387	-10.06
		(0.47)	(12.2)		(0.63)	(14.5)		(0.52)	(9.14)
(Other Coop.)x(1997 Expend.)			-0.157			0.676			0.644
			(0.78)			(0.93)			(0.60)
Private bank		0.499	-5.907		0.649	-7.913		0.449**	-6.849
		(0.40)	(12.7)		(0.41)	(13.0)		(0.21)	(4.53)
(Private bank)x(1997 Expend.)			0.388			0.527			0.445
			(0.81)			(0.83)			(0.29)
Outside Siblings	0.0115	0.0152	-0.0263	-0.00877	-0.00434	-0.0377	-0.00353	-0.00271	-0.0300
	(0.045)	(0.043)	(0.044)	(0.045)	(0.043)	(0.049)	(0.016)	(0.016)	(0.020)
Distance to HQ	-0.00278	-0.00530	-0.00269	0.00378	0.000847	0.00197	0.00591	0.00427	0.00484
	(0.0050)	(0.0056)	(0.0051)	(0.0072)	(0.0072)	(0.0066)	(0.0070)	(0.0061)	(0.0059)
% with Electricity	0.0118***	0.0104***	0.00354	0.0171***	0.0149***	0.00864**	0.0119**	0.00962**	0.00651
	(0.0032)	(0.0034)	(0.0028)	(0.0052)	(0.0044)	(0.0036)	(0.0058)	(0.0046)	(0.0042)
Number Households	0.00000874	0.00000443	-0.0000115	0.0000237	0.0000204	0.000000493	0.00000493	0.00000482	0.00000252
	(0.000014)	(0.000017)	(0.000021)	(0.000018)	(0.000021)	(0.000029)	(0.0000089)	(0.0000084)	(0.000013)
Language Dummies?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.333	1.749	23.26	-0.207	0.954	13.42	-0.694	-0.572	-0.599
	(0.56)	(1.18)	(16.7)	(0.83)	(1.18)	(10.8)	(0.84)	(0.68)	(3.80)
Observations	1973	1973	1920	2216	2216	2151	1708	1708	1654
R-squared	0.02	0.02	0.06	0.01	0.02	0.06	0.01	0.02	0.08

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

Table 1.9: Effect of Financial Institutions on Community Participation and Welfare

	(1)	(2)	(3)	(4)	(5)	(6)
COEFFICIENT	Δ Per Capita Participation (1997-2000)	Δ Per Capita Participation (1997-2000)	Δ Log Per Capita Expenditure (1997-2000)	Δ Log Per Capita Expenditure (1997-2000)	Δ Days Sick Per Child (1997-2000)	Δ Days Sick Per Child (1997-2000)
Change in FI options	-0.0650	-0.0614	-0.0701	-0.0372	-0.0209	-0.124
	(0.080)	(0.080)	(0.13)	(0.14)	(0.31)	(0.32)
Log(1993 per cap. exp.)	0.00696	0.00660	0.0440***	0.0449***	0.00357	-0.00384
	(0.0084)	(0.0084)	(0.015)	(0.016)	(0.037)	(0.042)
(Δ FIs)*(1993 Exp.)	0.00459	0.00476	0.00342	0.000973	-0.000516	0.00629
	(0.0057)	(0.0056)	(0.0092)	(0.0095)	(0.022)	(0.023)
Δ Outside Siblings		-0.00150		0.0689***		-0.0345***
		(0.0029)		(0.0096)		(0.012)
Distance to HQ		0.00109		0.0000558		-0.00136
		(0.00079)		(0.00091)		(0.0015)
% with Electricity		0.00127		-0.00202		0.000382
		(0.00082)		(0.0013)		(0.0022)
Number Households		0.00000334*		-0.00000547		0.00000979
		(0.0000017)		(0.0000057)		(0.0000071)
Constant	-0.369***	-0.513***	-0.535**	-0.350	-0.0174	0.0884
	(0.13)	(0.14)	(0.22)	(0.24)	(0.52)	(0.60)
Language Dummies?	No	Yes	No	Yes	No	Yes
Observations	6744	6210	6529	5962	3898	3541
R-squared	0.00	0.02	0.00	0.03	0.00	0.01

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

Table 1.10: Effect of Financial Institutions on Different Forms of Community Participation

	(1)	(2)	(3)	(4)	(5)
COEFFICIENT	Δ Community Meeting	Δ Cooperative	Δ Voluntary Labor	Δ Neighborhood Improvement	Δ Neighborhood Security
Change in FI options	-0.0136	-0.000186	-0.0124	-0.0405	0.0179
	(0.029)	(0.014)	(0.033)	(0.032)	(0.024)
Log(1993 per cap. exp.)	-0.00211	-0.000222	0.00398	0.0113***	-0.00429
	(0.0029)	(0.0014)	(0.0037)	(0.0038)	(0.0028)
(Δ FIs)*(1993 Exp.)	0.00128	0.000109	0.000364	0.00330	-0.00150
	(0.0020)	(0.00100)	(0.0023)	(0.0023)	(0.0016)
Δ Outside Siblings	-0.000479	0.000319	-0.00171	0.000899	-0.00199**
	(0.0011)	(0.00045)	(0.0012)	(0.00098)	(0.00078)
Distance to HQ	0.000571**	0.0000815	-0.000128	0.000839**	0.0000299
	(0.00024)	(0.00016)	(0.00031)	(0.00041)	(0.00028)
% with Electricity	0.000541**	-0.0000115	-0.000289	0.000472	0.000790***
	(0.00024)	(0.00013)	(0.00034)	(0.00036)	(0.00029)
Number Households	-0.000000394	0.00000205***	0.000000129	0.00000162**	-0.000000932*
	(0.0000011)	(0.00000034)	(0.00000084)	(0.00000081)	(0.00000055)
Language Dummies?	Yes	Yes	Yes	Yes	Yes
Constant	-0.0715	0.00438	-0.114*	-0.255***	-0.0913*
	(0.045)	(0.022)	(0.059)	(0.065)	(0.048)
Observations	6210	6210	6210	6210	6210
R-squared	0.01	0.01	0.02	0.03	0.02

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

Table 1.11: Effect of Different Types of Financial Institutions on Community Participation and Welfare

	(1)	(2)	(3)	(4)	(5)	(6)
COEFFICIENT	Difference in Per Capita Participation (1997-2000)	Difference in Per Capita Participation (1997-2000)	Difference in Log Per Capita Expenditure (1997-2000)	Difference in Log Per Capita Expenditure (1997-2000)	Difference in Days Sick Per Child (1997-2000)	Difference in Days Sick Per Child (1997-2000)
Log(1993 per capita Expend.)	0.00372	0.00649	0.0519***	0.0543***	0.0223	0.0167
	(0.0087)	(0.0086)	(0.015)	(0.016)	(0.036)	(0.042)
Δ Bank BRI	0.539	0.450	-0.601	-0.886**	0.636	0.638
	(0.50)	(0.50)	(0.57)	(0.44)	(1.83)	(1.84)
(Δ BRI)x(93 Exp.)	-0.0427	-0.0336	0.0444	0.0633**	-0.0477	-0.0492
	(0.034)	(0.035)	(0.038)	(0.032)	(0.13)	(0.13)
Δ People Credit Bank (BPR)	0.0991	0.239	-0.319	-0.402	-0.599	-1.075
	(0.21)	(0.22)	(0.40)	(0.43)	(0.78)	(0.86)
(Δ BPR)x(93 Exp.)	-0.00534	-0.0108	0.0196	0.0225	0.0493	0.0802
	(0.014)	(0.015)	(0.027)	(0.029)	(0.055)	(0.061)
Δ Village Credit Inst. (LKD)	-0.295	-0.429	-0.614	-0.711	-0.353	-0.584
	(0.27)	(0.26)	(0.47)	(0.45)	(0.92)	(0.98)
(Δ LKD)x(93 Exp.)	0.0156	0.0244	0.0380	0.0449	0.0250	0.0407
	(0.019)	(0.018)	(0.033)	(0.031)	(0.064)	(0.069)
Δ V. Cred. Fund Inst. (LDKP)	-0.278	-0.385	0.995	1.381*	-0.0911	-0.0916
	(0.41)	(0.43)	(0.68)	(0.72)	(1.36)	(1.39)
(Δ LDKP)x(93 Exp.)	0.0179	0.0239	-0.0712	-0.0966**	-0.00497	-0.00453
	(0.028)	(0.030)	(0.047)	(0.049)	(0.094)	(0.097)
Δ Village Unit Coop. (KUD)	0.117	0.132	-0.569	-0.334	-0.657	-0.796
	(0.22)	(0.21)	(0.47)	(0.45)	(0.80)	(0.82)
(Δ KUD)x(93 Exp.)	-0.00897	-0.00751	0.0339	0.0161	0.0473	0.0617
	(0.014)	(0.014)	(0.031)	(0.031)	(0.054)	(0.057)
Δ Other Formal Coop.	0.0126	-0.0616	-0.262	-0.122	0.828	0.709
	(0.20)	(0.20)	(0.43)	(0.46)	(0.78)	(0.81)
(Δ Other Coop.)x(93 Exp.)	0.00121	0.00537	0.0134	0.00397	-0.0652	-0.0580
	(0.013)	(0.014)	(0.029)	(0.030)	(0.054)	(0.057)
Δ Private bank	-0.271	-0.266	0.769**	0.680*	0.219	0.466
	(0.21)	(0.21)	(0.36)	(0.37)	(1.01)	(1.06)
(Δ Private bank)x(93 Exp.)	0.0208	0.0179	-0.0452*	-0.0364	-0.0211	-0.0400
	(0.015)	(0.014)	(0.024)	(0.025)	(0.069)	(0.073)
Δ Outside Siblings		-0.00159		0.0687***		-0.0337***
		(0.0029)		(0.0096)		(0.012)
Distance to HQ		0.00128		0.000229		-0.00117
		(0.00078)		(0.00094)		(0.0014)
% with Electricity		0.00132		-0.00240*		0.000635
		(0.00083)		(0.0012)		(0.0021)
Number Households		0.00000292*		-0.00000583		0.0000102
		(0.0000017)		(0.0000051)		(0.0000073)
Language Dummies?	No	Yes	No	Yes	No	Yes
Constant	-0.334**	-0.522***	-0.657***	-0.476**	-0.266	-0.193
	(0.13)	(0.14)	(0.22)	(0.24)	(0.51)	(0.59)
Observations	6744	6210	6529	5962	3898	3541
R-squared	0.00	0.02	0.01	0.03	0.00	0.01

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

Table 1.12: Ordered Logit for Deciles of Participation Change

COEFFICIENT	Decile of Participation Change
Change in FI options	-0.117
	(0.17)
Log(1993 per capita expenditure)	0.0145
	(0.018)
(Δ FIs)*(1993 Exp.)	0.00809
	(0.012)
Δ Outside Siblings	-0.00971
	(0.0060)
Distance to HQ	0.00187
	(0.0016)
% with Electricity	0.00283*
	(0.0017)
Number Households	0.00000666*
	(0.0000034)
Language Dummies?	Yes

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

Table 1.13: Probability of Being in the Given Decile for Change in Financial Institutions

	ΔFIs =				
Decile	-2	-1	0	1	2
1	0.0941	0.094	0.094	0.0939	0.0939
2	0.1198	0.1197	0.1197	0.1196	0.1196
3	0.0679	0.0679	0.0679	0.0678	0.0678
4	0.1092	0.1092	0.1091	0.1091	0.1091
5	0.1012	0.1012	0.1012	0.1012	0.1012
6	0.2185	0.2186	0.2186	0.2186	0.2186
8	0.0995	0.0996	0.0996	0.0996	0.0996
9	0.1039	0.104	0.104	0.1041	0.1041
10	0.0859	0.0859	0.0859	0.086	0.086

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Chapter 2

The Effects of Crime on Educational Investment: A Policy Simulation Approach

2.1 Introduction

Crime is an important feature of economic life in many countries, especially in the developing world. For example, in the 2004 International Crime Victims Survey, 28 percent of Mexican respondents reported being a victim of property crime. This figure rose to 42 percent among those with at least some college education. Among residents of Latin American countries surveyed in the 2006 Latinobarómetro poll, "crime/public security" was the most chosen answer to the question "What do you consider to be the most important problem in the country [for the period 2004-2006]?" for seven out of eighteen countries and ranked in the top four concerns for residents of fourteen of eighteen countries. As shown in figure 2.1, in several countries, thirty to forty percent of the population said this was the most important problem their country faced.

Crime distorts many economic decisions because it acts like an unpredictable tax on earnings. In particular, the threat of crime may influence people's willingness to invest in schooling or physical capital, because it decreases the returns to this investment, and may cause them to divert income toward preventing their becoming victims of crime or to reduce their losses from crime if they are victimized. Because crime increases uncertainty about the future, it can make contracts and long-term business plans more risky. Some transactions that would otherwise have occurred will not if they make those involved more vulnerable to crime, such as if large amounts of currency or other valuables must be kept on hand or transported.

This paper explores the questions "What influence do crime rates and levels of educational investment have on one another?" and "How do government policies affect the relationship between educational investment and crime?" by creating a simple structural model of crime and educational investment and attempting to fit this model to Mexican data. This model is designed to overcome the inherent endogeneity problem involved with this issue: we may hypothesize that higher levels of crime reduce educational investment by reducing the return to such investment, but, conversely, more educational investment may improve economic conditions, thus reducing the need for individuals to participate in crime. In addition, omitted variables may influence incentives both to commit crime and to invest in schooling. For example, government policy related to schooling or industrial development could increase the returns to schooling, which would make investment in schooling more valuable but also increase the pool of returns available for criminals to steal.

In the model, agents decide whether to be criminals or not and whether to become educated or not in order to maximize their expected utility. Government policy regarding incarceration of criminals and spending on schooling and police affects these decisions, as do wages. A method of simulated moments approach is used to estimate values of the parameters of the model that minimize the difference between moments of the actual Mexican data and the corresponding moments obtained by simulating the data. The method of simulated moments is useful for this estimation because of the difficulty in dealing analytically with the comparison of utilities with nonlinear arguments across agents' schooling and crime options, the presence of several other nonlinear functions in the model that need to be estimated, and the need to simulate the effect of agents' decisions on other agents' incentives until a stable configuration is reached. Given parameter estimates, simulating the data is relatively simple, which makes it possible to generate simulated moments and compare these with the corresponding moments in the data. For the minimization of the distance between the simulated and actual moments in the objective function, a simulated annealing process is used, which should generate a good estimate of the global minimum of the method of simulated moments objective function.

Mexican data has been chosen for this study because it is available and relatively complete and because it allows me to study the effect of crime and related policies in the context of Latin America, where–as mentioned already–these issues are very important to economic development and the welfare of the average citizen. Mexico also has a high crime rate and so will be a good illustration of the relevant issues.

This paper adds to a small but growing literature on the distortionary effects of crime, which have been studied in various contexts. For example, Zelekha and Bar-Efrat (2009) find that crime, along with corruption and terrorism, causes Israeli firms to reduce business investments significantly. Regarding the effects of crime, De Mello and Zilberman (2008) find that property crime has a significant influence on savings rates, but violent crime does not. This is to be expected, because violent crime is often carried out for motives that are not directly related to financial concerns. Violent crime is also only a minor portion of total crimes, so that the effect of property crimes is likely much larger in the aggregate than the effect of violent crime. This paper will thus focus primarily on property crime. Gaviria et al. (2008) discuss efforts to avoid becoming victims of crime by households in Bogotá, Colombia and conclude that the richest households spend 7.2 percent of their home value on preventing burglary.

Despite the negative effects of crime, government policy against crime in developing countries is often ineffective because of insufficient funding, corruption, or misplaced priorities. For example, in Central America, attempts to enforce the law have been hampered by corruption among police and judges, long court backlogs, frequent turnover in leadership, such as police directors and government ministers, and overcrowded prisons (United Nations Office on Drugs and Crime, 2007). Two main approaches to crime reduction are debated in many developing countries. One approach seeks to abate crime by increasing enforcement efforts and augmenting the severity of punishment, while the other focuses on removing the causes of crime by improving education and reducing inequality. For example, according to the United Nations Office on Drugs and Crime, as several Central American countries face stubborn gang problems, some politicians have pursued draconian anti-gang policies, overcrowding prisons in the process, while other voices in society call for an approach involving education, urban planning, gang member reintegration, and other "social crime prevention" policies (United Nations Office on Drugs and Crime, 2007). This research seeks to evaluate these proposals by simulating the effects of changing police spending, length of prison terms, and schooling subsidies on crime and investment in schooling. The per-peso effects of these policies on crime and investment are then compared and optimal levels of spending are computed.

The model predicts that increased police spending or a more severe sentence for apprehended criminals should result in reduced crime, as the returns to crime diminish, but the effects on investment in schooling are theoretically ambiguous, since skilled workers suffer fewer losses to crime but must pay higher taxes. Increasing schooling subsidies will increase the proportion of the population investing in schooling by reducing the costs of doing so but is predicted to increase crime by boosting the number of skilled workers and thus the returns to crime, since skilled workers are more lucrative victims. The policy simulations support the predictions for the effect of schooling subsidies on investment in schooling and the effects of police spending and sentence severity on criminal activity, but the model's prediction that schooling subsidies should have a positive effect on crime is contradicted by the simulation.

This paper is organized in six sections, counting this introduction. Section 2 examines the relevant literature. Section 3 explains the mathematical model. In sections 4 and 5, the data sources that will be used in the estimation are set forth and the method of simulated moments estimation is carried out. Section 6 provides the policy simulations, and section 7 concludes.

2.2 Literature Review

The literature on crime can be divided into work that studies the causes of crime and a more limited body of work that considers the effects of crime: both of these types of work are relevant to the research here. The existing paper that is the closest predecessor of this research is Fella and Gallipoli (2007), which also examines crime and education using a structural model. However, Fella and Gallipoli's model is significantly different from the one here, given that theirs is a life-cycle model with overlapping generations, while this model employs a single period. In addition, Fella and Gallipoli use US data, while this work will be focused on Mexico.

Lochner and Moretti (2004) find that schooling reduces criminal behavior and the probability of incarceration significantly, lending weight to the view that social policies that increase the level of investment in schooling will have the secondary benefit of reducing crime. Since these social benefits of crime reduction are not internalized by the student, public policy to reduce the costs of schooling may be necessary to achieve the social optimal level.

Soares (2004) uses crime victimization surveys to explain why crime is observed to vary a great deal across countries and concludes that development and crime are not correlated once reporting bias is accounted for. He also finds that crime rates are positively correlated with inequality and negatively correlated with growth rates and schooling. Soares claims that "[n]o significant work has been done" (p. 157) on the empirical relationship between crime and development and argues that this is because the corresponding theoretical link is ambiguous and because the reporting bias in the official statistics has invalidated most of the studies that addressed the issue. In support of the ambiguity of the relationship, he cites the model in Ehrlich (1973). Soares and Naritomi (2010) summarize the literature concerning the causes of crime in Latin America and conclude that most of the region's "seemingly excessively high violence can be explained by three factors: high inequality, low incarceration rates, and small police forces" (p. 22). However, many of the studies they examine are subject to the endogeneity critique, which may decrease the confidence that can be placed in them. The research in this paper will provide an alternative means of evaluating their explanations while attempting to account for endogeneity.

As seen in both Soares (2004) and Soares and Naritomi (2010), differing inequality is a common explanation for differences in crime rates. Demombynes and Özler (2005) address the effects of inequality on crime using South African data at a police precinct level. They attempt to differentiate between the economic explanation for the effect of inequality on crime (that greater inequality increases the benefits of committing crime because richer targets are available while lowering the opportunity cost for poor people to commit crime), and traditional sociological explanations by controlling directly for the costs and benefits of crime. This is done by including unemployment rates, average household expenditure, and a precinct's rank in average household expenditure in its area in their regressions. Demombynes and Özler find that property crimes are more likely to occur in areas that are wealthier and more unequal, while violent crimes are also more likely to occur in unequal areas and follow an inverted U pattern with respect to expenditure. The current paper will include wage inequality between more- and less-educated groups as a possible explanation for crime.

In a more theoretical approach to explaining the effect of inequality on crime, Cortes et al. (2009) create a model of crime and schooling decisions among young people and find that, especially when agents are only boundedly rational, government policies that decrease costs of school attendance among more talented students can actually increase the tendency of less talented young people to turn to crime. Though the causal mechanism is different in the model in the current paper (the results of their model derive from information transmission among agents about the relative benefits of schooling and crime), this paper will also explore the possible effects of reducing talented students' costs on the decisions of other students and argue that schooling subsidies may actually increase crime.

One important question that the literature on the effects of crime seeks to answer involves the effect of police and other institutions of crime detection and punishment on the incidence of crime. The main empirical problem in this literature involves disentangling the close relationship between the incidence of crime and the resources devoted to fighting crime. Di Tella and Schargrodsky (2004) use the placement of police near Jewish and Muslim sites in Buenos Aires in the aftermath of a terrorist attack as a source of exogenous variation in police presence. They find that an increase in police presence decreases crime. Levitt (1997) also attempts to obtain exogenous variation in police, in his case using variation in police around election time to find the relationship with crime. These papers provide some elasticities and other estimates that will be helpful for comparison with the results obtained here.

2.3 Model

This is a very simple model of two important decisions: whether to invest in schooling or not and whether to commit crime or not. In order to model these decisions, one must take into account the costs and benefits involved, as well as the aggregated influence that these decisions have on society-wide crime and schooling levels (which in turn affect individual incentives). Foremost among the influences on individual decisions are government policies regarding crime prevention and punishment, as well as education policy, since these play a large role in determining the environment and relevant tradeoffs that direct agents' decisions. This model is designed to capture the impact of these considerations on levels of crime and investment in schooling.

The model in this paper is a one-shot model, in which agents make all decisions at time zero, including whether to become criminals or not and whether to invest in schooling or not, based on the expected utility these options provide. No one will both be a criminal and choose to become educated in equilibrium, since schooling has costs but no benefits for the criminal. The sequencing of actions after time zero will not be addressed explicitly in the model; it will, however, attempt to provide some intuition for how this simplified model can be applied to the real world.

Because of the one-shot nature of the model, agents are assumed to abide by the decisions they have made and to stay in the same career track. Criminals, in particular, can be thought of as committing all their crimes at the beginning of their life, after deciding to become criminals, and then enjoying the proceeds of their crime over the rest of their life, unless they are caught, in which case they spend a proportion T of their life in prison and only have $(1 - T)$ of their life to enjoy what they have stolen. This is unrealistic for several reasons, not least because criminals often have day jobs where they earn a wage instead of specializing entirely in committing crime; however, the model does capture the idea that people allocate time and resources toward crime or toward legitimate pursuits and that opportunity costs are involved no matter what the decision.

2.3.1 Individual Agents

Consider a continuum of workers of measure one. Workers derive utility from consumption of a single aggregate consumption good, so that their utility may be represented as a function of income $u(y)$. Workers choose one of two possible levels of schooling, $e = 1$ or $e = 0$. The assumption of only two educational levels makes the model much easier to solve and should approximate fairly well the division into, for example, college-educated workers and those without a college education, which is the division that will be used in this paper. This division is used in much of the literature in labor economics on wage differentials by education (see, for example, Katz and Murphy (1992)).

Workers are ex-ante heterogeneous only in the ability parameter θ, which makes schooling cheaper and makes being punished for crime more costly. A single dimension of heterogeneity will be sufficient in this case to generate the necessary differences to separate the decisions of the three resulting groups (skilled workers, unskilled workers, and criminals) from one another in an orderly way. If the cost of schooling is denoted as c, an agent with ability θ will face educational costs $(1-\theta)c$ (some of which will be paid by a subsidy, as discussed in the section about the government). This feature attempts to capture the lower psychic and effort costs that a higher ability student encounters when seeking schooling. θ is uniformly distributed on the interval $[0,1]$. The qualitative conclusions of the the model will not be affected by this distributional assumption as opposed to positing some other distribution, though magnitudes of effects may be, as long as certain regularity conditions are satisfied, including continuity of the utility function and the stipulation that there should be no point masses in the distribution of θ. The uniform distribution has been chosen because it is very convenient for performing calculations in simulating the model and because there is not a strong existing prior in the literature on the distribution of ability.

2.3.2 Labor Market

Firms aggregate labor to produce the single aggregate consumption good x according to the constant elasticity of substitution production function

$$x = (\lambda L_1^{\delta} + (1-\lambda)L_0^{\delta})^{1/\delta}. \tag{2.1}$$

$\lambda \in [0,1]$ thus captures the relative productivity of skilled versus unskilled workers in the production function, while δ shows the substitutability of the two types of workers in production, with greater δ indicating more substitutability. If the elasticity of substitution is denoted s, $\delta = \frac{s-1}{s}$. Thus, as δ approaches $-\infty$, the labor inputs become perfect complements, and as δ approaches one, the labor inputs become perfect substitutes.

Workers earn w_e according to their schooling level, where skilled workers and unskilled workers are denoted with subscripts $e = 1$ and $e = 0$, respectively. Assume the labor market is competitive, so that each worker receives her marginal product:

$$w_1 = \frac{\partial x}{\partial L_1} = (1-\lambda)((1-\lambda) + \lambda(\frac{L_0}{L_1})^{\delta})^{\frac{1-\delta}{\delta}} \tag{2.2}$$

and

$$w_0 = \frac{\partial x}{\partial L_0} = \lambda(\lambda + (1-\lambda)(\frac{L_1}{L_0})^{\delta})^{\frac{1-\delta}{\delta}}. \tag{2.3}$$

Combining these equations, we obtain

$$\frac{w_1}{w_0} = \frac{1-\lambda}{\lambda}(\frac{L_1}{L_0})^{\delta-1}. \tag{2.4}$$

2.3.3 Government

In this model the government has only three functions. First, the government pays P to its police forces to increase the proportion of criminals who get arrested. Second, it provides a proportional schooling subsidy h for each individual that chooses $e = 1$, so that the cost of schooling to an individual with ability θ can be expressed as $(1-h)c(1-\theta)$. This assumes that all potential students have access to the same subsidy regardless of ability. The effects of the subsidy will not be materially changed if subsidies are offered only to students with a high θ: the difference in costs for high ability students relative to low ability students will simply be accentuated. Third, the government pays to incarcerate inmates. The cost of keeping an inmate in jail for the maximum punishment of $T = 1$ (where T is between 0 and 1, as explained below) is J (so that if the punishment is actually T, the cost is TJ). More intuition for interpreting the punishment T is in the next section. All this spending is financed by a proportional income tax τ. This means that a worker choosing schooling e will have after-tax income

$$y_e = (w_e(1-\tau) - (1-h)ec(1-\theta)). \tag{2.5}$$

In order to capture the fiscal tradeoffs that governments must make, a balanced budget constraint is imposed, in which the outlays for these categories of expenditure cannot exceed the tax revenue required to pay for them:

$$(L_1 w_1 + L_0 w_0)\tau = chL_1 + P + \rho TJL_C. \tag{2.6}$$

For simplicity's sake, other functions of the government are not incorporated in this model. Some types of government spending, such as defense spending, seem unlikely to influence educational investment or crime. Other types of government spending, such as social welfare and social insurance programs, could be incorporated into the model, but many assumptions on the form of the included program would need to be made and would not add very much to the conclusions.

2.3.4 Crime

Any given individual's probability of being a victim of crime is q, which does not vary by schooling level. This assumption is adopted primarily because the necessary data to calculate separate victimization probabilities by schooling level is lacking. If an individual is a victim of crime, she loses a proportion α_e of her wages, so that skilled and unskilled workers may face different losses from crime. This assumption of differential losses is important in a model that seeks to determine the effects of crime on educational decisions, and this assumption also allows more flexibility in fitting the data. Workers receive expected utility

$$qu((y_e(1-\alpha_e)) + (1-q)u(y_e). \tag{2.7}$$

The size of the take from a crime may vary according to the number of criminal opportunities available. For example, if few opportunities are available to rob skilled workers, the opportunities that are available may provide smaller amounts if there is more competition for them or larger amounts if skilled workers are easier targets when they are scarce. For example, when there are spillover effects from the efforts of other homeowners in a person's neighborhood to protect themselves from crime, the amount that criminals can take from that person may decrease. In order to represent these relationships, α_e, the amount a criminal is able to take from a victim with schooling e as a proportion of the victim's income, is a logistic function of the number of people with schooling e:

$$\alpha_e = \frac{\exp(\omega_e + \gamma_e L_e)}{(1 + \exp(\omega_e + \gamma_e L_e))}. \tag{2.8}$$

This will ensure that $\alpha_e \in [0, 1]$.

Criminals specialize in committing crimes against skilled or unskilled workers. With (endogenous) probability ϕ, they specialize in victims that have $e = 1$ and, with probability $1 - \phi$, in victims with $e = 0$. This specialization could be thought of as geographical or in terms of particular skills that aid in robbing one kind of victim more than the other. Within the group he has specialized for, a criminal commits n crimes against randomly selected victims. This is obviously a simplification, since empirically the number of crimes per criminal will follow a distribution. Nevertheless, for the purposes of this model, since criminals make the decision to be a criminal or not at time zero, their decisions are based on the expected number of crimes they will commit. Therefore, the assumption of an equal number of crimes per criminal should not materially affect the results. A fraction d of the loss to the victim from the crime is destroyed when the crime occurs, such that neither victim nor perpetrator of the crime receives it. This amount can be thought of as cost of the property damage necessary to commit the crime, as well as loss and deterioration of the assets taken. Because of this, each crime results in a take of $\alpha_e y_e(1-d)$. Thus, the criminal is able to take a total of

$$\beta_e = \alpha_e y_e(1-d)n. \tag{2.9}$$

Each criminal, however, faces a probability of being caught $\rho(P)$, which is an logistic function of police spending:

$$\rho = \frac{\exp(\eta + \kappa P + \nu)}{1 + \exp(\eta + \kappa P + \nu)}. \tag{2.10}$$

If the criminal is caught, he receives only a proportion $(1-\theta)(1-T)$ of the proceeds of his crime. $T \in [0,1]$ represents the severity of punishment and could be thought of as the proportion of his lifetime that a criminal spends in prison (and cannot enjoy the benefits of his crimes). The multiplication by $(1-\theta)$ represents the increasing costs of punishment to higher ability agents. This can be thought of as both increased psychic costs of incarceration and increased opportunity cost, though opportunity costs are not explicitly modeled here. Just as higher ability agents have lower psychic costs of schooling because they enjoy school more, they have higher psychic costs of incarceration because they dislike prison more. Thus, a criminal's expected utility over being caught or not and over having skilled or unskilled workers as victims is $E(u[criminal]) =$

$$\phi(\rho u[\beta_1(1-\theta)(1-T)] + (1-\rho)u[\beta_1]) + (1-\phi)(\rho u[\beta_0(1-\theta)(1-T)] + (1-\rho)u[\beta_0]). \tag{2.11}$$

Because of the one-shot nature of the model, the effect of punishment on crime in the model is all due to the threat of punishment, which deters individuals from committing crimes, and not to incapacitation of criminals who have already committed crimes, which would prevent them from carrying out further crime. Thus, the effect of punishment on crime is understated if incapacitation is a significant factor in reducing crime.

2.3.5 Equilibrium Solution

In equilibrium, the relationship $nL_C = qL_1 + qL_0$ must hold, so that the number of crimes committed (crimes per criminal times the number of criminals) is equal to the number of victims (probability of being a victim times number of workers).

An individual will choose to be a skilled worker rather than an unskilled worker if $E[u(e = 1)] > E[u(e = 0)]$. An individual will choose to be a criminal rather than being an unskilled worker if $E[u(e = 0)] < E[u(criminal)]$. Because the utility of being a skilled worker is increasing in θ, the utility of being a criminal is decreasing in θ, and the utility of being an unskilled worker does not depend on θ, there exist $\theta = \theta_C$ and $\theta = \theta_E$ such that agents with $\theta < \theta_C$ choose to become criminals and such that agents with $\theta > \theta_E$ choose to become educated. Those with θ in between θ_E and θ_C will choose to work with $e_i = 0$. This is illustrated with arbitrarily drawn utility functions U_1, U_0, and U_C for, respectively, skilled workers, unskilled workers, and criminals in Figure 2.2. This model will result in a proportion L_0 of unskilled workers, a proportion L_1 of skilled workers, and a proportion $L_C = 1 - L_0 - L_1$ of criminals. From the uniform distribution of θ and following the argument shown in figure 2.2, we know that $L_0 = \theta_E - \theta_C$ and $L_1 = 1 - \theta_E$.

2.3.6 Predictions

The model predicts that increasing police spending P should decrease L_C, the proportion of criminals, because increasing police increases the arrest rate and thus reduces the expected value of committing crime. The effect of increasing P on L_1, the proportion of skilled workers, is ambiguous, since crime decreases, which will reduce the expected losses to crime, but taxes increase as police spending increases, so that some agents may choose to become criminals to avoid the higher taxes or fail to get an education because of the smaller increase in expected utility from higher skilled wages. For the same reasons, increasing T should decrease L_C by reducing the expected payoff to crime but have a theoretically ambiguous effect on L_1, as crime decreases but taxes go up. Increasing the education subsidy h should increase L_1, because the benefits of the subsidy are fully absorbed by the educated but the tax burden is spread across all workers. Perhaps unexpectedly, the effect on L_C should be positive, since the members of this group are not on the margin to join L_1 and so are not directly affected by the education subsidy but do receive a greater take from the larger pool of highly paid people in L_1.

2.4 Data

A primary issue in measuring the level of crime is that not all crimes are reported to the police. Especially in developing countries, many crimes go unreported because of victim's doubts about the police's probity or efficacy or because they fear retaliation from the perpetrators of crime. Soares (2004) has a useful discussion of this issue. Crime victimization surveys are an alternative means of measuring the level of crime that avoids these issues. Thus, this estimation uses state-level observations from the 2007 and 2008 Encuestas nacionales sobre inseguridad (ENSI-5 and -6, in English, National Surveys on Insecurity) to provide the victimization rate from surveys among educated and uneducated workers. This paper also draws from a 2009 ICESI (Citizen Institute for Insecurity Studies) report, which provides information on the costs of crime to victims and the state and on police expenditures (see Mendoza Mora (2009)). For information on wages and education levels, this paper turns to the 2005 and 2006 ENIGH (Survey on household income and expenditures), which have 23,174 and 20,875 household observations, respectively. The ENIGH data is primarily used aggregated to the state level.

Several values have been taken directly from available data. From state-by-state records for 2009 from the ICESI report, police spending P was 1498 pesos per person per year. According to the ICESI report, among the thirteen (out of thirty-two) Mexican states reporting the cost of keeping inmates, the average cost of incarceration ranged from 22,157 to 88,602 pesos per year per inmate in 2008, with the median at 39,703. This median figure will be used as J in the model for the current analysis. Note that the exchange rate over the period 2004-2008 was between ten and twelve Mexican pesos per US dollar.

Since public universities in Mexico are free, a value for the subsidy to the cost of schooling of $h = 0.8$ has been chosen to reflect that the current higher education subsidy is relatively large, though there may be other costs to schooling and not all universities are public. From a list of selected private universities, the median cost of providing an education in 2008 was 58,900 pesos per student per year, which will be assumed holds across all universities.

Since this paper is working in the context of a one-shot model for education, work, and crime decisions, some way is needed of aggregating outcomes across time in the data. In the current analysis, the simple expedient is used of adding up across 45 years without discounting to match the "lifetime" of workers in the model. Thus, the total cost of school is the yearly cost times four; the payment for police, the public cost of incarceration, and the wage for non-college-educated workers are the yearly figures multiplied by 45; and the college-educated wage is the yearly wage times 41.

For the purposes of estimating the model, $u(y) = ln(1 + y)$ will be used. A more general constant relative risk aversion utility function produces similar results using log utility. The degree of concavity can have some quantitative effects, but does not change the model predictions. The addition of one in the utility function will help keep the argument positive (a negative argument could occur, for example, when the cost of education is greater than the skilled wage), as is necessary to have the log be defined, and can be thought of as a guaranteed income that all agents receive.

ρ is calculated as the ratio of reports to police of property crime to total property crimes as reported by victimization surveys. This will overstate the arrest rate somewhat, as not every report results in an arrest.

Summary statistics are in table 2.1.

2.5 Estimation

2.5.1 Empirical Strategy

To review, there are several key equations that make up the bulk of the model: equation (2.4), the relation between the ratio of skilled to unskilled workers and the relative wage of these groups; equation (2.10), the relation between police spending and arrests; equations (2.7) and (2.11), the respective expected utilities of workers and criminals, which agents compare to decide on the best career for them; equation (2.8), the relation between the proportional loss for each type of worker and the fraction of the population in their skill groups; and (2.6), the balanced budget constraint.

These equations embody the key channels by which the effects of government policy are seen. First, because of the budget-balance channel, an increase in any of the government policies discussed in this paper will require additional government expenditure and additional taxes. This will make being a skilled worker less attractive because of the lower post-tax returns to education. It will also make being a criminal more attractive because criminals do not pay taxes. Second, policies that affect the relative supply of skilled versus unskilled workers, such as the education subsidy, will cause the relative wages of these groups to change, changing the incentives of criminals as their pool of victims becomes richer or poorer. Third, increasing police spending or the severity of punishment raises the costs of committing crime by increasing the chances of being caught (assuming that police spending increases arrest rates) or the punishment that the caught criminal receives. This channel should thus reduce crime. Finally, education subsidies reduce the costs of education, which should increase educational investment.

The estimates for the various pieces of the model from the previous section, the estimated parameters of the wage equation, and initial guesses for the parameters that remain to be estimated are plugged into the equations above and the other relationships in the model. In this way, the utility functions, proportions of skilled workers, unskilled workers, and criminals, and other results of the model can be calculated, allowing moments to be computed and compared to the corresponding moments of the data. Simulated annealing is used to search for parameter estimates that minimize the distance between the simulated and actual moments. Some over-identification tests are carried out to see how omitting some moments affects the results. The plausibility of these estimates will also be briefly discussed.

The identification in this estimation comes primarily from the structure of the model; by representing important relationships such as the relation between police spending and arrests, other confounding factors can be eliminated. The fact that more moments are matched than there are parameters to estimate means that the model is over-identified, which also aids in ensuring that the parameters in the model are identified. Several assumptions are required for the parameters of the model to be identified correctly. First, budget balance must be maintained; in particular, the deficit or surplus that is run should not depend on levels of crime or educational investment. A constant level of budget imbalance that is unrelated to the outcome variables of interest is easy to incorporate into the model, but budget imbalance that depends on outcome variables will mean that the tax rate will not reflect accurately the costs to society of implementing the policy levels the government chooses. Second, relative demand for skilled versus unskilled workers must remain relatively constant over time, since this model focuses on relative supply relationships. Third, police spending decisions need to avoid dependence on arrest rates. If governments base decisions of how many police to hire on current arrest rates, then the relation between these variables will be incorrectly specified in the model, and the parameters of this relationship will be incorrectly estimated.

These assumptions seem more or less likely to hold for Mexico. The first assumption seems to hold: Mexico has fairly consistently run a budget deficit over the past ten years, but is difficult to separate out the portion of that deficit that is a result of crime and education policies, primarily because it is relatively small compared to the rest of the budget. This should allay our concerns somewhat. The second assumption, that relative demand for skilled workers remains roughly constant, is probably the most controversial of these necessary assumptions, given that Mexico has seen substantial technological progress and opening of trade over the past twenty years or so. If relative labor demand has been increasing over this time period, then we should expect relative wages to be more responsive to relative labor supply increases than what this paper assumes because increases in relative labor demand should have the opposite effect from relative labor supply increases. The third assumption, that government decisions about the level of police do not depend on current arrest rates, seems justified. Police spending certainly depends on *crime levels*, but it is unlikely that governments use or care about information about *arrest rates*, per se, separate from the amount of crime.

2.5.2 Wage Equation

Putting equation (2.4) in logs and including an error term, one can estimate the regression equation $log(\frac{w_1}{w_0}) = log(\frac{1-\lambda}{\lambda}) + (\delta - 1)log(\frac{L_1}{L_0}) + \epsilon$ to obtain λ and δ. This equation is estimated using the 2005 and 2006 ENIGH data aggregated to the state level, considering only male household heads, to obtain the parameter estimates $\lambda = 0.5973$ and $\delta = 0.7157$. For comparison, Katz and Murphy (1992) estimate the elasticity of substitution between college- and high-school-educated workers in the U.S. to be about 1.41, which would yield $\delta = 0.29$.

The restriction to male household heads is for consistency and because female workers differ more in labor market participation. w_1 and w_0 will be assumed to be log normally distributed, with w_0 having mean parameter μ_0 and variance parameter σ_0^2. w_1 is estimated using the wage equation $w_1 = w_0((1-\lambda)/\lambda) * (((1-\theta_E)/(\theta_E - \theta_C))^{\delta-1})exp(b_1)$, where b_1 is distributed $N(0, \upsilon)$, so that w_1 follows a log normal distribution.

2.5.3 Method of Simulated Moments

A method of simulated moments approach is used to numerically estimate the key model parameters (see McFadden (1989)). This is a natural choice in this case, because it provides the ability to address analytically difficult models that do not have tractable reduced form solutions, like the one in this paper. The vector of parameters to estimate includes T, the mean and variance of w_0, γ_0, γ_1, ω_0, ω_1, η, κ, and υ. Simulated annealing (see Kirkpatrick et al. (1983)) is used to find the values of these parameters that minimize the objective function $[simulated - data]'W[simulated -$

$data$], where the moments used are $\bar{L_1}/\bar{L_0}$, $\bar{w_1}$, $\bar{w_0}$, $\bar{w}$, $s^2(w_1)$, $s^2(w_0)$, $s^2(w)$, $\bar{q}$, $s^2(q)$, $\bar{\alpha_1}$, $\bar{\alpha_0}$, $\bar{\rho}$, and $s^2(\rho)$. W is the inverse of Ω, the optimal weighting matrix of second moments (variances and covariances) of the moments being matched in the data. Since multiple years of data would be necessary to calculate some of these second moments, they are calculated by bootstrapping the data.

The objective function minimization using simulated annealing compares the value of the objective function produced by the previous parameter vector to the value produced by the current parameter vector, which is selected from the neighborhood of the previous vector. If the current value is less than the previous value, the current vector of parameters is accepted and becomes the starting point for the next comparison. Vectors that do not improve the minimization are usually rejected but may be accepted, with a probability that declines as the process continues. Simulated annealing provides the advantage of being able to find a global optimum, since the process will be able to move out from local optima to find even better values, though it does take more computer processing time to find a solution than many local optimization algorithms.

The estimation simulates 100 agents in each of four "regions" in three repetitions (which allows moments to be calculated across repetitions). Values of ρ, α_1, and α_0 are calculated separately for each region. All monetary amounts are in hundreds of thousands of pesos.

Using initial guesses of these parameters and the values cited above for P, J, h, c, and q, it is possible to solve for μ_1, n, α_e, w_1 for each agent, and hence the utility of each of the three options for each individual. Thus, each agent is assigned the option that provides the highest utility, which allows calculation of the moments to be simulated.

Because agents' decisions within the moment simulation process should influence other agents' incentives, an iterative looping is performed in every repetition of the simulation. The θ_E and θ_C values resulting from each repetition are used in the subsequent repetition, until the values of α_1, α_0, and the mean of w_1 stabilize. In the few occasions when this stabilization does not occur, the loop is terminated, and the process is restarted with new parameter guesses in the neighborhood of the previous vector of guesses.

2.5.4 Results

The resulting parameters from the method of simulated moments procedure are in the first column of table 2.2. Standard errors are calculated using the asymptotic variance-covariance matrix

$$(G'\Omega^{-1}G)^{-1}, \tag{2.12}$$

where Ω is the optimal weighting matrix and G is the matrix of derivatives of moments with respect to the parameters at the estimated parameter values.

In order to check the soundness of the estimation, the parameter estimates should be examined to see if they make sense in the Mexican context: $T = 0.0826$ corresponds to a 3.7 year prison sentence out of a 45 year career, which does not seem unreasonable for multiple property crimes. The simulation produces the relationships $\alpha_1 = \frac{\exp(3.0221+0.7393L_1)}{1+\exp(3.0221+0.7393L_1)}$ and $\alpha_0 = \frac{\exp(-0.4921+0.6187L_0)}{1+\exp(-0.4921+0.6187L_0)}$, indicating that proportional losses to crime are increasing among both skilled and unskilled workers as there are respectively more in each group. Given the values of these coefficients, α_1 is always greater than α_0, which does not match the data well, in which α_1 and α_0 are roughly equal. The police-arrest-rate relationship is estimated as $\rho = \frac{\exp(0.8903+0.5934P)}{1+exp(0.8903+0.5934P)}$, indicating that arrest rates are estimated to increase with police spending, as we might expect.

Over-identification is checked by comparing the estimation results to results obtained with some of the moment conditions being unused. The results of this are in table 2.2. The first column has the results using all eighteen moments. The second column has the results using all the moments except the means and variances of α_1 and α_0, the proportional losses to crime. The third column has the results using all the moments except the mean and variance of q, the victimization rate. One would hope that the results would be similar across columns because this would be a sign that the results are not sensitive to the precise specification used. In general, the results are similar across the three specifications, though the difference is sometimes statistically significant because of small standard errors. The likelihood ratio tests for the difference produced very large χ^2 statistics, which would indicate that significant differences do exist.

Table 2.3 shows the effect of individually changing the moments from the data slightly to observe the change induced in the estimated parameters, where these effects are calculated per unit of change in the moments.

2.6 Policy Experiments

With the parameter estimates from the previous section, simulations can be carried out to experiment with the consequences that changing various policy parameters has on crime and investment in schooling, as well as on overall welfare, measured as the sum of utilities of all agents. The parameters that the government can change for the purposes of the simulation are P (police spending), T (severity of punishment), and h (proportional subsidy to schooling). The policy simulation uses the same procedure to produce the outcomes of interest as was employed in each moment simulation repetition in the simulated annealing optimization process, with the estimated parameter values plugged in and the policy variable of interest ranging across some set of limits.

Figures 2.3-2.9 show the results of these policy simulations. Values are varied from zero to 200,000 pesos for police spending P, from 0 to 1 for the schooling subsidy h, and from 0 to 1 for punishment severity T.

As predicted, increasing the schooling subsidy tends to significantly increase the proportion of skilled workers as shown in figure 2.3. However, contrary to the prediction, increases in the schooling subsidy tend to slightly decrease the proportion of criminals L_C, as seen in figure 2.4.

Police spending and sentence length, as seen in figures 2.5 and 2.6, decrease the proportion of agents that decide to be criminals, as predicted by the model. Increased sentence length is much more effective than police spending at reducing crime in the simulation. Neither police spending nor sentence length has an appreciable effect on investment in schooling, which should not be surprising, given that the predictions of the model were ambiguous as to this effect.

From figure 2.9, we see that increasing the schooling subsidy had a positive effect on overall welfare, showing that the higher wages paid to the increased number of skilled workers more than offset the costs to society of providing these individuals with schooling. In figure 2.10, it is evident that increased severity of punishment had a strongly negative effect on welfare, because the gains to society from having less crime were outweighed by the increased costs of having more criminals in prison. Increasing police spending decreased welfare, but only slightly, as shown in figure 2.11.

2.7 Conclusion

This paper has examined the influence of government policies on crime and investment in schooling by constructing a simple structural model of individuals' schooling and crime decisions and the effect that these decisions have on overall levels of schooling and crime. This paper has estimated the parameters of this model, and used them to simulate and predict the effect of changing government policies relating to schooling subsidies, police spending, and the severity of punishment for crime on schooling investment and crime.

The results of the simulation are that, as predicted by this paper's model, increasing schooling subsidies increases the number of people who invest in schooling and that increasing police spending and the length of prison sentences decreases the number of criminals. Police spending and punishment severity have very little effect on educational investment, and schooling subsidies slightly reduce the number of criminals, contradicting the predictions of the model. Increased schooling subsidies increase total utility significantly, while increased punishment severity reduces total utility significantly and police spending has only a small negative effect.

Thus, in response to the ongoing crime reduction policy debate between proponents of increased emphasis on law enforcement and supporters of striking at the root of crime by increasing social support, such as subsidies for schooling, this research suggests that both strategies may have a role to play, though increasing sentence length was the most effective crime-reduction policy in the simulation. The results also indicate that creating a better environment for investment in schooling may be insufficient and that direct subsidies to schooling may be more effective in this respect.

There are obviously some important extensions that this paper could still make. First, other government policies can be evaluated, such as a minimum wage policy. Second, it would be interesting to see how government policy affects other outcomes, such as wages. Third, the relative importance of the various channels of influence that policy can have needs to be determined. This can be done by closing off each of these channels in turn and observing the outcome. For example, wages could be fixed instead of being allowed to vary with the ratio of skilled to unskilled workers. Finally, individuals and households often incur significant expenditure to avoid becoming victims of crime, particularly in developing countries. The model in this paper could be extended to model this preventative spending.

2.8 Figures and Tables

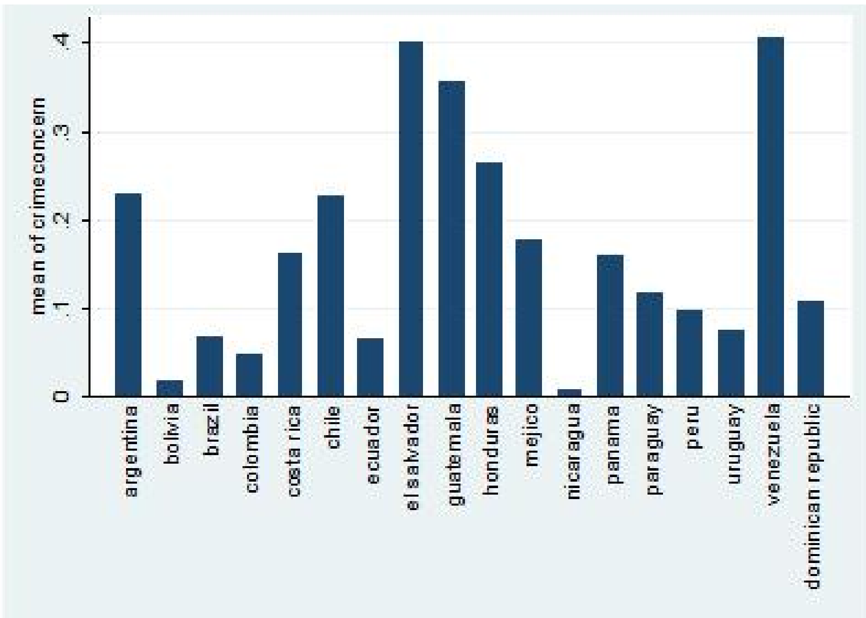

Figure 2.1: Proportion in 2006 Latinobarómetro answering that crime/public security is most important problem

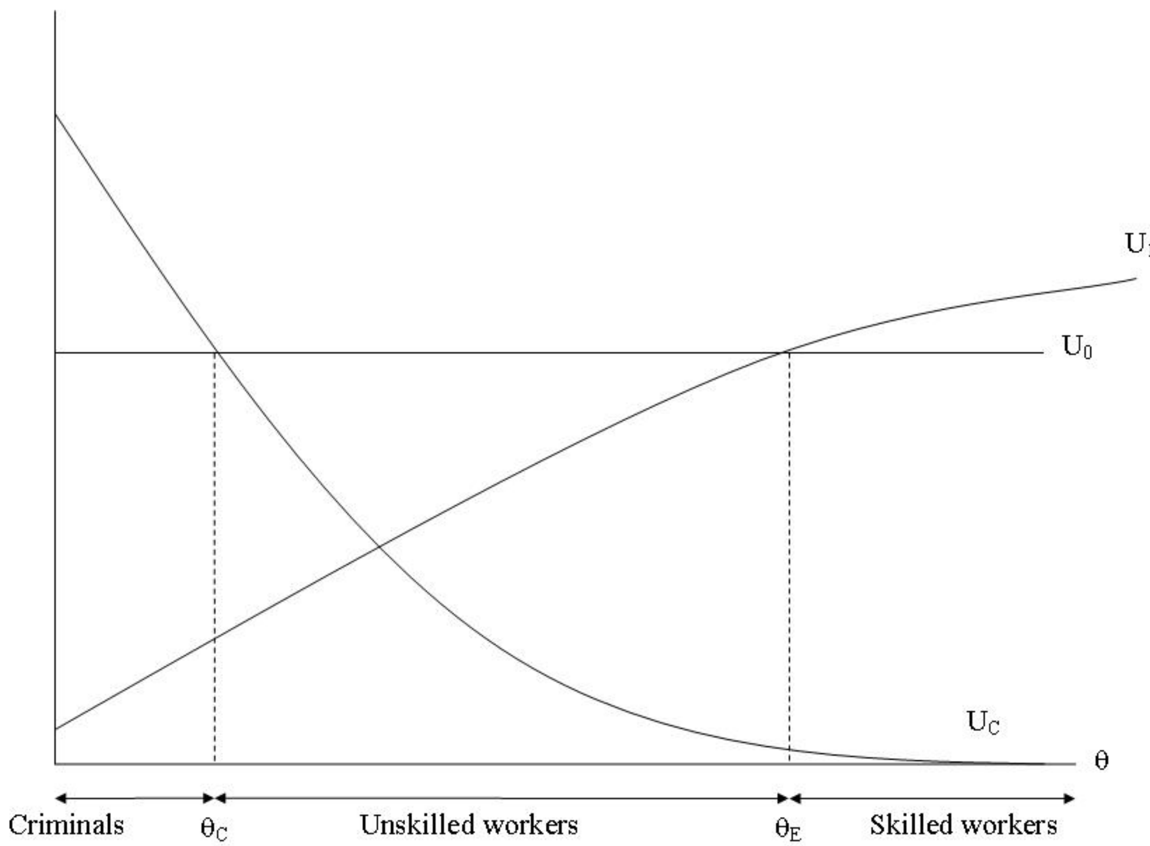

Figure 2.2: An Example of Utility of Criminal and Education Options for Different Ability Levels

Table 2.1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
α_1: 2008	30	0.5810	0.72471	0.14494	3.4877
α_0: 2008	30	0.5961	0.73468	0.15563	3.3328
Average unskilled wage: 2006	32	29412.2	11260.6	14136.0	63092.0
Average skilled wage: 2006	32	30274.0	11255.0	12881.9	54330.0
Average unskilled wage: 2005	32	28924.7	12665.3	8655.40	69829.4
Average skilled wage: 2005	32	31732.0	17756.5	9471.27	90155.2
Number skilled workers: 2005	32	102.75	91.752	33	502
Number unskilled workers: 2005	32	426.94	337.76	200	1947
Number skilled workers: 2006	32	88.781	47.673	39	250
Number unskilled workers: 2006	32	378.88	190.93	132	1112
Per capita state police spending: 2007	32	771.6563	411.569	377	2656
Per capita loss by victims of crime: 2008	30	15975.97	17413.6	4843	79296
q: 2007	32	0.08445	0.03969	0.02754	0.20681
ρ: 2004	32	0.14198	0.06838	0.02347	0.32209

Table 2.2: Estimation Results (Standard Errors in Parentheses)

Parameter	Using all moments	Excluding mean and variance of α_1 and α_0	Excluding mean and variance of q
T (sentence length)	0.0826 (0.0778)	0.1458 (2.345)	0 (1.1475)
μ_0 (mean parameter for log-normal w_0)	-0.9237 (0.0207)	-0.9254 (0.0543)	-1.0072 (0.4535)
σ_0 (variance parameter for log-normal w_0)	2.174 (0.0158)	2.1659 (0.0001)	2.2063 (0.2434)
γ_1 (slope parameter for α_1)	0.7393 (3.124)	-0.6218 (5.9816)	0.6086 (5.4229)
γ_0 (slope parameter for α_0)	0.6187 (0.3394)	0.9033 (4.7313)	1.5209 (3.2319)
ω_1 (intercept parameter for α_1)	3.0221 (1.9176)	2.862 (5.9446)	1.3723 (1.2032)
ω_0 (intercept parameter for α_0)	-0.4921 (0.2455)	-0.233 (1.7169)	-0.3585 (1.5141)
υ (variance parameter for log-normal w_1)	-1.0934 (0.0035)	-1.1279 (0.0304)	-1.1251 (0.0106)
η (intercept parameter for ρ)	0.8903 (1.8074)	1.0051 (1.614)	1.2889 (1.8377)
κ (slope parameter for ρ)	0.5934 (2.8136)	0.4666 (2.4157)	1.202 (2.8322)

Table 2.3: Numerically Calculated Derivative for Effect on Estimated Parameter Values of Changing Value of Moments

Moment	T (sentence length)	μ_0 (mean parameter for log-normal w_0)	σ_0 (variance parameter for log-normal w_0)	γ_1 (slope parameter for α_1)	γ_0 (slope parameter for α_0)
$\frac{L_1}{L_0}$	-0.00369	0.006118	0	0.311975	-0.00587
$\overline{w_1}$	0.000236	-0.0003	0	-0.00054	-0.00023
variance of w_1	2.61E-06	-3.4E-08	0	0.002309	0
$\overline{w_0}$	0.000333	0	-5E-05	2.72E-05	0
variance of w_0	0.000175	0	3.76E-06	0.0042	-0.00021
$\overline{w}$	0.017959	0.000137	4.42E-05	0.008767	-0.01142
variance of w	-0.00091	0.000397	0	-0.00245	0.001704
$\frac{L_C}{L_1+L_0}$	-0.01415	0.009639	0	0.484225	-0.0085
$\overline{\alpha_1}$	0.143984	0	0	-0.07271	-0.02788
$\overline{\alpha_0}$	0.013329	0.006455	0	0.312739	-0.0094
$\overline{\rho}$	-0.00384	-0.00359	0	0.014968	0
variance of ρ	49.34643	-0.00255	0	15.98755	-20.9689
skewness of w_1	0.003387	0.000583	-0.00132	0.011385	0
skewness of w_0	0.230071	-1.2E-05	0	0.07454	-0.09776
skewness of w	0.001113	-0.00025	-0.00117	0.035164	0.000931
variance of α_1	0.261382	-0.01086	-0.00023	0.807396	-0.13702
variance of α_0	-0.00429	-8.1E-06	0	-0.02016	-0.00263
$\overline{q}$	0.023516	-0.0148	0	0.044139	0

Moment	ω_1 (intercept parameter for α_1)	ω_0 (intercept parameter for α_0)	υ (variance parameter for log-normal w_1)	η (intercept parameter for rho)	κ (slope parameter for ρ)
$\frac{L_1}{L_0}$	0.004625	0.021121	0	0.048246	-0.05194
$\overline{w_1}$	-1.1E-05	0	0	0.000333	-0.00109
variance of w_1	-0.00054	-3.1E-06	0	-1.3E-06	-1.9E-05
$\overline{w_0}$	0.00041	0	0	2.79E-05	-0.00092
variance of w_0	0.002358	-8.6E-05	0	-0.00028	-0.00026
$\overline{w}$	0.027109	-0.02172	-2.7E-05	0.022188	-0.049
variance of w	-0.00044	-0.00116	1.56E-05	-5.4E-05	-0.00494
$\frac{L_C}{L_1+L_0}$	0.009472	0.032985	0	0.066973	-0.06017
$\overline{\alpha_1}$	-0.00045	-0.03331	0	0.155064	-0.00672
$\overline{\alpha_0}$	0.171119	0.063381	0	0.066977	-0.04587
$\overline{\rho}$	0.000868	0	0	0.031827	-0.04699
variance of ρ	9.506015	-3.22981	-4.41049	13.55875	-0.39321
skewness of w_1	-0.0001	-0.00018	4.89E-05	0.00495	-0.02294
skewness of w_0	0.04432	-0.01506	-0.02056	0.063216	-0.00183
skewness of w	-0.00144	0	0	-0.01307	0.00662
variance of α_1	0.335883	-0.0853	0.034238	-0.18259	-0.48928
variance of α_0	0.015164	-0.00067	-0.00079	-0.00679	-0.12845
$\overline{q}$	0.016605	0	0	-0.00352	-0.03794

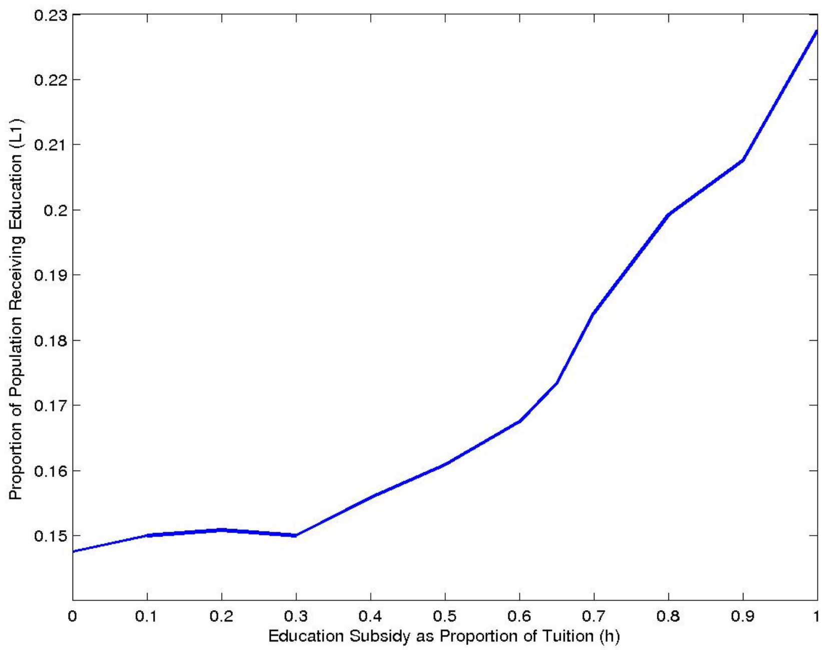

Figure 2.3: Effect of Education Subsidy on Proportion Educated

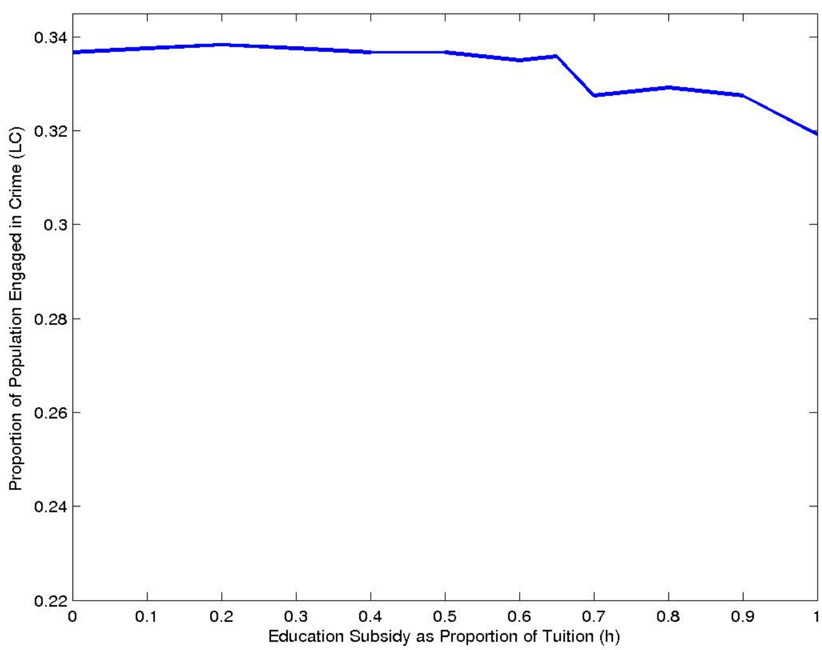

Figure 2.4: Effect of Education Subsidy on Proportion of Criminals

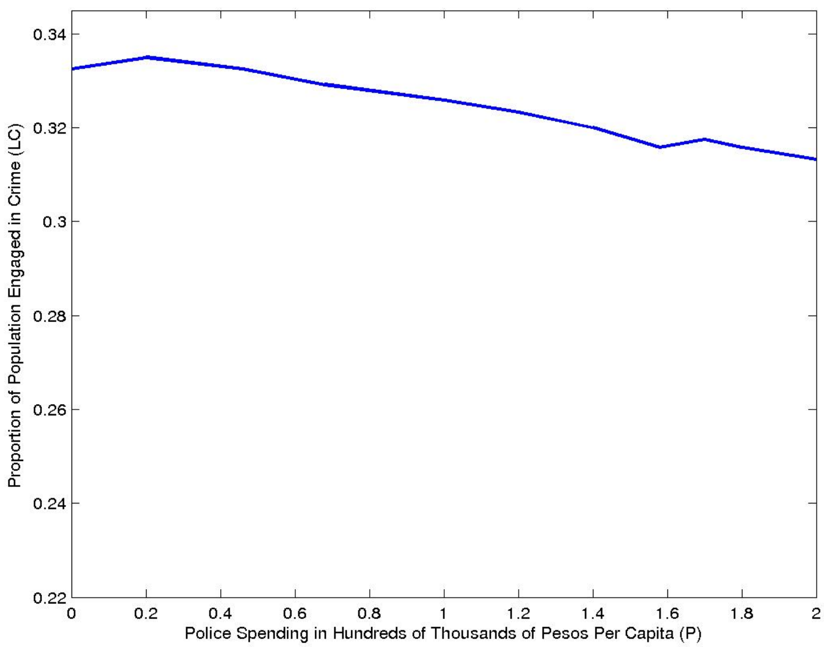

Figure 2.5: Effect of Police Spending on Proportion of Criminals

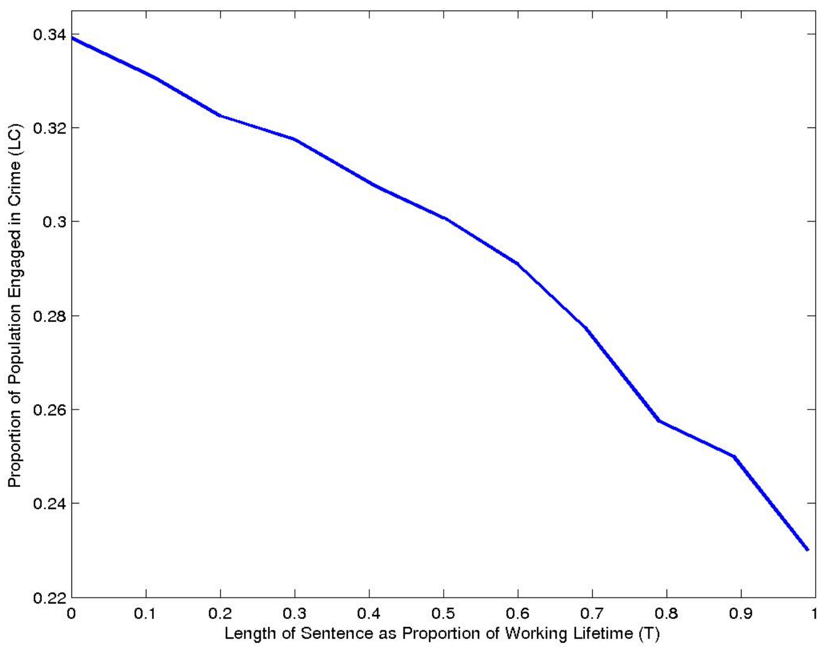

Figure 2.6: Effect of Sentence Length on Proportion of Criminals

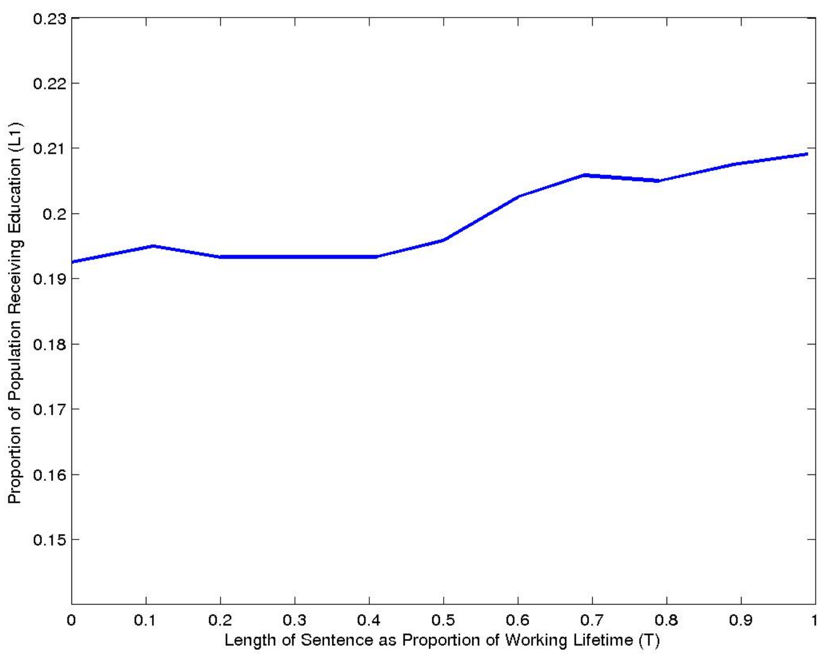

Figure 2.7: Effect of Sentence Length on Proportion Educated

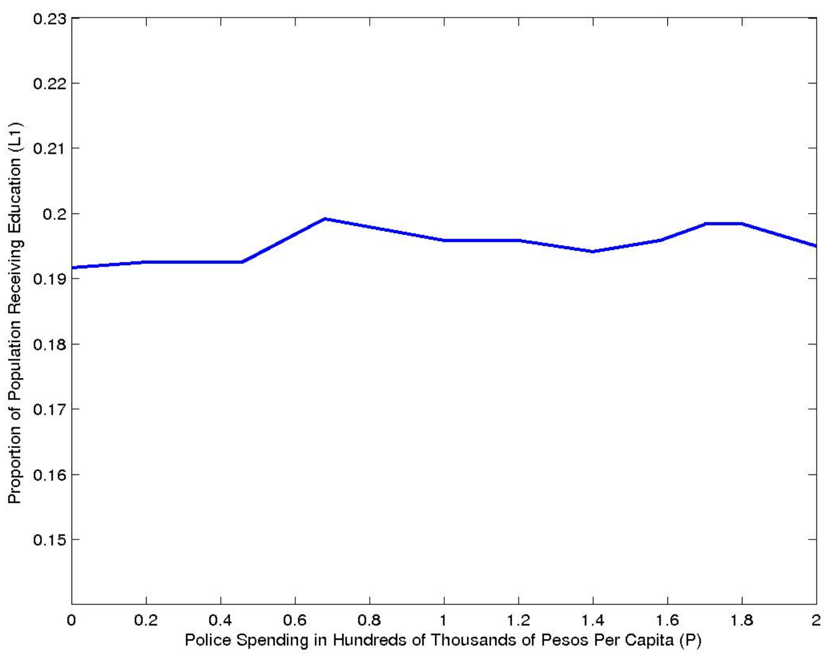

Figure 2.8: Effect of Police Spending on Proportion Educated

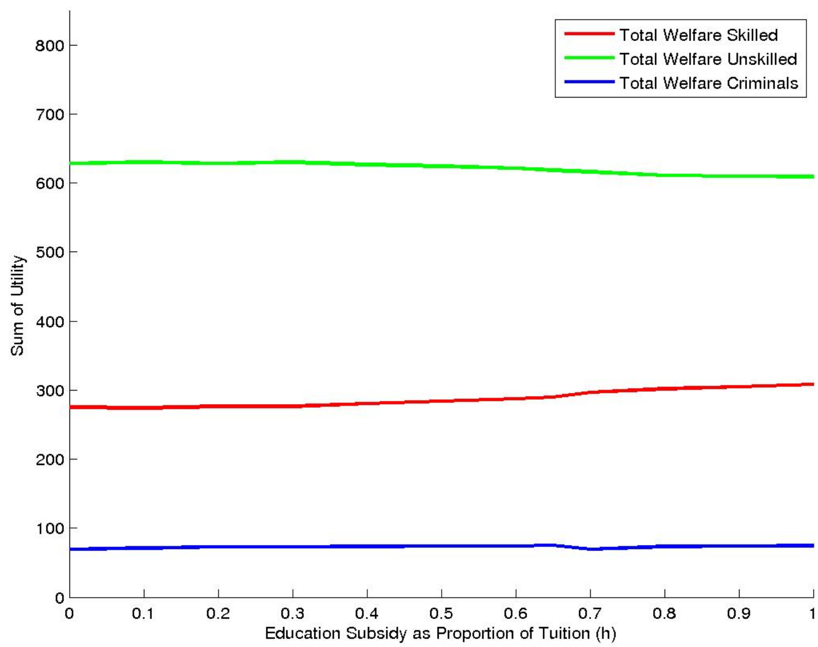

Figure 2.9: Effect of Education Subsidy on Total Utility

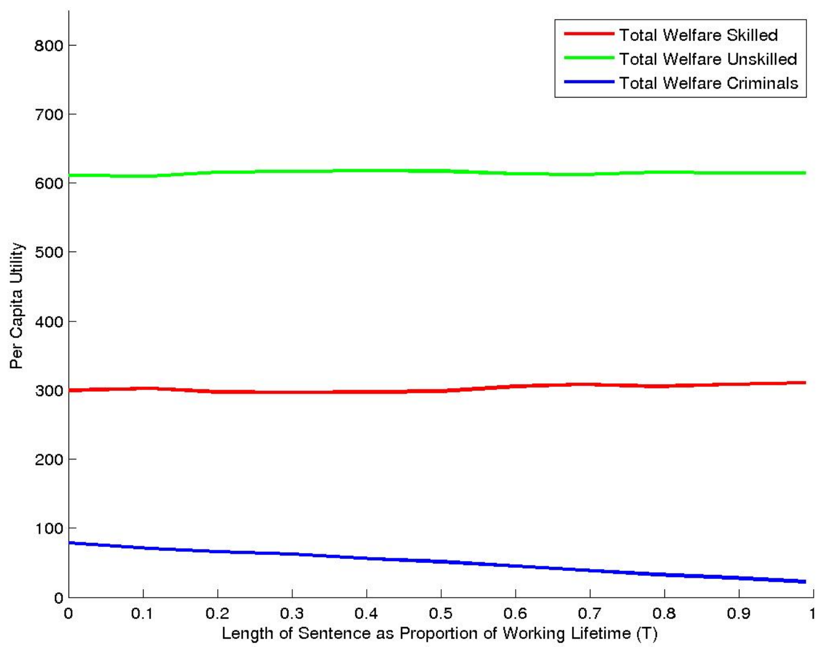

Figure 2.10: Effect of Sentence Length on Total Utility

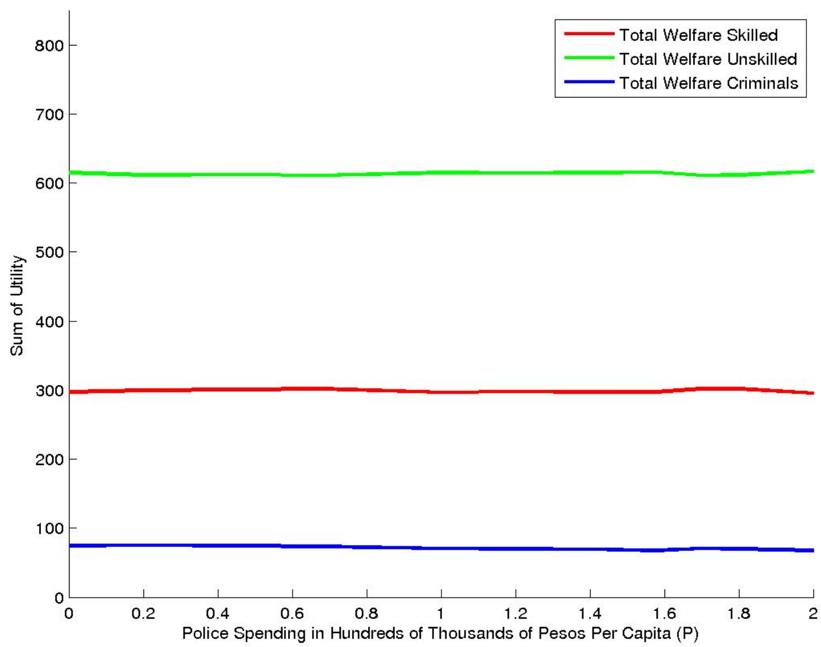

Figure 2.11: Effect of Police Spending on Total Utility

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Chapter 3

The Gender Gap in Mathematics: Evidence and Analysis from Middle- and Low-Income Countries

3.1 Introduction

Throughout much of the developing world, women tend to be disadvantaged in terms of job opportunities, wages, education, and so on (Sen, 1999). It is however true that the gender gap in education seems to be closing for recent cohorts and for some measures, e.g. college enrollment, it is currently reversed in some LDC's (World Development Report 2012) and in the US (Goldin et al., 2006)).

In this paper we look at one particular aspect of the gender gap in education: mathematical test scores. We look at whether and why they differ between boys and girls, with a specific focus on the top end of the distribution. There is a fundamental reason to look at the gender gap in mathematics rather then verbal tests: the robust positive effect of math score on future income (Paglin and Rufolo, 1990; Murnane et al., 1995; Grogger and Eide, 1995; Altonji and Blank, 1999; Weinberger, 1999, 2001; Murnane et al., 2000). In addition, there is a parallel literature which focuses on the (low) presence of women in technical jobs (Blau and Kahn, 2000; Brown and Corcoran, 1997; Weinberger, 2005) and partially attributes that to the gap at the top end. Our analysis begins by looking at a series of comparable data across countries: the PISA-OECD scores taken around age 15. Then we move to a much richer dataset from Chile where we have the (almost) full set of administrative data for 4th and 8th grade math scores in the country-wide standardized tests known as the SIMCE. We can match those scores with a rich set of socio-demographics as well as parental investment information.

For all the countries we consider, we show a substantial gap in mathematical test scores opening up as low as the median level and getting larger towards the top of the distribution. This means that the median boy and girl perform differently at age 15, with boys doing better than girls by 10% of a standard deviation. What is also quite striking is that the gap expands as we move along the distribution. In fact the gap is quite large at the top, where the 90th and 95th percentile scores for a boy are about 30% and 35% (of a standard deviation) larger than for a girl. Another way to look at this gap is that there are about 1.4 to 1.5 boys per girl in the top 10% of the distribution.

As we shall see later such a gap is also present in the Chilean data where we have the full population of individuals born since 1992. In the SIMCE scores at age 9 and 10 (grade 4) we see already a sizeable gap in the mean and median achievement. At the same time we note that these gaps expand substantially at ages 13 and 14 (grade 8).

Figure 3.1 shows the size of the gender gap across different quantiles of the distribution of math scores for ten developing countries, plus the US as a comparison. For seven of the eight countries, the gender gap is already present at the median and increases for higher quantiles. Thus, while the median boy may have a higher test score than the median girl, this disparity becomes especially pronounced at higher quantiles.[1]

Having found a consistent and substantial test gap across all the countries considered, we ask, "Why do such gaps exist?"

We list several theories that might be able to explain the gender gap in math scores. First, parents may invest more in boys than in girls. This differential investment could occur in prenatal care, as Bharadwaj and Nelson (2010) find in India, China, and several other countries. Under-investment in girls could also occur later, as parents' preference for sons leads them to spend more time and resources on their male children's education. This differential investment can also be a function of the wage gap and employment gap commonly observed between males and females.

[1]The gender gap in this figure is the coefficient on a dummy variable for being male in a quantile regression of standardized PISA math scores on "male" and a set of control variables for the fiftieth, seventy-fifth, ninetieth, and ninety-fifth percentiles. The PISA data will be described more in the data section.

Second, there could be differences in inherent ability between boys and girls in certain subjects. One way that these differences could manifest is through a difference in the test score variance between boys and girls. Machin and Pekkarinen (2008) find that boys have a higher variance in math and reading for most countries they examined. This increased variance for males appears to have some biological foundation, at least for traits that are linked to the X chromosome (Strauss and Strauss, 2009).

Third, schools could invest different amounts of resources in boys and girls or boys and girls could attend schools with different levels of resources, so that the "educational production function" determining scores would have different inputs for boys and girls. Macdonald et al. (2010) find that disparate school characteristics play a role in several Latin American countries in increasing the gender gap.

Fourth, girls might put less effort into learning certain subjects than boys, perhaps because girls believe that the return to effort in learning math or science will be lower for them. For example, Goldin et al. (2006) argue that women enrolled in college more and took more math and science classes in high school "beginning in the late 1960s and early 1970s, [because] young women's expectations of their future labor force participation radically changed" (p. 133).

Fifth, girls may need a different environment or teaching techniques than boys to learn well or to display their abilities. Men have been shown to perform better in and to seek out competitive environments more than women in experiments (Niederle and Vesterlund, 2007; Gneezy et al., 2003), which Niederle and Vesterlund (2010) argue may cause female students to perform worse on math tests than males with equal subject knowledge.

Sixth, cultural norms could discourage or inhibit girls' learning stereotypically male subjects. For example, Guiso et al. (2008) find, using the 2003 PISA data set, that the gender gap in math is narrower in countries with more gender equality.[2]

[2] It is however true that even for more gender-equal countries the gap at the top of the distribution

This paper seeks to make several contributions to this literature. First, we focus on low- to middle-income countries where such differences could be more pronounced. Second, we try to address the theories discussed above in a consistent framework, using the wealth of data available to us. We are able to investigate the existence of the gap at a relatively early age in the Chilean data; at the same time we have administrative data for almost the full relevant population. Our main findings are that the gender gap in test scores is substantial and it already opens in the middle of the distribution and as early as age 9, getting monotonically wider for the higher quantiles and at older ages. The gap does not close as we control for several of the possible confounders as mentioned in the possible explanations for that gap. For example, controlling for family background, parental investment, prenatal care, school and classroom characteristics plus "genetic" traits change very little the unconditional test gap. These findings suggest that the puzzle is still open and that the theories we propose are not able to explain much of the male-female gap in math.

As mentioned, we couple two main data sources: i. the PISA-OECD dataset, and ii. administrative data from Chile. The PISA data have an interesting cross-country dimension and a great wealth of information on household and school background characteristics. On the other hand, the Chilean administrative data are very informative in many respects; in particular, these are population data where the test scores for 4th and 8th grades are recorded for the entire population. At the same time, there is a wealth of information on parental investment, schools, and classrooms plus the opportunity of using the sample of twins for testing some of the previous hypotheses.

The policy relevance of the questions addressed in this study is rather immediate, as understanding the causes of such a gap is crucial for policy interventions. If class composition, competition, and teaching styles are the main cause of this gap, then

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does not seem to close. In fact, the male-female ratio for the 99th percentile of the distribution is above 1.6 in 36 out of the 40 countries in Guiso et al. (2008). See also our Figure 3.1.

one can design classroom and teaching strategies that might correct the imbalance. On the other hand if parental preferences and investment behavior are responsible for the gap then the "required" policy intervention would be fundamentally different.

The rest of the paper proceeds as follows: Section 3.2 describes the data sources used; Section 3.3 describes the empirical strategy, main tests, and results; finally, Section 3.4 concludes.

3.2 Data

3.2.1 PISA Data

This paper uses data from the 2006 and 2009 PISA (Programme for International Student Assessment) tests. The PISA is designed by the OECD to produce student outcomes that are comparable across countries and to provide information about the characteristics of successful students, families, schools, and national educational systems. Four waves of the PISA have been carried out (2000, 2003, 2006, and 2009), but we use only the two most recent, because the earlier waves do not contain as many countries, especially the developing countries we focus on in this paper.

The PISA data includes four distinct components: a student questionnaire, a parent questionnaire, a school questionnaire, and the results of three tests, for mathematics, science, and reading. We use primarily the student questionnaire responses and test results. The parental questionnaire was not administered for many of the countries in our set of countries of interest, but much of the information on parental education, occupation, wealth, and migrant status is available in the student questionnaire as well.

For the portions of this paper that use PISA data from multiple countries, we focus on a set of 10 countries (plus the US) that fulfill all the following criteria:

1. The country has a 2010 per capita purchasing power parity (PPP) adjusted GDP of $16,000 or less.

2. The country is not in Europe.

3. The country is not and is not a part of a former or current Communist country.

4. Data exists for the country for both the 2006 and 2009 waves of PISA.

Criterion 1 is imposed so as to focus the analysis on middle- and low- income countries. Criteria 2 and 3 are used to exclude countries with a different historical and institutional context than we are interested in. Criterion 4 is to ensure that the necessary data exists. The countries that fulfill all these criteria are Argentina, Brazil, Chile, Colombia, Indonesia, Mexico, Thailand, Tunisia, Turkey, and Uruguay. We also include the United States in the set of countries under analysis to allow us to make comparisons with a more economically developed country.[3]

Tables 3.1, 3.2, and 3.3 contain descriptive statistics for the variables of interest in the PISA dataset for these countries. Table 3.4 includes data by sex from UNESCO (2010) on survival rates to grade five (the percentage of students that eventually finish fifth grade) and the secondary school net enrollment rate (the percentage of people who are in the age range for secondary school that are actually enrolled in secondary school). It should be noted that the secondary school enrollment rates given here would underestimate the relevant enrollment rates for our analysis as we focus on grade 10 and below for most countries in the analysis, which is below compulsory schooling age for a regular schooling path.

[3] An exception to the selection rule above is the exclusion of Jordan that would satisfy all of the above criteria, but we do not find the results on that country believable. In any case the inclusion of Jordan in the analysis changes the results very little.

3.2.2 Administrative Data from Chile

In addition to the picture that the PISA data provides us, we will also use detailed Chilean administrative data, including the SIMCE. The SIMCE (loosely translated as System for Measuring Educational Quality) is a national test administered in Chile for all 4th graders. On alternate years, 8th and 10th grade students are also given this test. The 4th grade SIMCE was first administered in 2002 and subsequently on a yearly basis from 2005. We use the 8th grade SIMCE as administered in 2007 and 2009. While there were waves of the 8th grade SIMCE administered prior to 2007, we do not use them, as the cohort that took those tests were born prior to 1992 and hence were not available in the vital statistics database.

The SIMCE test for 4th graders consists of reading, math, and a social science component. For detailed information on the SIMCE and sample questions one can visit http://www.simce.cl/. One can think of the SIMCE tests as being evaluation tests. These results are published at various levels to track performance of schools and (what would be the equivalent of) school districts.

The Chilean administrative data we use in this paper allows us, in several ways, to go beyond what is possible with the PISA data. First, the SIMCE data covers almost all children in the relevant grades over multiple years, which allows us to examine students who took the SIMCE in both fourth and eighth grades to see how the gender gap in math scores changes as students grow older while eliminating possible selection effects. At the same time, as we are dealing with population data, we can analyze the very top performers, such as the top 1% or the top 5%. According to UNESCO (2010), the survival rate to fifth grade in the 2007 school year was 96 percent, indicating that selection of students out of school is unlikely to bias the analysis for fourth grade. From the same source, the 2010 net enrollment rate for secondary school as a whole was 84 percent among boys and 87 percent among girls, indicating that differential dropout rates are unlikely to bias the eighth grade results either.

Because we are interested in understanding outcomes at the top end of the distribution, we should consider whether the SIMCE data does a better job than the PISA data of distinguishing students at the very top end of the distribution from one another. For example, can these tests tell us with some certainty that a student at the 99th percentile on a test is actually better at math than a student at the 95th percentile? Test design is an important issue when considering this question, as Ellison and Swanson (2010) show at length. Both the SIMCE and the PISA are designed to be broad-based tests that can be used at a national level (and an international level in the case of PISA) to compare regional performance and not to look at the performance of high achievers specifically. Both tests, however, do provide enough difficulty that very few students answer all the questions correctly, which increases our confidence that they can distinguish students at the top. Though both tests should be able to do a decent job, the SIMCE seems better able to address the gender gap at the top end of the distribution because of its structure and scope. The sample size of the SIMCE is much larger, so that we simply have more high achievers in the sample and can reduce the standard error of our estimates when dealing with them. In addition, the SIMCE is better able to help us understand individual performance because it is longer and more uniform across individuals, while the PISA is shorter and uses different modules with different students, which allows for comparability across countries but does not give as much information about an individual student's performance as we would like.

Second, because we have the data for almost the entire relevant population of Chile for children born over a period of several years, we have a large number of sets of twins and of siblings, which allows us to control for family background, as well as unobserved school and neighborhood characteristics that are in common. We cannot entirely control for genetic ability using this data, unlike studies that use genetically identical homozygotic twins, but the fact that twins of opposite gender share more genetic information, on top of identical prenatal care, than two randomly chosen students of opposite gender will help us understand the genetic component of the gender gap.

Third, this administrative data includes information on birth weight and gestational age (the time from when a child is conceived to when he or she is born). This data allows us to control for differential parental investment in boy children relative to girl children. It may also relate to some components of ability, if ability is considered to be the initial potential skill or genetic endowment a person has at birth. Electronic birth records started in 1992 in Chile; detailed information is collected about every birth, such as birth weight, birth length, and gestational age, as well as basic parental characteristics, such as mother's age, education, and occupational status. The vital statistics used in this paper stem from the same data base as used in Bharadwaj and Neilson (2011). That paper shows that the vital statistics records in the dataset match rather well to nationally published records on births and deaths by year. Under the guidance of the Ministries of Health and Education, the vital statistics data were matched with the educational records for each child. Again, Bharadwaj and Neilson (2011) show that a large fraction of the population is observed with valid schooling data.

Fourth, some parental time investment variables are available in this data. These come from questions asked to parents, such as whether they do homework with their child or read to their child. This data will help us understand the role of differential postnatal parental investment in boys and girls on the gender gap.

Fifth, the SIMCE data includes the school and classroom of each student in the sample, so that we can include school and classroom fixed effects to control for the influence of these environments on the student. We can also examine the effect of classroom size or the gender composition of the classroom on the size of the gender gap, which will be important if boys and girls perform differently in different classroom environments, perhaps because of different attitudes toward competition or because of the need for different teaching styles.

The descriptive statistics for the SIMCE and other Chilean administrative data used are in table 3.5. Some characteristics to note in the data are that the modal level of education for mothers that have children in the data set is high school, that most mothers do not work (and the majority were unmarried), and that about a quarter of twin pairs are mixed sex.

3.3 Empirical Analysis

In the empirical analysis we will first establish the main facts about the math gender gap in selected countries, as well as specifically for Chile. After we have done so, we will move into the analysis of why such a gap exists. We will spell out our hypotheses and testing strategy as we go.

Just to review, we propose the following reasons for the math gender gap: (i) parental investment, (ii) ability, (iii) school resources, (iv) individual investment and effort, (v) competitive environment, and (vi) cultural norms.[4]

We begin our analysis by estimating simple quantile or mean models of test scores where the gender gap is captured by a dummy for being male. We also run a parallel analysis on probability models for falling in various top quantiles of the distribution of test scores. The main specification is as follows:

$$y_{ihst} = \alpha + \beta Male_i + \gamma X_{ihst} + \epsilon_{ihst} \tag{3.1}$$

where y is the standardized (at the country level) test score in math, and the X variables are controls for characteristics at the level of the individual, family, school,

[4] Though we are inclined to dismiss cultural norms from the start, as the gender gap is essentially the same in the US as in these developing countries.

etc. Controls are introduced to be consistent with the hypotheses we test. i indexes individuals, h households, s schools, and t is for the year or, more precisely, the cohort. Our main parameter of interest, β, is meant to capture the gender gap. The quantile version of this specification would require some extra notation but is essentially the same. In addition to this, we also estimate a linear probability model for the probability of being in the top 25%, 10%, and so on of the distribution of test scores.

3.3.1 PISA-OECD Evidence

Existence of the Gender Gap

We start off with the pooled countries quantile regression. As we move from left to right in Table 3.6, we move across quantiles. For each quantile we have two columns, the first with the simple gap and the second with additional controls for household and school characteristics. The analysis in Table 3.6 always includes country and year fixed effects plus age and grade of the student.[5]

The median regression shows a substantial gap in mathematical test score: the median male score is about 10% of a standard deviation higher than for females. Such gaps increase monotonically along the distribution, and for the top twentile the gap is as high as 35% of a standard deviation. As we shall see later these aggregate estimates mask some substantial heterogeneity across countries.[6]

Another way to look at the gender gap is to compute the ratio of males to females at various quantiles of the distribution, while adding the same controls as in the quantile regressions. This is exactly what we do in Table 3.7, where at the bottom of the table we present the male-female ratio for each regression. The main finding of

[5] In the PISA-OECD analysis we do not present the results for the top percentile (1%) as in this case we would be dealing with a very small number of observations.

[6] The median gap is of the order of magnitude of the class-size effect and other educational resources found in several studies.

this latter approach is that the male-female ratio increases from 1.1 in the top half of the distribution to 1.6 in the top 5%.[7]

Parental Background and School Characteristics

Two of our proposed explanations for the gender gap in math are (i) family background and (ii) school characteristics. It is possible that boys or girls are more likely to be present in specific households because of gender selective fertility and abortion (for a recent review of the literature, see Pörtner, 2010). At the same time, it is also possible that boys and girls are found in different schools. We therefore test for such hypotheses by adding additional controls to the simple mean or quantile differences discussed so far. The results of this exercise are presented in the even columns of Tables 3.6 and 3.7.[8] The previous findings remain unaltered as we add parental background controls such as mother's education, parental occupation category, immigration status, wealth, number of books at home, and so on. To reiterate, the test score gaps increase from 10% to about 35% of a standard deviation as we move from the middle to the top 5% of the distribution.[9]

Such statistics, however, mask some substantial heterogeneity across the countries considered; in fact, that heterogeneity emerges quite clearly in Figure 3.1, where one can see that the male-female ratios range, for the highest twentile, from 1.1 to 2. As mentioned, all these results also hold true when school fixed effects are included in individual country regressions, though these are not included in the pooled regression for computational reasons.

[7]Although we present a linear probability model in Table 3.7 the results from a probit model are essentially identical.

[8]As mentioned, for computational reasons we do not add school fixed effects in the pooled regressions, but country specific regressions with added school fixed effects produce very similar results to those presented here. These additional regressions are available from the authors.

[9]In the reported tables we do not use father's education, as that is not available for the Chilean administrative data. Adding this control does not change the results.

As we mentioned, proposed explanations include differential backgrounds between boys and girls and self-selection into schools and classes. We provide evidence in this section against family background and school selection as the main causes of such a gap. When we control for school as well as family background characteristics (such as education of the parents, wealth, occupation, and number of books in the household), as we do in each second column within each quantile in Tables 3.6 and 3.7, we find that the gap remains unaltered from the mere "unconditional" gap found in the odd columns of the same tables. The take-home message of this analysis is that one should look beyond parental background and school selection in the attempt to uncovering the roots of such an achievement gap.[10]

Family Composition, Parental Investment, and Competition

We can test the hypothesis that boys have higher math scores than girls because of differential parental investment or because of competition among siblings by examining family composition and how this affects test scores. If parents have a preference toward their male children, we would expect that female students would receive less parental investment if they have one brother and no sisters than if they have one sister and no brothers. If girls perform worse than boys do when placed in competition with male siblings, we should observe lower test scores for girls with brothers than boys with brothers or girls with no brothers. Unfortunately, we do not have full data on family composition and we have no data on birth order within the family, but the 2009 PISA data set does have questions in the student questionnaire asking whether the respondent has at least one sister living at home and whether they have at least one brother living at home, which will allow us to make some conclusions about the effects of family composition.

[10] Another point worth reporting is that the achievement gap is not closing between the two years we use for the study, 2006 and 2009. If we run an interaction model between them, we cannot reject the equality of the gaps for the two years, though this is admittedly a very limited time frame.

Using this data, we perform a quantile regression of test scores on the "male" dummy and the controls from the other quantile regressions, along with dummy variables that capture the different sibling situations we can distinguish among (at least one brother and no sisters at home, at least one sister and no brothers at home, at least one brother and one sister at home, and no brothers or sisters at home, which will be the excluded category) along with interactions of these with "male." The results of this are in Table 3.8. The inclusion of these sibling variables reduces the coefficient on "male," indicating that these variables play some role in the gender gap. The base "no brother, no sister" category produces the lowest test scores, followed by "brother and sister," "brother, no sister," and "no brother, sister" categories, in order; this means that girls do the best with a sister and no brother, which is consistent with either the parental investment or the inter-sibling competition hypothesis.[11] The outcomes for boys follow the same ranking, however, with all the effects being larger for them, so that boys appear to be more sensitive to family composition than girls but to be affected similarly. The size of these effects is also increasing for higher quantiles, indicating a larger role for family composition for higher-scoring students. The overall ranking of these outcomes does not seem to follow a consistent story about why parental investment or inter-sibling competition would work this way, so probably the most we can say from this data is that family composition matters for test scores, though not in a simple way. In particular, the competition story would predict that a girl with a brother should do worse than a girl with no brother (or just a sister), but the findings only partially support this prediction: a girl with a brother (and no sister) does worse than a girl with only sisters but does better than a girl with no siblings or a girl with both a brother and a sister.

We get similar results, which are shown in Table 3.9, from including the sibling

[11]For example, the quantile regression at the 90th percentile produces a coefficient on "male" of 0.273 without the sibling variables but only 0.198 with them. Similar patterns hold for the other quantiles.

variables in a linear regression for the probability of being in the top percentiles of the distribution.[12]

3.3.2 Analysis from Chilean Administrative Data

The addition of our Chilean administrative data allows us to go well beyond what is possible using the PISA-OECD data alone. As mentioned in Section 3.2, the Chilean data are extremely rich in many respects, including (i) population data (among other things we are now able to look at the top 1% of achievement), (ii) family background variables, (iii) twins and siblings sample, (iv) a panel dimension of the SIMCE testing, and (v) pre- and post-natal parental investment including vital statistics.

Existence of the Gender Gap

Table 3.10 has simple OLS regressions that use the standardized SIMCE math test scores as the dependent variable, with fourth grade scores being used in the first through third columns and eighth grade scores in the fourth through sixth columns. The first and fourth columns report the results of the most basic, "unconditional" regression of test score on a dummy variable for whether a student is male. We will discuss the remaining columns in the next sections.

The most important result of this exercise is that the coefficient on "male", which measures the gender gap, remains substantially the same as these control variables are added, at around 0.08 of a standard deviation for fourth grade and around 0.2 of a standard deviation for eighth grade, suggesting that the gender gap is not the result of boys' and girls' having systematically different family, classroom, or school environments.[13] It is also striking to observe that the gender gap more than doubles

[12]Probit results are also similar.

[13]One reassuring outcome is that the results of this regression with regard to the eighth grade gender gap are very similar to what the regression using the PISA data for Chile produces for students who are only a year or so older.

between fourth and eighth grade. This doubling also occurs when the sample of students is limited to those for whom we have both fourth grade and eighth grade scores, so that selection is not a plausible cause of this phenomenon. Fryer and Levitt (2010) find a similar pattern among US schoolchildren, that "[t]here are no mean differences between boys and girls upon entry to school, but girls lose more than two-tenths of a standard deviation relative to boys over the first six years of school" (p. 210). In the Chilean data, for computational reasons, we do not run quantile regressions, but we still investigate the distributional gap through the probability model (the linear probability model and the probit model produce very similar results, so we omit the probit here). The main findings from the probability model are that the unconditional male-female ratios increase from about 1.3 to 1.9 for 4th graders between the top 10% and the top 1% (Table 3.11). What is again striking is a large jump in the gaps for older children: for 8th graders the male-female ratios jump to 1.4 and 2.6 for the top 10% and 1% respectively (Table 3.11).[14]

Family Background, School and Class Characteristics

In order to test whether family background and school and class characteristics are crucial in explaining the gap, we first add control variables able to capture such confounders, such as birth weight and gestational age of the student and the education, employment, marital status, and age of the student's mother (we do not have corresponding variables for fathers given the nature of the data). The second and fifth columns also include school fixed effects, while columns 3 and 6 have classroom fixed effects instead.

Once again, columns 2, 3, 5, and 6 of Table 3.10 confirm the previous "unconditional" findings reported in columns 1 and 4. The average gender gap can be explained

[14] One would also have to consider the possibility that the 4th grade test is not able to capture the very top performances as well as the 8th grade test.

neither on the basis of the maternal characteristics included nor on classroom and school selection. Looking at the control variables in Table 3.10, the children of more educated women had much better test scores, while the children of older mothers and married mothers did somewhat better. The log of birth weight also has a statistically significant impact of about 0.25 standard deviations on both fourth grade and eighth grade test scores, indicating that a student who had a birth weight that was ten percent higher could expect a math test score 0.025 standard deviations higher.

Despite this gender gap in test scores, women receive more years of school than men on average in Chile, which one could hypothesize would compensate for some of the test score difference. Ñopo (2006) shows that, over the period from 1992 to 2003, women had 1.6 more years of schooling on average than men in rural areas and 0.5 years more in urban areas. Interestingly, the gender gap in wages was nonexistent in rural areas and quite large in urban areas, and the largest gender gap in wages by far was among college graduates. Education levels were increasing throughout this period. Nevertheless, women had relatively low, though increasing, rates of labor force participation during this period, around 35 percent.

We can look at the right tail of the distribution by using the probability analysis technique used above on the PISA data, with the results shown in Table 3.11. We examine how the probability of being in the top 1, 5 or 10% relates to the dummy variable for being male and the same set of control variables used in Table 3.10. In order to have a consistent basis of comparison as the base percentage changes, as for the PISA-OECD analysis, we also calculate the predicted male-to-female ratio. We find that, as in the PISA data, the gender gap increases at higher scores: for the fourth grade specification with class fixed effects, there are predicted to be 1.27 male students for every female in the top 10%, 1.35 males per female in the top 5%, and 1.86 males per female in the top 1%, while–consistent with the increase in coefficient in the OLS regression above–these ratios are 1.41, 1.50 and 2.33 among eighth graders.

These results are not sensitive to the use of fixed effects at the school instead of the class level.[15]

This gender gap in test scores may influence later wage differentials by gender. At the very least, the description of the math test score gender gap from the previous paragraph is consistent with the form that the wage gender gap among adults takes on. Ñopo (2006), for example, finds that the unexplained gender gap in wages in Chile is at around twenty-five percent of average female wages with an increasing gap by wage percentile: "While for the lowest percentiles of the wage distribution, males tend to earn an unexplained premium of 10 percent to 20 percent over comparable females, at the top of the distribution this premium increases to 40 percent to 80 percent, depending on the set of matching characteristics" (p. 31).

We additionally performed exactly the same analysis for the twins sample both on the continuous (mean) test outcome as well as on the top end of the distribution. For a detailed discussion on the twins sample and how it relates to the general population see Bharadwaj and Neilson (2011). The findings of this analysis are presented in Table 3.12. This specific cut of the data is meant to speak to several of the proposed explanations for the gender gap. In this section, however, the focus is on parental background, which twins typically share. As is clear from the table, if anything the gap is larger across the board for twins.

Parental Investment

Prenatal Investment It has been hypothesized that parents have a preference for boys over girls and therefore they invest more in boys. This type of investment can happen quite early, such as in the womb or once the baby is born. We have a couple

[15] Once again because of standard concerns with predictions from a linear probability model like this (in the tails), we also ran the probit version of it, finding that the results are not substantially different.

of ways to check whether the gender gap we found comes from very early investment in nutrition, health, and so on.

Studies have shown that boys typically tend to perform worse on early assessments of health such as APGAR scores (Gissler et al., 1999), even though they are typically born with higher birth weight. Moreover, in terms of early childhood cognitive achievement, females tend to perform better. Early studies such as Willerman et al. (1970), using data from the US, show that females perform significantly better on tests such as the Bayley Motor Test (administered at an age of 8 months). According to the same study, females also perform better at the Binet IQ test administered at age 4. Simple correlations using data from the *Children of the NLSY* 1979 sample suggest that females do indeed perform better on early motor and social development skills tests (administered to children between the ages of 0 and 3). However, in tests such as the Peabody Picture and Vocabulary Test (PPVT), administered to children ages 3 and up, gender gaps appear in later ages, with males performing slightly better than females. Hence it appears that girls do better than boys along various health and cognitive measures in very early childhood.

The most convincing evidence we provide relies on the twins sample, since twins are subjected to the same investment or care in the womb. The richness of the data allows us to fully difference out prenatal investment and family background characteristics through the use of data on twins. This is not to say that twins are a representative sample of the population; in fact, they are quite clearly at the bottom end of the distribution in many respects including test scores.

Table 3.12 contains the results of OLS and probability regressions similar to those above with the sample restricted to twins. These results display the same trend of a gender gap that increases with age and at higher percentiles of the score distribution seen in previous tables. In fact, the twins results display an even larger gender gap than that in the overall sample. Twins are, of course, not average individuals, but the persistence of the gender gap among them does allow us to conclude that prenatal parental investment is not the cause of this gap. As we can see from Table 3.12, girls fare worse than boys in math test scores even between twins. The same can be said for siblings, though those results are not shown here.

Post-Natal Investment It is still possible that parents invest more into boys than girls, because of son preference or because of higher returns on the investment (wage differentials).[16] We have some measures of parental investment in the Chilean data which can be summarized as mathematical or reading investments. For example, for the year 2002 data on 4th graders, the only year of data used in this part of the analysis, parents were asked: "How often do you pose math problems to your child?" They could reply in 5 categories from 1 (never) to 5 (very often). Similar questions were asked for reading investment.[17] We introduce such variables in our empirical model for the 4th grade test as continuous controls, the intuition being that if post-natal parental investment is the fundamental cause of the gender gap in math, once one controls for that (and other correlated confounders) the gap should shrink or disappear.[18] Clearly parental investment is not a random event, so here the analysis is just exploratory, but the twins sample might provide some more credible indication. Indeed we actually find that males receive more parental investment in math while the opposite is true for reading, interestingly these results are reversed in the twins sample (although not significant). The main results of this exercise, shown in Table 3.13 are that the gap is fundamentally unchanged in the mean and the top end of the distribution compared to Tables 3.10 and 3.11. Once again, using the twins sample,

[16]Another possibility which we do not investigate fully is that the child herself invests less than a boy because of lower returns or cultural norms.

[17]We construct the reading investment variable as the (child) mean of the following questions. How often do you: i. Give book or school help like encyclopedias, ii. talk with the child; iii. incentivize child to read.

[18]The large majority of the students, 93% of the 4th graders with valid SIMCE score, have valid parental investment information.

as shown in Table 3.14, qualitatively confirms the results for the general population, although for this exercise we lose the significance of some of the gaps as we are now using a fairly small sample.[19]

The take home message is that parental investment, measured as time spent challenging the little kids in math and reading, has a positive and significant impact on the overall performance of boys and girls but does not explain the gender gap, while at the same time we do find some indication for differential investment between boys and girls.

Competition

A very influential experimental literature finds that females tend to shy away from competition and that such behavior can explain a substantial part of the gender gap in performance in many realms that involve a significant competitive element, such as taking tests in school. It would be very hard, however, to square these results in particular experiments with experiments that involve verbal competition tasks, where it appears that girls do better than boys. In order to investigate such an issue, we introduce amongst the control variables the classroom composition in terms of share of male students. The thought experiment is the following: as the fraction of males in the classroom increases, females would feel a higher competitive pressure, which would hamper their performance. If this is a principal cause of the gender gap, female students should perform the same as males in predominantly female classrooms.

To investigate the influence of the competitive environment in the classroom on boys and girls, we regressed fourth and eighth grade test scores on different combinations of the male dummy, the proportion of males in the student's fourth grade class, the number of students in the student's fourth grade class, and interactions of "male"

[19] There is enough within-twin-pair variation in the investment variables to estimate those parameters.

with proportion male and class size. Table 3.15 reports the results of these regressions. We find that test scores go down for both boys and girls in fourth grade as the proportion of the class that is male increases, and that the effect is not significantly different by sex. For the eighth grade, we find that both sexes again do worse in the presence of more boys and that, in this case, boys experience this effect even more strongly than girls. Class size has a small negative effect on girls and a small positive effect on boys in fourth grade and a small positive effect on both sexes in eighth grade even controlling for school fixed effects. We might be concerned that a few outliers, classes which had almost all boys or almost all girls, are inordinately driving these results, so we also include the results of the regression excluding schools in which all students are of the same gender. This does not materially change the results. Thus, because we do not see a strong positive coefficient on the interaction of "male" and "fraction male," we learn from these class composition regressions that competition between boys and girls does not seem to be the main fact explaining the gender gap in math test scores either.[20]

The household composition regression using the PISA data is also relevant in this discussion, since siblings may compete within the household for resources as well as for grades and performances. As stated earlier, we found evidence that both sexes did better with certain combinations of siblings than others, but we did not find that the ordering of these outcomes supported the hypothesis of competition for household and parental resources or grades, especially because the ordering of outcomes was the same for both sexes.

[20]On a related note it would hard to explain why the competition explanation would hold for mathematical testing but not for reading, unless some further explanations are added on top of that.

Ability

We mentioned that a proposed explanation for the gender gap could be an innate ability difference between boys and girls in mathematical subjects in particular at the top of the distribution. Our analysis can indirectly speak to the ability explanation. First, we already mentioned that on many measures of health and cognitive ability girls tend to do better than boys at early ages. Our own simple analysis of correlations using data from the *Children of the NLSY* 1979 sample suggest that females do indeed perform better on early motor and social development skills tests (administered to children between the ages of 0 and 3). While boys tend to do better in the Peabody Picture and Vocabulary Test (PPVT), this is only at later ages. Hence it appears that girls do better than boys along various health and cognitive measures in very early childhood.

As mentioned in the Chilean data we have the ability to look into the mixed-gender twins portion of the data. Following a very influential paper in the education literature (Ashenfelter and Krueger, 1994), we consider twins as sharing a large component of the genetic map, in addition to the same level of prenatal care and investment. We believe that the initial conditions of mixed gender twins are quite similar so that if those initial conditions were to be the fundamental reason for the gender gap we should see a negligible gap within mixed gender pairs of twins. As can be seen from Table 3.12, that prediction is not borne out by the data, and, in fact, the gap is larger for twins than for the rest of the population. As mentioned, we know that twins are located in the lower part of the test score (as well as health) distribution so that one cannot lightly draw implications from this sample. We also notice that in the lower part of the distribution there is not much of a gap for the general population so that this would be a further reason for not finding any gap in the twins sample.

3.4 Concluding Remarks

A substantial gender gap in mathematical performance is found in several countries both in the middle and, more pronounced, at the top end of the distribution. It is also clear that while such gaps exist for a large number of countries there is a substantial heterogeneity in size. We also notice, from our Chilean data, that the gap increases over time so that smaller differences by grade 4 translate into quite big ones at later stages (grade 8).

We attempt to explain where this gap is coming from. We proposed several hypotheses from parental behavior to school and class selection, ability, and cultural norms. None of those seems to be able to account for the existence of such a gap. We however conjecture that the evidence we provide points towards an explanation (or multiple ones) that is behavioral in nature and that appear to intervene (at least initially) between birth and the first reliable test we have, i.e. 4th grade. This could be, for example, differential child investment due to lower labor market returns.

We are somehow left with a even bigger puzzle than we started with.

3.5 Figures and Tables

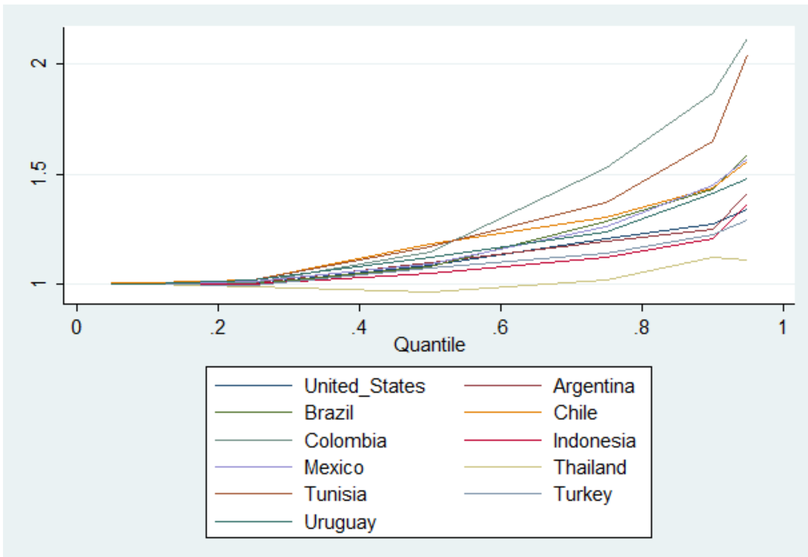

Figure 3.1: Gender Gap Size By Quantile

Table 3.1: PISA Descriptive Statistics by Year and Country: Argentina-Colombia

	Argentina		Brazil		Chile		Colombia	
	2006	2009	2006	2009	2006	2009	2006	2009
male	0.4566	0.4573	0.4581	0.4522	0.5408	0.5063	0.4562	0.4685
	(0.4982)	(0.4982)	(0.4983)	(0.4977)	(0.4984)	(0.5)	(0.4981)	(0.499)
broXsis		0.3871		0.2676		0.2815		0.2434
		(0.4871)		(0.4427)		(0.4498)		(0.4292)
broXnosis		0.248		0.2842		0.2784		0.2594
		(0.4319)		(0.451)		(0.4482)		(0.4384)
nobroXsis		0.1891		0.1544		0.2104		0.1896
		(0.3917)		(0.3613)		(0.4077)		(0.392)
nobroXnosis		0.1757		0.2938		0.2297		0.3075
		(0.3806)		(0.4555)		(0.4207)		(0.4615)
age	15.69	15.7	15.78	15.87	15.82	15.79	15.85	15.84
	(0.2789)	(0.2829)	(0.2876)	(0.281)	(0.2812)	(0.2821)	(0.2862)	(0.2798)
grade8orbelow	0.1224	0.1558	0.4058	0.2435	0.0285	0.0333	0.1679	0.1396
	(0.3278)	(0.3627)	(0.4911)	(0.4292)	(0.1663)	(0.1795)	(0.3738)	(0.3466)
grade9	0.1574	0.1975	0.4087	0.3981	0.1898	0.1963	0.222	0.2086
	(0.3642)	(0.3982)	(0.4916)	(0.4895)	(0.3921)	(0.3973)	(0.4156)	(0.4063)
grade10	0.6681	0.5905	0.1775	0.328	0.7193	0.7171	0.4015	0.4474
	(0.4709)	(0.4918)	(0.3821)	(0.4695)	(0.4494)	(0.4505)	(0.4903)	(0.4973)
grade11orabove	0.0408	0.0448	0.008	0.0304	0.0625	0.0533	0.2086	0.2044
	(0.1978)	(0.2069)	(0.0889)	(0.1716)	(0.2421)	(0.2246)	(0.4063)	(0.4033)
momisced0	0.1189	0.0788	0.1732	0.1052	0.0833	0.0529	0.1516	0.1367
	(0.3237)	(0.2694)	(0.3785)	(0.3068)	(0.2764)	(0.2239)	(0.3587)	(0.3436)
momisced1	0.2086	0.1768	0.175	0.2216	0.0476	0.0504	0.1829	0.1692
	(0.4063)	(0.3815)	(0.38)	(0.4153)	(0.2129)	(0.2189)	(0.3866)	(0.3749)
momisced2	0.1106	0.1052	0.2003	0.1951	0.2028	0.2071	0.136	0.1774
	(0.3137)	(0.3068)	(0.4003)	(0.3963)	(0.4021)	(0.4053)	(0.3428)	(0.382)
momisced3	0	0	0	0.0277	0.0976	0	0	0
	(0)	(0)	(0)	(0.164)	(0.2969)	(0)	(0)	(0)
momisced4	0.1883	0.173	0.131	0.2055	0.2591	0.4034	0.1251	0.1565
	(0.391)	(0.3783)	(0.3375)	(0.4041)	(0.4382)	(0.4906)	(0.3308)	(0.3634)
momisced5	0.1327	0.164	0.0543	0.043	0.0787	0.1055	0.1536	0.185
	(0.3393)	(0.3703)	(0.2267)	(0.2029)	(0.2693)	(0.3072)	(0.3606)	(0.3883)
momisced6	0.1798	0.2321	0.2205	0.1771	0.1546	0.1316	0.1811	0.1602
	(0.384)	(0.4222)	(0.4146)	(0.3817)	(0.3616)	(0.3381)	(0.3852)	(0.3668)
momlowerblue	0.0922	0.1422	0.2484	0.2508	0.3742	0.188	0.182	0.2193
	(0.2893)	(0.3493)	(0.4321)	(0.4335)	(0.484)	(0.3908)	(0.3859)	(0.4138)
momupperblue	0.032	0.0184	0.04	0.0832	0.0361	0.0411	0.0601	0.061
	(0.1761)	(0.1345)	(0.196)	(0.2761)	(0.1866)	(0.1985)	(0.2376)	(0.2393)
momupperwhite	0.2459	0.2715	0.2882	0.2361	0.1657	0.1877	0.2146	0.2173
	(0.4307)	(0.4448)	(0.453)	(0.4247)	(0.3718)	(0.3905)	(0.4106)	(0.4124)
momlowerwhite	0.1839	0.1546	0.16	0.1597	0.198	0.2805	0.1536	0.1434
	(0.3875)	(0.3615)	(0.3666)	(0.3664)	(0.3985)	(0.4493)	(0.3606)	(0.3505)
dadlowerblue	0.1399	0.2302	0.3827	0.1668	0.254	0.2433	0.2508	0.2449
	(0.3469)	(0.421)	(0.4861)	(0.3728)	(0.4353)	(0.4291)	(0.4335)	(0.4301)
dadupperblue	0.2616	0.203	0.1015	0.3332	0.2366	0.2321	0.2416	0.2564
	(0.4395)	(0.4023)	(0.3019)	(0.4714)	(0.425)	(0.4222)	(0.4281)	(0.4367)
dadupperwhite	0.2593	0.2748	0.3029	0.2393	0.2285	0.2464	0.2872	0.2543
	(0.4383)	(0.4465)	(0.4595)	(0.4267)	(0.4199)	(0.431)	(0.4525)	(0.4355)
dadlowerwhite	0.2159	0.159	0.0633	0.1202	0.159	0.1545	0.0907	0.0764
	(0.4115)	(0.3657)	(0.2434)	(0.3252)	(0.3657)	(0.3615)	(0.2872)	(0.2656)
mommigrant	0.0523	0.058	0.0432	0.0115	0.0111	0.0115	0.0074	0.0077
	(0.2227)	(0.2338)	(0.2034)	(0.1065)	(0.1047)	(0.1065)	(0.0855)	(0.0874)
wealth	-1.309	-0.9536	-1.523	-1.344	-0.9987	-0.6254	-1.67	-1.284
	(0.8972)	(0.8919)	(0.9489)	(0.8679)	(0.952)	(0.9768)	(1.054)	(1.078)
numbooks0to10	0.2936	0.2652	0.3521	0.362	0.2102	0.1942	0.312	0.2977
	(0.4555)	(0.4415)	(0.4777)	(0.4806)	(0.4075)	(0.3956)	(0.4633)	(0.4573)
numbooks11to25	0.2768	0.256	0.3045	0.3128	0.2828	0.2653	0.2845	0.3046
	(0.4475)	(0.4365)	(0.4602)	(0.4636)	(0.4504)	(0.4415)	(0.4512)	(0.4603)
numbooks26to100	0.2512	0.2591	0.2132	0.2151	0.3088	0.3235	0.2582	0.2707
	(0.4338)	(0.4382)	(0.4096)	(0.4109)	(0.462)	(0.4679)	(0.4377)	(0.4443)
numbooks101to200	0.0885	0.0987	0.0598	0.0553	0.0996	0.1152	0.0717	0.074
	(0.2841)	(0.2982)	(0.2372)	(0.2286)	(0.2994)	(0.3193)	(0.258)	(0.2618)
numbooks201to500	0.044	0.0507	0.0263	0.0206	0.0466	0.0529	0.0326	0.0234
	(0.2052)	(0.2194)	(0.1599)	(0.1419)	(0.2109)	(0.2239)	(0.1776)	(0.151)
numbooksmorethan500	0.023	0.0287	0.0144	0.0143	0.0214	0.0252	0.0109	0.0077
	(0.1501)	(0.167)	(0.1192)	(0.1186)	(0.1447)	(0.1568)	(0.104)	(0.0874)

Table 3.2: PISA Descriptive Statistics by Year and Country: Indonesia-Tunisia

	Indonesia		Mexico		Thailand		Tunisia	
	2006	2009	2006	2009	2006	2009	2006	2009
male	0.4969	0.4934	0.4581	0.4761	0.4212	0.4307	0.472	0.4761
	(0.5)	(0.5)	(0.4982)	(0.4994)	(0.4938)	(0.4952)	(0.4993)	(0.4995)
broXsis		0.2897		0.3568		0.1605		0.5134
		(0.4537)		(0.4791)		(0.3671)		(0.4999)
broXnosis		0.1752		0.2256		0.217		0.1935
		(0.3802)		(0.418)		(0.4123)		(0.3951)
nobroXsis		0.147		0.1705		0.2032		0.0977
		(0.3541)		(0.3761)		(0.4024)		(0.2969)
nobroXnosis		0.388		0.2471		0.4193		0.1954
		(0.4874)		(0.4313)		(0.4935)		(0.3965)
age	15.76	15.76	15.72	15.72	15.68	15.7	15.88	15.88
	(0.2867)	(0.2862)	(0.2783)	(0.2784)	(0.2875)	(0.2906)	(0.2823)	(0.2776)
grade8orbelow	0.1136	0.072	0.0567	0.0561	0.0118	0.0071	0.2858	0.2129
	(0.3173)	(0.2586)	(0.2312)	(0.2302)	(0.1079)	(0.0838)	(0.4518)	(0.4094)
grade9	0.474	0.4509	0.1488	0.2175	0.3169	0.2448	0.2235	0.2662
	(0.4993)	(0.4976)	(0.3558)	(0.4126)	(0.4653)	(0.43)	(0.4166)	(0.442)
grade10	0.3657	0.4278	0.6712	0.7188	0.6386	0.7173	0.4455	0.4696
	(0.4817)	(0.4948)	(0.4698)	(0.4496)	(0.4805)	(0.4504)	(0.4971)	(0.4991)
grade11orabove	0.0467	0.0493	0.1066	0.0066	0.0328	0.0308	0.0453	0.0513
	(0.211)	(0.2164)	(0.3087)	(0.0807)	(0.1781)	(0.1729)	(0.2079)	(0.2206)
momisced0	0.1035	0.116	0.1195	0.125	0.0754	0.0694	0.1037	0.2737
	(0.3046)	(0.3203)	(0.3243)	(0.3307)	(0.2641)	(0.2541)	(0.3049)	(0.4459)
momisced1	0.2606	0.3144	0.1922	0.2018	0.4144	0.457	0.2543	0.2226
	(0.439)	(0.4643)	(0.394)	(0.4014)	(0.4927)	(0.4982)	(0.4355)	(0.416)
momisced2	0.1822	0.1939	0.2238	0.2668	0.1378	0.1099	0.1569	0.1447
	(0.386)	(0.3954)	(0.4168)	(0.4423)	(0.3447)	(0.3128)	(0.3637)	(0.3518)
momisced3	0.0508	0.0327	0.0198	0.0205	0.0363	0.0275	0.0175	0.0327
	(0.2196)	(0.1779)	(0.1394)	(0.1417)	(0.1871)	(0.1635)	(0.131)	(0.1779)
momisced4	0.239	0.22	0.0872	0.1055	0.1743	0.1648	0.2476	0.1717
	(0.4265)	(0.4143)	(0.2821)	(0.3073)	(0.3794)	(0.371)	(0.4317)	(0.3772)
momisced5	0.0482	0.0448	0.1109	0.1015	0	0	0.0599	0.0486
	(0.2142)	(0.2068)	(0.314)	(0.302)	(0)	(0)	(0.2374)	(0.2151)
momisced6	0.1047	0.0664	0.2091	0.1591	0.1408	0.1578	0.1474	0.0486
	(0.3062)	(0.249)	(0.4067)	(0.3658)	(0.3479)	(0.3645)	(0.3546)	(0.2151)
momlowerblue	0.0922	0.1258	0.1398	0.1579	0.1508	0.1687	0.0899	0.1041
	(0.2894)	(0.3316)	(0.3468)	(0.3647)	(0.3579)	(0.3745)	(0.286)	(0.3055)
momupperblue	0.124	0.1421	0.0416	0.0383	0.2917	0.2667	0.042	0.046
	(0.3296)	(0.3492)	(0.1996)	(0.1919)	(0.4546)	(0.4423)	(0.2007)	(0.2095)
momupperwhite	0.1078	0.1131	0.187	0.1857	0.2285	0.2071	0.1114	0.1007
	(0.3102)	(0.3168)	(0.3899)	(0.3889)	(0.4199)	(0.4052)	(0.3147)	(0.301)
momlowerwhite	0.1097	0.0898	0.2031	0.1881	0.1672	0.1274	0.0407	0.0444
	(0.3125)	(0.2859)	(0.4023)	(0.3908)	(0.3731)	(0.3334)	(0.1977)	(0.206)
dadlowerblue	0.2546	0.2662	0.2702	0.2987	0.23	0.2199	0.3888	0.3891
	(0.4357)	(0.442)	(0.444)	(0.4577)	(0.4208)	(0.4142)	(0.4875)	(0.4876)
dadupperblue	0.2935	0.3248	0.235	0.2184	0.3004	0.2736	0.1711	0.1845
	(0.4554)	(0.4683)	(0.424)	(0.4131)	(0.4585)	(0.4458)	(0.3767)	(0.3879)
dadupperwhite	0.1797	0.1579	0.2725	0.2644	0.2566	0.2469	0.2707	0.2303
	(0.3839)	(0.3647)	(0.4452)	(0.441)	(0.4368)	(0.4312)	(0.4444)	(0.421)
dadlowerwhite	0.1512	0.1369	0.1414	0.1289	0.1056	0.0831	0.1067	0.1417
	(0.3583)	(0.3438)	(0.3484)	(0.3351)	(0.3074)	(0.276)	(0.3087)	(0.3488)
mommigrant	0.0039	0.0031	0.0225	0.0209	0.0061	1.60E-04	0.0192	0.0133
	(0.0619)	(0.0557)	(0.1484)	(0.1432)	(0.0781)	(0.0127)	(0.1372)	(0.1147)
wealth	-2.614	-1.775	-1.373	-1.561	-1.418	-1.172	-1.882	-1.669
	(1.257)	(1.242)	(1.076)	(1.139)	(1.08)	(0.9934)	(1.163)	(1.105)
numbooks0to10	0.203	0.2305	0.3535	0.3692	0.235	0.1979	0.3631	0.3758
	(0.4022)	(0.4212)	(0.4781)	(0.4826)	(0.424)	(0.3985)	(0.481)	(0.4844)
numbooks11to25	0.3861	0.3701	0.289	0.2911	0.3191	0.3052	0.2959	0.3391
	(0.4869)	(0.4829)	(0.4533)	(0.4543)	(0.4662)	(0.4605)	(0.4565)	(0.4734)
numbooks26to100	0.2718	0.2625	0.2248	0.2107	0.2842	0.3046	0.203	0.1804
	(0.4449)	(0.44)	(0.4175)	(0.4078)	(0.4511)	(0.4603)	(0.4023)	(0.3846)
numbooks101to200	0.0641	0.0592	0.0664	0.061	0.0888	0.0988	0.0468	0.0357
	(0.245)	(0.236)	(0.249)	(0.2393)	(0.2845)	(0.2984)	(0.2112)	(0.1856)
numbooks201to500	0.0201	0.0259	0.0302	0.0281	0.042	0.0535	0.0181	0.0174
	(0.1403)	(0.1588)	(0.1711)	(0.1651)	(0.2006)	(0.225)	(0.1333)	(0.1306)
numbooksmorethan500	0.0167	0.0218	0.0138	0.0139	0.0182	0.0288	0.0149	0.0149
	(0.1282)	(0.1461)	(0.1165)	(0.1169)	(0.1339)	(0.1671)	(0.121)	(0.1213)

Table 3.3: PISA Descriptive Statistics by Year and Country: Turkey-Uruguay

	Turkey		United States		Uruguay	
	2006	2009	2006	2009	2006	2009
male	0.5366	0.5106	0.5061	0.5135	0.4695	0.4717
	(0.4987)	(0.4999)	(0.5)	(0.4999)	(0.4991)	(0.4992)
broXsis		0.297		0.2649		0.2647
		(0.457)		(0.4413)		(0.4412)
broXnosis		0.2456		0.2717		0.2706
		(0.4305)		(0.4449)		(0.4443)
nobroXsis		0.211		0.236		0.214
		(0.408)		(0.4247)		(0.4102)
nobroXnosis		0.2464		0.2274		0.2506
		(0.431)		(0.4192)		(0.4334)
age	15.9	15.82	15.82	15.79	15.87	15.86
	(0.2875)	(0.2806)	(0.2952)	(0.2964)	(0.2853)	(0.2774)
grade8orbelow	0.0235	0.0274	0.0057	7.60E-04	0.1414	0.1731
	(0.1514)	(0.1633)	(0.0753)	(0.0276)	(0.3484)	(0.3783)
grade9	0.4061	0.2518	0.1098	0.108	0.1575	0.2182
	(0.4912)	(0.4341)	(0.3126)	(0.3104)	(0.3643)	(0.4131)
grade10	0.5405	0.6791	0.7161	0.6916	0.6222	0.5625
	(0.4984)	(0.4669)	(0.4509)	(0.4619)	(0.4849)	(0.4961)
grade11orabove	0.0299	0.0416	0.1681	0.1997	0.0789	0.0462
	(0.1705)	(0.1998)	(0.374)	(0.3998)	(0.2697)	(0.2099)
momisced0	0.0552	0.1311	0.0248	0.0174	0.0773	0.0522
	(0.2285)	(0.3375)	(0.1554)	(0.1307)	(0.2671)	(0.2225)
momisced1	0.346	0.4742	0.0214	0.0266	0.1819	0.2646
	(0.4757)	(0.4994)	(0.1447)	(0.1608)	(0.3858)	(0.4411)
momisced2	0.2036	0.1667	0.0736	0.0663	0.1769	0.2704
	(0.4027)	(0.3728)	(0.2612)	(0.2488)	(0.3816)	(0.4442)
momisced3	0.0089	0.006	0	0	0.0134	0.0151
	(0.0939)	(0.0773)	(0)	(0)	(0.1151)	(0.122)
momisced4	0.2293	0.1147	0.4058	0.4097	0.0899	0.1427
	(0.4204)	(0.3187)	(0.4911)	(0.4918)	(0.2861)	(0.3498)
momisced5	0.048	0.016	0.1285	0.1525	0.2565	0.0995
	(0.2137)	(0.1255)	(0.3347)	(0.3595)	(0.4367)	(0.2994)
momisced6	0.0979	0.0512	0.2816	0.3046	0.1383	0.1131
	(0.2973)	(0.2205)	(0.4498)	(0.4603)	(0.3452)	(0.3168)
momlowerblue	0.018	0.0268	0.0611	0.0688	0.1965	0.2056
	(0.133)	(0.1616)	(0.2396)	(0.2531)	(0.3974)	(0.4042)
momupperblue	0.0374	0.0254	0.0219	0.0302	0.049	0.0571
	(0.1898)	(0.1574)	(0.1464)	(0.1711)	(0.2158)	(0.232)
momupperwhite	0.0645	0.0689	0.4507	0.4714	0.2668	0.2473
	(0.2458)	(0.2532)	(0.4976)	(0.4992)	(0.4423)	(0.4315)
momlowerwhite	0.0362	0.0476	0.2834	0.279	0.255	0.2357
	(0.1869)	(0.213)	(0.4507)	(0.4485)	(0.4359)	(0.4245)
dadlowerblue	0.1297	0.1753	0.1704	0.1599	0.2186	0.2364
	(0.336)	(0.3803)	(0.376)	(0.3666)	(0.4134)	(0.4249)
dadupperblue	0.3191	0.2548	0.1673	0.2024	0.2271	0.2434
	(0.4662)	(0.4358)	(0.3733)	(0.4018)	(0.419)	(0.4292)
dadupperwhite	0.3112	0.3088	0.3782	0.3732	0.2852	0.2303
	(0.463)	(0.4621)	(0.485)	(0.4837)	(0.4515)	(0.4211)
dadlowerwhite	0.1453	0.1313	0.0781	0.0948	0.1442	0.1675
	(0.3524)	(0.3378)	(0.2683)	(0.2929)	(0.3514)	(0.3735)
mommigrant	0.015	0.0142	0.1864	0.2253	0.0223	0.021
	(0.1215)	(0.1184)	(0.3895)	(0.4178)	(0.1477)	(0.1433)
wealth	-1.497	-1.02	0.151	0.4138	-1.084	-0.6823
	(1.005)	(1.247)	(0.7984)	(0.8911)	(0.9591)	(0.9141)
numbooks0to10	0.2252	0.2342	0.1586	0.1989	0.2191	0.2928
	(0.4178)	(0.4235)	(0.3654)	(0.3992)	(0.4136)	(0.4551)
numbooks11to25	0.2709	0.2496	0.154	0.1752	0.2439	0.2431
	(0.4445)	(0.4328)	(0.361)	(0.3802)	(0.4294)	(0.429)
numbooks26to100	0.3029	0.2972	0.286	0.2777	0.2817	0.2481
	(0.4596)	(0.4571)	(0.452)	(0.4479)	(0.4499)	(0.432)
numbooks101to200	0.101	0.1151	0.18	0.1628	0.1269	0.0977
	(0.3013)	(0.3192)	(0.3842)	(0.3692)	(0.3329)	(0.2969)
numbooks201to500	0.0587	0.0588	0.1301	0.1116	0.063	0.053
	(0.235)	(0.2354)	(0.3364)	(0.3149)	(0.243)	(0.2241)
numbooksmorethan500	0.0304	0.0312	0.0761	0.0592	0.0327	0.0302
	(0.1716)	(0.1739)	(0.2652)	(0.2361)	(0.1777)	(0.1712)

Table 3.4: Survival Rates to Grade 5 and Secondary Enrollment Rates by Sex

	Survival Rate to Grade 5		Net Secondary Enrollment Rate	
Country	Female	Male	Female	Male
Argentina	98	95	84	75
Brazil	NA	NA	85	78
Chile	97	96	87	84
Colombia	88 (Avg.)	88 (Avg.)	75	68
Indonesia	89	83	68	69
Mexico	95	93	74	71
Thailand	NA	NA	77	68
Tunisia	96	96	76	67
Turkey	94	94	70	77
United States	94 (Avg.)	94 (Avg.)	89	88
Uruguay	96	93	71	64

NA: Data not available

Avg: Average across both sexes. Data not available by sex.

Data: UNESCO (2010)

Table 3.5: Descriptive Statistics for Chilean Administrative Data

	Observations	Mean	Standard Deviation
Birth Weight (in Grams)	2582154	3336.6	548.7
Fraction Fullterm Births (38-40 Weeks Gestation)	2582154	0.795	0.404
Fraction of Mothers Married	2332924	0.439	0.496
Mother's Education: Primary School	2563158	0.282	0.450
Mother's Education: High School	2563158	0.576	0.494
Mother's Education: College	2563158	0.142	0.349
Fraction of Mothers Employed	2580879	0.247	0.431
Fraction Twins Both Male	41929	0.356	0.479
Fraction Twins of Mixed Sex	41929	0.243	0.429
Fraction Twins Both Female	41929	0.399	0.490
Fraction of Students Male in Sample	2582154	0.511	0.500
Class size in 4th grade	1765155	30.33	10.43
Fraction Male in 4th Grade	2685373	0.511	0.149
Class size in 8th grade	844145	29.06	10.76
Fraction Male in 8th Grade	2685418	0.511	0.110

Table 3.6: Quantile Regressions Using Pooled PISA Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	stdscorem	stdscorem	stdscorem	stdscorem	stdscorem	stdscorem	stdscorem	stdscorem
Quantile	50	50	75	75	90	90	95	95
male	0.111***	0.116***	0.209***	0.183***	0.289***	0.273***	0.362***	0.337***
	(0.0055)	(0.0052)	(0.0052)	(0.0064)	(0.0080)	(0.010)	(0.014)	(0.014)
age	-0.102***	-0.0564***	-0.117***	-0.0614***	-0.121***	-0.0704***	-0.172***	-0.0771***
	(0.010)	(0.0095)	(0.0095)	(0.012)	(0.014)	(0.019)	(0.025)	(0.025)
year2009	-0.0467***	-0.0511***	-0.0314***	-0.0191***	-0.0497***	-0.0359***	0.00435	0.0256*
	(0.0056)	(0.0053)	(0.0053)	(0.0065)	(0.0081)	(0.011)	(0.014)	(0.014)
grade8orbelow	-0.220***	-0.178***	-0.394***	-0.304***	-0.597***	-0.428***	-0.784***	-0.553***
	(0.010)	(0.0096)	(0.0096)	(0.012)	(0.015)	(0.019)	(0.026)	(0.026)
grade10	0.314***	0.264***	0.520***	0.405***	0.733***	0.539***	0.868***	0.631***
	(0.0069)	(0.0066)	(0.0065)	(0.0080)	(0.0099)	(0.013)	(0.017)	(0.018)
grade11orabove	0.415***	0.314***	0.682***	0.502***	0.963***	0.710***	1.154***	0.887***
	(0.013)	(0.012)	(0.012)	(0.015)	(0.018)	(0.024)	(0.032)	(0.033)
momisced1		0.00501		0.00865		0.0349**		0.0492**
		(0.0091)		(0.011)		(0.018)		(0.024)
momisced2		0.0242***		0.0516***		0.0732***		0.119***
		(0.0093)		(0.011)		(0.018)		(0.025)
momisced3		0.0738***		0.129***		0.220***		0.341***
		(0.020)		(0.024)		(0.039)		(0.053)
momisced4		0.0511***		0.103***		0.166***		0.237***
		(0.010)		(0.012)		(0.019)		(0.026)
momisced5		0.0175		0.0532***		0.0950***		0.176***
		(0.012)		(0.014)		(0.023)		(0.031)
momisced6		0.0800***		0.146***		0.242***		0.359***
		(0.011)		(0.013)		(0.021)		(0.028)
momupperblue		0.0662***		0.0977***		0.138***		0.186***
		(0.011)		(0.013)		(0.022)		(0.030)
momupperwhite		0.156***		0.212***		0.314***		0.336***
		(0.0079)		(0.0095)		(0.015)		(0.020)
momlowerwhite		0.0813***		0.0971***		0.128***		0.137***
		(0.0075)		(0.0091)		(0.015)		(0.020)
dadupperblue		-0.00316		0.00414		0.00678		0.00453
		(0.0069)		(0.0084)		(0.014)		(0.018)
dadupperwhite		0.118***		0.197***		0.255***		0.306***
		(0.0075)		(0.0090)		(0.014)		(0.019)
dadlowerwhite		0.0382***		0.0742***		0.0941***		0.0998***
		(0.0086)		(0.010)		(0.017)		(0.023)
mommigrant		-0.110***		-0.149***		-0.156***		-0.147***
		(0.016)		(0.020)		(0.031)		(0.043)
wealth		0.0521***		0.0783***		0.0990***		0.111***
		(0.0029)		(0.0035)		(0.0057)		(0.0078)
numbooks11to25		0.0237***		0.0303***		0.0338**		0.0470***
		(0.0067)		(0.0082)		(0.013)		(0.018)
numbooks26to100		0.0958***		0.163***		0.250***		0.300***
		(0.0074)		(0.0089)		(0.014)		(0.019)
numbooks101to200		0.144***		0.248***		0.402***		0.511***
		(0.011)		(0.013)		(0.021)		(0.029)
numbooks201to500		0.238***		0.390***		0.582***		0.638***
		(0.015)		(0.018)		(0.028)		(0.039)
numbooksmorethan500		0.188***		0.341***		0.536***		0.569***
		(0.019)		(0.023)		(0.037)		(0.051)
Constant	1.147***	0.396***	1.955***	0.950***	2.651***	1.576***	3.896***	1.997***
	(0.16)	(0.15)	(0.15)	(0.18)	(0.23)	(0.29)	(0.39)	(0.40)
Country Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	200428	199268	200428	199268	200428	199268	200428	199268

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

Table 3.7: Linear Regression of Top Scores for Pooled PISA Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	above50	above50	above75	above75	above90	above90	above95	above95
male	0.0473***	0.0422***	0.0588***	0.0530***	0.0374***	0.0334***	0.0227***	0.0201***
	(0.0022)	(0.0022)	(0.0019)	(0.0019)	(0.0014)	(0.0014)	(0.00099)	(0.00098)
age	-0.0397***	-0.0291***	-0.0362***	-0.0229***	-0.0114***	-0.00265	-0.00413**	0.00133
	(0.0040)	(0.0040)	(0.0035)	(0.0035)	(0.0025)	(0.0025)	(0.0018)	(0.0018)
year2009	-0.0494***	-0.0521***	-0.0276***	-0.0277***	0.00508***	0.00577***	-0.00385***	-0.00334***
	(0.0022)	(0.0023)	(0.0020)	(0.0020)	(0.0014)	(0.0014)	(0.0010)	(0.0010)
grade8orbelow	-0.118***	-0.0980***	-0.111***	-0.0890***	-0.0546***	-0.0402***	-0.0260***	-0.0175***
	(0.0040)	(0.0041)	(0.0035)	(0.0035)	(0.0025)	(0.0025)	(0.0018)	(0.0018)
grade10	0.131***	0.107***	0.144***	0.114***	0.0827***	0.0624***	0.0454***	0.0329***
	(0.0028)	(0.0028)	(0.0024)	(0.0024)	(0.0017)	(0.0017)	(0.0012)	(0.0012)
grade11orabove	0.163***	0.131***	0.182***	0.140***	0.100***	0.0728***	0.0648***	0.0478***
	(0.0052)	(0.0052)	(0.0046)	(0.0045)	(0.0032)	(0.0032)	(0.0023)	(0.0023)
momisced1		0.01000***		0.000495		0.00290		-0.000486
		(0.0038)		(0.0033)		(0.0024)		(0.0017)
momisced2		0.0218***		0.0124***		0.0111***		0.00174
		(0.0039)		(0.0034)		(0.0024)		(0.0017)
momisced3		0.0215**		0.0281***		0.0316***		0.0186***
		(0.0084)		(0.0072)		(0.0051)		(0.0037)
momisced4		0.0265***		0.0280***		0.0224***		0.00993***
		(0.0042)		(0.0037)		(0.0026)		(0.0019)
momisced5		0.0178***		0.0142***		0.0109***		0.00542**
		(0.0050)		(0.0043)		(0.0031)		(0.0022)
momisced6		0.0252***		0.0393***		0.0395***		0.0263***
		(0.0047)		(0.0040)		(0.0029)		(0.0021)
momupperblue		0.0314***		0.0275***		0.0158***		0.00962***
		(0.0047)		(0.0040)		(0.0029)		(0.0021)
momupperwhite		0.0401***		0.0616***		0.0402***		0.0229***
		(0.0034)		(0.0029)		(0.0021)		(0.0015)
momlowerwhite		0.0319***		0.0344***		0.0167***		0.00735***
		(0.0032)		(0.0027)		(0.0020)		(0.0014)
dadupperblue		-0.00314		-0.00631**		-0.00132		0.000681
		(0.0029)		(0.0025)		(0.0018)		(0.0013)
dadupperwhite		0.0313***		0.0474***		0.0370***		0.0221***
		(0.0032)		(0.0027)		(0.0020)		(0.0014)
dadlowerwhite		0.0138***		0.0146***		0.0118***		0.00674***
		(0.0036)		(0.0032)		(0.0022)		(0.0016)
mommigrant		-0.0605***		-0.0279***		-0.0105**		-0.00203
		(0.0068)		(0.0059)		(0.0042)		(0.0030)
wealth		0.0258***		0.0238***		0.0120***		0.00831***
		(0.0012)		(0.0011)		(0.00076)		(0.00055)
numbooks11to25		0.0133***		0.0109***		0.00321*		0.00151
		(0.0028)		(0.0025)		(0.0017)		(0.0013)
numbooks26to100		0.0392***		0.0482***		0.0312***		0.0179***
		(0.0031)		(0.0027)		(0.0019)		(0.0014)
numbooks101to200		0.0440***		0.0700***		0.0485***		0.0332***
		(0.0046)		(0.0040)		(0.0028)		(0.0021)
numbooks201to500		0.0637***		0.104***		0.0742***		0.0439***
		(0.0063)		(0.0054)		(0.0039)		(0.0028)
numbooksmorethan500		0.0575***		0.0827***		0.0646***		0.0452***
		(0.0081)		(0.0070)		(0.0050)		(0.0036)
Constant	1.026***	0.844***	0.773***	0.531***	0.207***	0.0373	0.0685**	-0.0342
	(0.063)	(0.063)	(0.055)	(0.055)	(0.039)	(0.039)	(0.028)	(0.028)
Country Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	200428	199268	200428	199268	200428	199268	200428	199268
R-squared	0.03	0.05	0.04	0.07	0.03	0.06	0.02	0.04
Above Quantile	50	50	75	75	90	90	95	95
Male-Female Ratio	1.0993	1.0881	1.2665	1.2369	1.4606	1.3995	1.5843	1.5044

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

Table 3.8: Quantile Regressions Including Sibling Data Using Pooled PISA Data

	(1)	(2)	(3)	(4)
COEFFICIENT	stdscorem	stdscorem	stdscorem	stdscorem
Quantile	50	75	90	95
male	0.0752***	0.118***	0.198***	0.231***
	(0.014)	(0.016)	(0.026)	(0.042)
broXsis	0.0402***	0.0870***	0.102***	0.129***
	(0.014)	(0.015)	(0.024)	(0.039)
broXnosis	0.0673***	0.129***	0.189***	0.236***
	(0.015)	(0.016)	(0.026)	(0.042)
nobroXsis	0.117***	0.167***	0.217***	0.246***
	(0.016)	(0.017)	(0.028)	(0.045)
maleXbroXsis	0.0553***	0.0795***	0.0976***	0.118**
	(0.020)	(0.022)	(0.035)	(0.056)
maleXbroXnosis	0.0637***	0.0917***	0.107***	0.124**
	(0.021)	(0.023)	(0.037)	(0.060)
maleXnobroXsis	0.0752***	0.113***	0.0958**	0.165**
	(0.023)	(0.025)	(0.040)	(0.065)
age	-0.0627***	-0.0888***	-0.105***	-0.158***
	(0.014)	(0.015)	(0.024)	(0.039)
grade8orbelow	-0.130***	-0.229***	-0.332***	-0.422***
	(0.014)	(0.015)	(0.024)	(0.039)
grade10	0.248***	0.400***	0.556***	0.687***
	(0.0094)	(0.010)	(0.017)	(0.027)
grade11orabove	0.389***	0.614***	0.902***	1.141***
	(0.020)	(0.022)	(0.035)	(0.057)
momisced1	-0.00306	0.00828	0.0322	0.0196
	(0.013)	(0.014)	(0.023)	(0.037)
momisced2	0.0201	0.0576***	0.0743***	0.0696*
	(0.013)	(0.015)	(0.024)	(0.038)
momisced3	0.0663**	0.153***	0.249***	0.339***
	(0.030)	(0.033)	(0.053)	(0.085)
momisced4	0.0332**	0.0944***	0.130***	0.154***
	(0.015)	(0.016)	(0.026)	(0.041)
momisced5	0.0173	0.0555***	0.110***	0.117**
	(0.018)	(0.019)	(0.030)	(0.049)
momisced6	0.0397**	0.101***	0.154***	0.233***
	(0.017)	(0.018)	(0.028)	(0.045)
momupperblue	0.0641***	0.110***	0.166***	0.221***
	(0.016)	(0.018)	(0.028)	(0.046)
momupperwhite	0.143***	0.200***	0.307***	0.389***
	(0.012)	(0.013)	(0.020)	(0.033)
momlowerwhite	0.0764***	0.0911***	0.137***	0.163***
	(0.011)	(0.012)	(0.019)	(0.031)
dadupperblue	0.00442	0.00245	0.0206	-0.00248
	(0.0098)	(0.011)	(0.017)	(0.028)
dadupperwhite	0.112***	0.198***	0.279***	0.342***
	(0.011)	(0.012)	(0.018)	(0.029)
dadlowerwhite	0.0316**	0.0529***	0.0619***	0.0959***
	(0.012)	(0.014)	(0.022)	(0.035)
mommigrant	-0.104***	-0.144***	-0.197***	-0.230***
	(0.024)	(0.027)	(0.042)	(0.068)
wealth	0.0494***	0.0777***	0.104***	0.135***
	(0.0043)	(0.0047)	(0.0075)	(0.012)
numbooks11to25	0.0238**	0.0254**	0.0289*	0.0250
	(0.0096)	(0.011)	(0.017)	(0.027)
numbooks26to100	0.0863***	0.143***	0.188***	0.206***
	(0.011)	(0.012)	(0.018)	(0.030)
numbooks101to200	0.102***	0.216***	0.354***	0.487***
	(0.016)	(0.017)	(0.027)	(0.045)
numbooks201to500	0.249***	0.350***	0.514***	0.566***
	(0.022)	(0.024)	(0.037)	(0.060)
numbooksmorethan500	0.133***	0.284***	0.414***	0.456***
	(0.028)	(0.031)	(0.049)	(0.079)
Constant	0.401*	1.284***	1.986***	3.181***
	(0.22)	(0.24)	(0.38)	(0.62)
Observations	108542	108542	108542	108542

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

Table 3.9: Linear Regressions Including Sibling Data Using Pooled PISA Data

	(1)	(2)	(3)	(4)
COEFFICIENT	above50	above75	above90	above95
male	0.0339***	0.0386***	0.0244***	0.00956***
	(0.0057)	(0.0049)	(0.0036)	(0.0025)
broXsis	0.0264***	0.0265***	0.0125***	0.000410
	(0.0055)	(0.0047)	(0.0034)	(0.0024)
broXnosis	0.0396***	0.0402***	0.0224***	0.00695***
	(0.0058)	(0.0049)	(0.0036)	(0.0025)
nobroXsis	0.0541***	0.0519***	0.0295***	0.00820***
	(0.0062)	(0.0053)	(0.0039)	(0.0028)
maleXbroXsis	0.0155**	0.0204***	0.0120**	0.0113***
	(0.0078)	(0.0066)	(0.0049)	(0.0034)
maleXbroXnosis	0.00641	0.0226***	0.0139***	0.0125***
	(0.0083)	(0.0070)	(0.0052)	(0.0036)
maleXnobroXsis	0.00994	0.0190**	0.0156***	0.0179***
	(0.0091)	(0.0077)	(0.0056)	(0.0040)
age	-0.0234***	-0.0215***	-0.00575*	-0.00294
	(0.0055)	(0.0047)	(0.0034)	(0.0024)
grade8orbelow	-0.0789***	-0.0705***	-0.0308***	-0.0145***
	(0.0055)	(0.0047)	(0.0034)	(0.0024)
grade10	0.0959***	0.113***	0.0663***	0.0335***
	(0.0037)	(0.0032)	(0.0023)	(0.0016)
grade11orabove	0.128***	0.171***	0.106***	0.0633***
	(0.0080)	(0.0068)	(0.0050)	(0.0035)
momisced1	0.00926*	0.00435	0.00482	-0.00105
	(0.0052)	(0.0044)	(0.0032)	(0.0023)
momisced2	0.0234***	0.0157***	0.0112***	-0.0000830
	(0.0053)	(0.0046)	(0.0033)	(0.0024)
momisced3	0.0484***	0.0368***	0.0352***	0.0210***
	(0.012)	(0.010)	(0.0074)	(0.0053)
momisced4	0.0261***	0.0290***	0.0204***	0.00652**
	(0.0058)	(0.0050)	(0.0036)	(0.0026)
momisced5	0.0183***	0.0204***	0.0135***	0.00519*
	(0.0070)	(0.0059)	(0.0043)	(0.0031)
momisced6	0.0194***	0.0291***	0.0321***	0.0199***
	(0.0067)	(0.0057)	(0.0042)	(0.0029)
momupperblue	0.0303***	0.0319***	0.0201***	0.0123***
	(0.0063)	(0.0054)	(0.0039)	(0.0028)
momupperwhite	0.0373***	0.0611***	0.0392***	0.0200***
	(0.0048)	(0.0041)	(0.0030)	(0.0021)
momlowerwhite	0.0269***	0.0320***	0.0188***	0.00796***
	(0.0043)	(0.0037)	(0.0027)	(0.0019)
dadupperblue	0.00218	-0.00289	-0.000479	0.000217
	(0.0039)	(0.0033)	(0.0024)	(0.0017)
dadupperwhite	0.0329***	0.0486***	0.0382***	0.0240***
	(0.0043)	(0.0036)	(0.0026)	(0.0019)
dadlowerwhite	0.0131***	0.0136***	0.00601**	0.00417*
	(0.0049)	(0.0042)	(0.0031)	(0.0022)
mommigrant	-0.0587***	-0.0244***	-0.0143**	-0.00781*
	(0.0096)	(0.0082)	(0.0060)	(0.0042)
wealth	0.0194***	0.0212***	0.0144***	0.00830***
	(0.0017)	(0.0014)	(0.0011)	(0.00075)
numbooks11to25	0.0132***	0.00941***	0.00308	0.00151
	(0.0038)	(0.0032)	(0.0024)	(0.0017)
numbooks26to100	0.0346***	0.0411***	0.0265***	0.0144***
	(0.0042)	(0.0036)	(0.0026)	(0.0019)
numbooks101to200	0.0359***	0.0591***	0.0465***	0.0315***
	(0.0063)	(0.0054)	(0.0039)	(0.0028)
numbooks201to500	0.0631***	0.0980***	0.0670***	0.0330***
	(0.0086)	(0.0073)	(0.0054)	(0.0038)
numbooksmorethan500	0.0387***	0.0656***	0.0517***	0.0323***
	(0.011)	(0.0094)	(0.0069)	(0.0049)
Constant	0.641***	0.479***	0.0706	0.0262
	(0.086)	(0.074)	(0.054)	(0.038)
Observations	108542	108542	108542	108542
R-squared	0.05	0.08	0.06	0.04
Male-Female Ratio	1.070179	1.167317	1.277904	1.211411

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

Table 3.10: Main Regression Specification Using SIMCE Results

	Standardized 4th grade SIMCE			Standardized 8th grade SIMCE		
Dummy for Male	0.075	0.081	0.087	0.192	0.202	0.208
	[0.002]***	[0.002]***	[0.002]***	[0.003]***	[0.003]***	[0.003]***
lnweight		0.253	0.247		0.245	0.245
		[0.005]***	[0.005]***		[0.008]***	[0.008]***
fullterm		0.002	0.001		-0.001	-0.003
		[0.002]	[0.002]		[0.003]	[0.003]
Birth_Mother_Age		0.002	0.002		0.001	0.001
		[0.000]***	[0.000]***		[0.000]***	[0.000]***
Unmarried Mother		-0.04	-0.035		-0.022	-0.018
		[0.002]***	[0.002]***		[0.003]***	[0.003]***
Mother attended High School		0.238	0.219		0.162	0.145
		[0.002]***	[0.002]***		[0.003]***	[0.003]***
Mother attended College		0.437	0.411		0.347	0.322
		[0.004]***	[0.004]***		[0.006]***	[0.006]***
Mother Employed		0.083	0.076		0.062	0.057
		[0.002]***	[0.002]***		[0.003]***	[0.003]***
Additional controls		School FE	Class FE		School FE	Class FE
Constant	-0.038	-2.33	-2.292	-0.096	-2.246	-2.247
	[0.002]***	[0.042]***	[0.041]***	[0.003]***	[0.063]***	[0.063]***
Observations	1321749	1107627	1107627	441408	436835	436835
R-squared	0	0.26	0.35	0.01	0.35	0.4

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in brackets
All specifications have year of test fixed effects

Table 3.11: Linear Regression of Top Scores from SIMCE Data

	Standardized 4th grade SIMCE								
	Probability of being in the top 10%			Probability of being in the top 5%			Probability of being in the top 1%		
Male	0.024	0.023	0.024	0.015	0.014	0.015	0.006	0.005	0.006
	[0.001]***	[0.001]***	[0.001]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
lnweight		0.041	0.042		0.025	0.025		0.009	0.009
		[0.002]***	[0.002]***		[0.001]***	[0.001]***		[0.001]***	[0.001]***
fullterm		0	-0.001		0	0		0	0
		[0.001]	[0.001]		[0.001]	[0.001]		[0.000]	[0.000]
Mother Char:									
Birth Age		0	0		0	0		0	0
		[0.000]***	[0.000]***		[0.000]***	[0.000]***		[0.000]***	[0.000]***
Unmarried		-0.007	-0.007		-0.004	-0.004		-0.002	-0.002
		[0.001]***	[0.001]***		[0.000]***	[0.000]***	[0.000]***	[0.000]***	
High School		0.028	0.026		0.015	0.013		0.004	0.004
		[0.001]***	[0.001]***		[0.000]***	[0.000]***		[0.000]***	[0.000]***
College		0.089	0.085		0.055	0.053		0.019	0.019
		[0.001]***	[0.001]***		[0.001]***	[0.001]***		[0.001]***	[0.001]***
Employed		0.017	0.016		0.01	0.01		0.004	0.004
		[0.001]***	[0.001]***		[0.001]***	[0.001]***		[0.000]***	[0.000]***
Controls		School FE	Class FE		School FE	Class FE		School FE	Class FE
Constant	0.095	-0.274	-0.276	0.052	-0.174	-0.176	0.017	-0.06	-0.063
	[0.001]***	[0.013]***	[0.014]***	[0.001]***	[0.010]***	[0.010]***	[0.000]***	[0.006]***	[0.006]***
Male/Female	1.27	1.26	1.27	1.35	1.33	1.35	1.86	1.67	1.86
Obs.	1321749	1107627	1107627	1321749	1107627	1107627	1321749	1107627	1107627
R-squared	0	0.12	0.17	0	0.08	0.13	0	0.04	0.09
	Standardized 8th grade SIMCE								
	Probability of being in the top 10%			Probability of being in the top 5%			Probability of being in the top 1%		
Male	0.035	0.033	0.034	0.022	0.02	0.02	0.009	0.008	0.008
	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.000]***	[0.000]***	[0.000]***
lnweight		0.039	0.038		0.025	0.025		0.01	0.01
		[0.003]***	[0.003]***		[0.002]***	[0.002]***		[0.001]***	[0.001]***
fullterm		0	0		-0.001	-0.001		0.001	0.001
		[0.001]	[0.001]		[0.001]	[0.001]		[0.000]	[0.000]*
Mother Char:									
Birth Age		0	0		0	0		0	0
		[0.000]***	[0.000]***		[0.000]***	[0.000]**		[0.000]	[0.000]
Unmarried		-0.005	-0.005		-0.003	-0.003		-0.001	-0.001
		[0.001]***	[0.001]***		[0.001]***	[0.001]***		[0.000]**	[0.000]
High School		0.016	0.014		0.007	0.006		0.001	0.001
		[0.001]***	[0.001]***		[0.001]***	[0.001]***		[0.000]***	[0.000]***
College		0.079	0.075		0.049	0.047		0.021	0.02
		[0.002]***	[0.002]***		[0.002]***	[0.002]***		[0.001]***	[0.001]***
Employed		0.012	0.011		0.009	0.009		0.004	0.003
		[0.001]***	[0.001]***		[0.001]***	[0.001]***		[0.001]***	[0.001]***
Controls		School FE	Class FE		School FE	Class FE		School FE	Class FE
Constant	0.093	-0.245	-0.243	0.049	-0.168	-0.165	0.016	-0.074	-0.074
	[0.001]***	[0.020]***	[0.020]***	[0.001]***	[0.015]***	[0.016]***	[0.000]***	[0.009]***	[0.009]***
Male/Female	1.42	1.40	1.41	1.56	1.50	1.50	2.64	2.33	2.33
Obs.	441408	436835	436835	441408	436835	436835	441408	436835	436835
R-squared	0	0.23	0.26	0	0.18	0.21	0	0.09	0.12

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in brackets
All specifications have year of test fixed effects

Table 3.12: Regressions on Twins Sample

	Standardized 4th grade SIMCE					Standardized 8th grade SIMCE				
	Mean	Probability of being in the top percentile				Mean	Probability of being in the top percentile			
		25	10	5	1		25	10	5	1
Dummy for Male	0.149	0.057	0.05	0.033	0.007	0.262	0.111	0.062	0.032	0.011
	[0.018]***	[0.009]***	[0.007]***	[0.006]***	[0.004]*	[0.031]***	[0.017]***	[0.013]***	[0.011]***	[0.006]
Constant	-0.184	0.205	0.074	0.037	0.013	-0.228	0.19	0.072	0.041	0.012
	[0.009]***	[0.005]***	[0.004]***	[0.003]***	[0.002]***	[0.016]***	[0.009]***	[0.007]***	[0.005]***	[0.003]***
Male to female ratio		1.26	1.67	1.99	2.08		1.57	1.90	1.94	3.44
Observations	20130	20130	20130	20130	20130	6560	6560	6560	6560	6560
Number of Twin Groups	11206	11206	11206	11206	11206	3954	3954	3954	3954	3954

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3.13: Parental Investments and SIMCE Scores from 2002

	OLS			Marginal Effects from Probit Regression					
				Top 10%		Top 5%		Top 1%	
Investments in Math	0.045	0.048	0.047	0.007	0.007	0.004	0.004	0.002	0.002
	[0.003]***	[0.003]***	[0.003]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.000]***	[0.000]***
Investments in Reading	0.129	0.041	0.037	0.023	0.01	0.015	0.007	0.005	0.002
	[0.004]***	[0.003]***	[0.003]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.000]***
Male	0.09	0.095	0.097	0.022	0.02	0.015	0.013	0.007	0.005
	[0.005]***	[0.004]***	[0.004]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***
lnweight		0.264	0.263		0.045		0.031		0.01
		[0.013]***	[0.013]***		[0.005]***		[0.003]***		[0.002]***
fullterm		0.014	0.012		0.005		0.002		0
		[0.005]**	[0.005]**		[0.002]***		[0.001]*		[0.001]
Birth_Mother_Age		0.001	0		0.001		0.001		0
		[0.000]*	[0.000]		[0.000]***		[0.000]***		[0.000]***
Mother married		-0.035	-0.03		-0.025		-0.015		-0.006
		[0.005]***	[0.005]***		[0.002]***		[0.001]***		[0.001]***
Mother attended high school		0.214	0.201		0.068		0.037		0.013
		[0.005]***	[0.005]***		[0.002]***		[0.001]***		[0.001]***
Mother attended college		0.405	0.389		0.166		0.094		0.033
		[0.009]***	[0.009]***		[0.002]***		[0.002]***		[0.001]***
mother employed		0.091	0.087		0.035		0.022		0.007
		[0.005]***	[0.005]***		[0.002]***		[0.001]***		[0.001]***
Controls		school FE	classroom FE						
Constant	-0.696	-2.707	-2.672	-0.358	-0.758	-0.266	-0.522	-0.13	-0.201
	[0.014]***	[0.106]***	[0.105]***	[0.004]***	[0.037]***	[0.004]***	[0.027]***	[0.002]***	[0.014]***
Male-Female Ratio				1.2472	1.2222	1.3529	1.2989	2.0769	1.6667
Observations	181676	179816	179816	181638	179776	181628	179776	181518	179671
R-squared	0.02	0.29	0.33						

* significant at 10%; ** significant at 5%; *** significant at 1%
Standard errors or robust standard errors in brackets

Table 3.14: Parental Investments and SIMCE Twins Results

	OLS	Linear Probability Model of being in the top		
		10%	5%	1%
Investments in Math	0.051	0.005	0.032	0.018
	[0.050]	[0.022]	[0.017]*	[0.011]*
Investments in Reading	0.122	0.035	-0.012	0.004
	[0.071]*	[0.030]	[0.024]	[0.016]
Male	0.104	0.029	0.04	0.014
	[0.052]**	[0.022]	[0.017]**	[0.011]
lnweight	0.571	0.172	0.099	0.025
	[0.149]***	[0.064]***	[0.051]*	[0.033]
Constant	-5.298	-1.412	-0.816	-0.27
	[1.193]***	[0.512]***	[0.404]**	[0.263]
Male-Female Ratio		1.3392	2.3333	5.6667
Observations	2716	2716	2716	2716
Number of Id_Twins	1605	1605	1605	1605
R-squared	0.02	0.01	0.01	0.01

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3.15: SIMCE Scores Regressed on Class Size and Composition

	4th grade SIMCE scores				8th grade SIMCE scores			
		Full Sample		Excluding single-sex schools		Full Sample		Excluding single-sex schools
Male X Class Size	0.002		0.002	0.002	0.001		0.001	0.001
	[0.000]***		[0.000]***	[0.000]***	[0.000]***		[0.000]**	[0.000]**
Male	0.01	0.078	0.012	0.017	0.163	0.245	0.223	0.226
	[0.006]*	[0.009]***	[0.011]	[0.011]	[0.011]***	[0.012]***	[0.017]***	[0.018]***
Class Size	-0.001		-0.001	-0.001	0.006		0.006	0.006
	[0.000]***		[0.000]**	[0.000]**	[0.001]***		[0.001]***	[0.001]***
Male X Fraction Male		0.015	0.022	0.006		-0.066	-0.054	-0.054
		[0.018]	[0.018]	[0.018]		[0.022]***	[0.022]**	[0.024]**
Fraction Male		-0.116	-0.108	-0.141		-0.087	-0.031	-0.028
		[0.014]***	[0.014]***	[0.018]***		[0.009]***	[0.009]***	[0.010]***
Constant	-2.299	-2.274	-2.251	-2.286	-2.45	-2.205	-2.653	-2.725
	[0.044]***	[0.043]***	[0.044]***	[0.046]***	[0.066]***	[0.064]***	[0.067]***	[0.070]***
Observations	1107627	1107627	1107627	1014609	436835	436835	425785	384698
R-squared	0.26	0.26	0.26	0.25	0.35	0.35	0.36	0.33

Robust standard errors in brackets. Clustered at the classroom level
* significant at 10%; ** significant at 5%; *** significant at 1%
Controls include Birth Weight, Gestational Age, Mother's Age and Education, Mother Employment status, and School FE

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