Schooling, Wages, and the Role of Unobserved Ability in the Philippines

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ABSTRACT

Yaraslau Zayats: Schooling, Wages, and the Role of Unobserved Ability in the Philippines

(Under the direction of Thomas Mroz)

The dissertation analyzes the impacts of an individual's unobserved ability on schooling and wages in the context of a developing country using rich data from the Cebu (Philippines) Longitudinal Health and Nutrition Survey. Unlike any previous study, my model allows for grade repetition and school reentry after dropping out of school. Both phenomena are common in developing countries in general, and in the Philippines in particular. Semiparametric approach is used to control for an individual's unobserved ability. The results indicate that children with lower innate ability enter school at a later age and complete fewer years of school. They are also more likely to drop out of school at all levels of education, but the effect of lower ability diminishes at higher levels of education. A standard Mincer-type regression appears to be misspecified. Results strongly suggest presence of heterogeneity in the returns to education by an individual's ability. Rates of return to education appear to be nonlinear differing across three educational levels.

To my parents, Zoya and Vladimir.
Without them I would not be who I am.

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CHAPTER I

INTRODUCTION

The primary challenge in studying the effect of education on wages is the fact that more able individuals choose more education. If an individual's ability is poorly controlled for by the measured variables, it is possible that the more educated individuals would have received higher wages even without their additional schooling. In other words, it is difficult to identify how much of the observed association between wages and completed schooling is due to the causal effect of education and how much is due to unobserved factors. The measured effects of schooling on wages, therefore, potentially incorporate the effects of ability on wages, giving rise to what is called ability bias in the returns to schooling. Economists have used multiple approaches to resolve it. However, it remains one of the most challenging identification problems in empirical research. Recently, concerns have been raised in the literature regarding the magnitude of the bias, pointing toward the need for more flexible estimation techniques and better controls for unobserved ability. While the accumulated evidence on the significance of ability bias in the estimated returns to schooling in the United States is quite impressive, few studies for developing countries have addressed this issue directly.

My analysis aims to fill that void in the literature. I analyze the impacts of an individual's unobserved ability on schooling and wages in the context of a developing country. Using data from the Cebu Longitudinal Health and Nutrition Survey, from the Philippines, I try to answer the following questions that are crucial for public policy in developing countries. Are low-ability individuals more likely to drop out of school than people with higher ability? If so, what can be done to keep the low-ability dropouts in school longer? More importantly, would this additional schooling benefit individuals in the labor market? In other words, do we see a significant return to schooling when we look at their wages? Does this return differ by an individual’s ability?

Numerous questions to which this study seeks to find answers are potentially relevant for many other developing countries. The Philippines, and the Cebu region in particular, have been undergoing a rapid transition from agriculture and low-skill manufacturing to a service and technology oriented economy during the last twenty years. This is the type of transition that one can expect many other developing countries to go through in the next few decades.

I use an economic model of schooling, test scores, and wages. I model both school attendance and school completion for each school year. I allow for grade repeats and school reentry after dropping out of school. Both phenomena are common in the Philippines in particular. None of the previous studies addressed the problem of grade repeats and school reentry at the individual level. I model cognitive achievement test scores similar to the analysis by Hansen, Heckman, and Mullen (2004). The relationships among these sets of outcomes provide a semiparametric identification of the unobservable “ability.” The inclusion of a key unobserved factor as a determinant of cognitive achievement test scores and IQ test scores provides a reason to label the unobserved factor as “ability.” It is important to note, however, that “ability” as used in the paper only refers to those unobserved characteristics that impact each of the modeled outcomes.

The results strongly indicate that children with lower innate ability enter school at a later age and complete fewer years of school. They are also more likely to drop out of school at all levels of education, but the effect of lower ability diminishes at higher levels of education. A standard Mincer-type regression appears to be misspecified for two reasons. First, I find significant heterogeneity in the returns to schooling by an individual's ability. Second, rates of return to education appear to be strongly nonlinear.

The next section discusses the existing literature. Section 3 describes the data and poses major questions of interest. Section 4 presents the model. Section 5 discusses the results. Section 6 highlights a number of important extensions. Section 7 concludes.

CHAPTER II

LITERATURE

Ability bias represents one of the oldest problems in labor economics. The literature dedicated to this issue is voluminous, especially as it affects estimates of the returns to schooling. The approaches used in the literature to remove the ability bias can be classified into several groups. One approach dates back to Griliches and Mason (1972) and involves the use of available measures of ability as proxies for unobserved ability that is rewarded in the labor market. Including such measures in the regression should mitigate the endogeneity of schooling, but not completely eliminate it as long as the measures of ability are not perfect proxies. Empirically, the estimated return to schooling is generally reduced when unobserved ability is proxied. One of the recent examples of this approach is the work by Blackburn and Neumark (1995), in which ASVAB (Armed Services Vocational Aptitude Battery) test scores from the NLSY data are used as proxies for ability. The model allows for measurement error in the test scores by instrumenting the scores with family background variables. Endogeneity of schooling and experience is addressed by instrumenting both variables with family background characteristics. The results of the study indicate that the usual OLS estimates, with proxies for ability omitted, are upward biased by roughly 40%.

A second approach uses the differences across siblings in levels of schooling and wages, relying on the assumption that much of the unobserved ability is common across siblings and is consequently differenced out. Based on this assumption, comparing monozygotic twins is even better since they share identical genetic endowments and potentially are exposed to more similar environments than dizygotic twins or siblings in general. The relevant studies include Behrman and Taubman (1976), Ashenfelter and Krueger (1994), Ashenfelter and Rouse (1998), and Behrman and Rosenzweig (1999), to name a few. The within-twins estimators generally indicate an upward bias in the OLS estimates if ability is ignored, but differ significantly in the magnitude of the bias. However, as Griliches (1979) pointed out "one has to keep in mind that they [siblings data] are not a panacea and that simple within (between brothers or between twins) estimates are not necessarily closer to the 'truth'". Twenty years later Bound and Solon (1999) and Neumark (1999) emphasize this point and argue that between-twins differences in schooling are not random, but are chosen endogenously. Moreover, differencing between twins wipes out much of the exogenous variation and inevitably exacerbates the measurement error problem (Griliches 1979).

A third approach exploits natural variation in determinants of schooling decisions, such as the interactions between quarter of birth and compulsory schooling laws, to create valid instruments for schooling as in Angrist and Krueger (1991, 1992). This approach tends to find at best no omitted-ability bias in the estimated returns to schooling.[1] Bound, Jaeger, and Baker (1995) show, however, that Angrist and Krueger's estimates may suffer from finite-sample bias that arises from weak correlation between quarter of birth and schooling. Staiger and Stock (1997) reanalyze the 1980 Census sample used by Angrist and Krueger and compute a range of asymptotically valid confidence intervals for standard IV and limited information maximum likelihood (LIML) estimates. Their preferred LIML estimates, that involve quarter of birth interacted with state of birth and year of birth as instruments, are

[1] They either find no significant changes in the estimates or a *negative* bias in the OLS estimates. A negative bias in the OLS estimate would indicate a presence of a measurement error in schooling rather than omitted-ability bias (omitted-ability bias is expected to have a *positive* bias in the OLS estimates).

above the corresponding two-stage least squares estimates and 50-70 percent higher than the OLS estimates. Hence, their results are in a broad agreement with Angrist and Krueger's results.

Bound and Jaeger (1997) criticized Angrist and Krueger's findings from another angle. They argue that quarter of birth may be correlated with unobserved ability differences. The authors examine earlier cohorts of men who were not subject to compulsory schooling and find evidence of seasonal patterns. They also discuss relevant sociobiology and psychobiology literature that suggest that season of birth is related to family background. If children born earlier in the year come from poorer families one might expect them to have low schooling and low earnings. They also show that while the association between quarter of birth and educational attainment has declined (between cohorts born in the 1920s and those born during the 1940s) no similar decline took place for the association between quarter of birth and earnings.

Rosenzweig and Wolpin (2000) discuss natural experiments in great detail and analyze a variety of recently used instruments that are based on natural experiments. The authors point out an extraordinary range of estimates across the studies that use instruments based on natural experiments. They argue that, in the presence of heterogeneity in returns to schooling, instruments identify local average treatment effects (Imbens and Angrist 1994), that is, the effects for the group or groups whose behavior is influenced by intervention, and different instruments affect different groups of people. Using a very simple model of schooling choice, they show that the date-of-birth (as in Angrist and Krueger 1991) and child-gender (as in Butcher and Case 1994) instruments identify the returns to schooling for different ability groups in the population. A similar concern but from a different perspective is expressed by

Card (2001) who suggests that if there is underlying heterogeneity in the returns to schooling then IV estimates that are based on supply-side innovations, like compulsory school attendance laws or the accessibility of schools, might recover returns to schooling only for a subgroup of population, those with relatively high returns to education. Supply-side innovations are most likely to affect schooling decisions of those individuals who would otherwise have relatively low amount of schooling. If these individuals generally acquire low schooling because they face higher-than-average costs of financing schooling and not because of lower-than-average returns to schooling, then IV estimators based on supply-side innovations will yield the estimates of the return to schooling above the average marginal return to schooling in the population.

Heckman and Vytlacil (2001) discuss another aspect of ability bias – strong dependence between education and ability. They argue that if this dependence becomes too strong, it is impossible to isolate the effect of schooling from ability even when the latter is perfectly observed. They call this sorting bias, and it is closely related to perfect multicollinearity. The authors illustrate this problem through tabulation of completed schooling by ability quartile for a sample of white males from the NLSY. It appears that for many schooling-ability pairs the cells are either entirely or nearly empty. For example, there are no individuals with postgraduate education in the lowest-ability quartile. That makes it difficult to isolate separate ability effects and schooling effects. In the limit, if ability and education are perfectly stratified, returns to education cannot be isolated from returns to ability. The authors use the first principal component of the ASVAB test scores, which supposedly represents general intelligence, as the measure of ability to nonparametrically estimate the returns to schooling on a sample from the NLSY. The results reveal that education and cognitive ability are so strongly associated that the wage effects of the two cannot be separated for all groups.

Another group of methods involves semiparametric and nonparametric estimation techniques for tackling the problem of ability bias. For instance, Belzil and Hansen (2002) use a panel of white males from the NLSY and estimate a structural dynamic programming model of schooling decisions with unobserved heterogeneity in both school ability and market ability, in which the wage regression is estimated using splines. The results cast doubt on the validity of the high returns to education reported in the literature. Contrary to conventional wisdom (Card 1999), the log wage regression is found to be convex in schooling. Namely, the marginal returns to schooling are 1 percent per year or less until grade 11, then increase to 3.7 percent in grade 12, and exceed 10 percent only between grade 14 and 16. The average return, measured from grade 7, increases smoothly from 0.4 percent (grade 7) to 4.6 percent (grade 16). A linear wage regression appears to be severely misspecified. The analysis strongly rejects the hypothesis of orthogonality between market ability and realized schooling and indicates the existence of a positive ability bias. Interestingly enough, the correlation between school ability and market ability is found to be very high, 0.95.

Essential to our analysis is the study by Hansen, Heckman and Mullen (2004). One dimension of the study is a semiparametric model that the authors develop for estimating the effect of schooling on achievement test scores. Assuming that a person's *latent* ability cannot be affected by schooling, the authors test whether *manifest* ability, as measured by ASVAB achievement tests, is affected by schooling when both schooling and manifest ability are allowed to be affected by latent ability. The amount of completed schooling is modeled via specifying utility functions for all levels of potential completed schooling (high school dropouts, high school graduates, some college, 4-year college graduates). The utility functions are linear in exogenous characteristics (family background variables for all choices and local labor market characteristics as choice-specific), latent ability and an error term. It is assumed that schooling decision is made only once, implying perfect foresight. Once in school there are no grade repeats and dropping out of school is an absorbing state. The age when child starts school is introduced as a dummy variable (on-time entry vs. late entry) and modeled nonparametrically by pairing each schooling choice with the age at entry. This leads to an eight school-choice function instead of four. They model test scores as a function of exogenous characteristics (family background characteristics and age), schooling, latent ability and error term. All error terms are independent of each other and of latent ability. In other words, the equations are related only via what they call unobserved innate ability. The authors prove nonparametric identification of the distribution of latent ability. The structural model is estimated on a sample of white males from the NLSY using Bayesian MCMC as a computational tool. The results indicate that the effects of schooling on test scores for a given level of ability are approximately linear across schooling levels. One year of schooling increases the AFQT score between 2.79 and 4.2 percentage points on average. Also, the authors estimate Mincer-type wage equation with OLS-residualized AFQT as the measure of unobserved ability to results from the Mincer-type wage regression with the estimated latent ability measure. While estimated latent ability measure represents the measure purged of the effect of schooling on ability, OLS-residualized AFQT inherently includes the effect of schooling on ability. Therefore, one would expect the estimated return to schooling to increase when comparing the wage equation with OLS-residualized AFQT to the wage equation with estimated latent ability measure. This is exactly what their results reveal: the use of OLS-residualized AFQT yields the estimate of the return equal to 10.22% and the use of estimated latent ability measure increases the estimated return by 1.5 percentage points.

The literature on the returns to schooling and ability bias in the context of developing countries deserves a separate discussion. If in the United States a private return to education is in the range of 5-12 percent (Burtless 1996), in developing countries this return is found to be generally much higher. Psacharopoulos (1994) reports the average private return to education in developing countries to be 29 percent for primary education, 18 percent for secondary education, and 20 percent for higher education. Even though there has been an enormous number of studies that estimate Mincer-type wage equations using data from developing countries (see the reviews in Schultz 1988, Strauss and Thomas 1995), very few studies have a measure of ability available in the data. Boissiere, Knight, and Sabot (1985), Psacharopoulos and Velez (1992), Alderman et al. (1996a), and Glewwe (1996) are the notable exceptions. In two of these studies, sample sizes are either less than or barely exceed two hundred. All the authors use Raven’s test score (Raven’s Progressive Matrices) as a measure of innate ability. Raven’s test scores tend to have little direct effect on wages, but considerably affect achievement scores, which in turn significantly affect wages. The effects of completed schooling are similar to those of Raven’s tests: schooling’s effect on wages is mostly indirect, operating through the cognitive skills as measured by achievement tests.

It is worth noting, however, that the use of Raven’s tests as a measure of innate ability is controversial. The major concern is well expressed by Glewwe and Jacoby (1994, 851), who point out that: “This test [the Raven’s abstract thinking test] was never intended as such [as an indicator of “innate” ability, independent of schooling]”. In the data they use, there is, conditional on age, a strong positive association between Raven's scores and years of acquired schooling. Their data set is not the only example – in the Pakistani data that Alderman et al. (1996a) use, Raven's test scores are significantly higher for men than for women. This difference in Raven's test scores is potentially related to the fact that men acquire more schooling than women in Pakistan, which would imply that Raven's test scores are influenced by schooling. This point is reinforced by the fact that the difference in the amount of completed schooling appears to be unrelated to possible differences in innate ability between Pakistani men and women – single-sex schools are predominant in Pakistan and the girls are disadvantaged in terms of school availability (Alderman et al. 1996b).

The literature review would be incomplete if I did not mention the research that has been done on returns to schooling in the Philippines. Lanzona (1998) analyzes the migration of workers in rural communities of the Philippines. The study uses data from the Bicol Multipurpose Surveys conducted in 1978, 1983 and 1994. The results indicate that the more educated and experienced individuals are more likely to outmigrate, causing a sample selection bias in the estimation of returns to schooling. The migration should not be surprising, however, given that: 1) the Bicol Multipurpose Surveys cover only one region, which happens to be one of the poorest regions in the country[2], and 2) during the time period that this study covers the Philippines have been undergoing a rapid transition from agriculture and low-skill manufacturing to a service and technology oriented economy.

Schady (2003) uses data from a recent nationwide household survey, the 1998 Annual Poverty Indicator Survey, to estimate returns to schooling for Filipino men. The results suggest convexity – the returns to both primary and secondary education are lower than those

[2] For example, in 1994 it had the highest poverty rate (Lanzona, 1998).

for tertiary education. As a result, the returns to primary and secondary education are considerably smaller than the conventional rates in the literature. Depending on the specification, the mean rate of return ranges from 6.2 to 9.4 percentage points for primary education and 6.9-10.0 percent for secondary education (based on Schady 2003, Table 2). Schady also finds sheepskin effects in the returns, i.e., within a given level of education, the returns to completing the last year of primary school, high school, or college are higher than the returns to any year below the last one. Both of these results can be driven by ability bias. Data limitations preclude the author from fully exploring such a possibility.[3]

In summary, for the last forty years the literature has recognized ability bias as a serious econometric problem. Economists used multiple approaches to resolve it. None of them provides a universal fix. Recently, concerns have been raised regarding the magnitude of the bias, pointing toward the need for more flexible estimation techniques and better controls for unobserved ability. While the accumulated evidence on ability bias in the United States is quite impressive, few studies for developing countries have addressed this issue directly.

[3] His analysis partially controls for ability by including measures of parental education and by using within-sibling estimates. He finds no significant changes in the results. It is unclear, however, to what extent these measures can control for innate ability.

CHAPTER III
DATA

The data come from the Cebu Longitudinal Health and Nutrition Survey (CLHNS). The CLHNS follows a representative cohort of Filipino children born between May 1, 1983 and April 30, 1984 in 33 randomly chosen barangays[4] (17 urban and 16 rural) of the Metropolitan Cebu region.[5] Metro Cebu is the second largest metro area in the Philippines, with a population of 1.4 million (as of the 1990 census). Contrary to the commonly held view that a "metro area" is urban by definition, Metro Cebu encompasses vast agricultural areas reaching deep into Cebu Island. At the time of the 1980 census, for instance, Metro Cebu included 155 urban and 88 rural barangays based on the Census Bureau classification (148 urban and 95 rural barangays based on the reclassification made by the CLHNS researchers).

Multiple follow-up surveys have been made for the last twenty years, tracking the children from their birth up to the present day. The latest surveys are 1991-1992, 1994-1995, 1998-1999, 2002-2003, and 2005 follow-up surveys, with the latter survey being finished this fall. The CLHNS data sets provide detailed, up-to-date information on each child, including early childhood development, family background, household, and community characteristics,

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[4] "Barangay" is the smallest administrative unit in the Philippines; it can be thought of as a community or district.

[5] First, a single-stage cluster sampling procedure was used to randomly select 33 barangays from the Metro Cebu area. Then the barangays, which contained about 28,000 households, were completely surveyed in late 1982 and again in early 1983 to locate all pregnant women. Women of the selected communities who gave birth between May 1, 1983 and April 30, 1984 were included in the sample.

as well as information on the characteristics of schools children attended. As with any longitudinal data, the sample attrition across the surveys is of potential concern. My analysis hinges on surveys starting from the 1991-1992 survey (the first that provides information on schooling). During the 1991-1992 survey 2,260 children were surveyed, and the 2002-2003 survey (the latest survey with available data) contains information about schooling decisions for 2,040 individuals. The attrition appears to be fairly low. Looking across all the surveys, most of the attrition happened during early childhood. Out of 3,080 nontwin live births, only 2,600 households were surveyed during the first two years of children's lives. The attrition was mostly due to death or migration out of Metro Cebu. The actual sample that I use includes only those for whom it was feasible to construct complete schooling trajectories from the panels. Since the data from the 2005 survey became available only in April 2006 and not in its entirety (for instance, data for community characteristics has not been processed) first part of my analysis will use data only up to the 2002-2003 survey. That sample consists of 1982 individuals. When adding the most recent data from the 2005 survey the sample size reduces to 1831 individuals. Descriptive statistics of the variables are reported below in Tables 1-4. Details on the construction of the variables are provided in Appendix A.

Table 1. Summary Statistics of Key Time-Invariant Variables

Variable	Mean	Std. Dev.	Min	Max
Male	.5292	.4993	0	1
Low birth weight	.1231	.3262	0	1
Entered school on time	.7674	.4226	0	1
Math test	30.5621	11.0814	0	58
English test	27.4187	10.4548	0	59
IQ test	32.8548	6.6368	5	47
Mother’s education (log)	1.9795	.4885	0	2.9444
Father’s education (log)	1.8554	.5598	0	2.8904
Local pupil-teacher ratio	39.1714	5.1930	22.5	55.6
Fraction of public schools in the area	.9547	.0639	.6988	1

As can be seen from Table 1, about 77 percent of the sample entered school “on time”. Parental completed education is relatively low, with the mean of 7.2 years for mothers and 6.4 for fathers. Class size, as proxied by local pupil-teacher ratio, appears to be relatively large, over 39 pupils per teacher, on average.

Table 2. Summary Statistics of Key Time-Specific Variables

Variable	Mean	Std. Dev.	Min	Max
Height at 2nd birthday (log)	-.2339	.0440	-.4155	-.1109
Age as of IQ test date	8.6600	.2756	8.1667	9.0833
Age as of achievement test date	11.7402	.4066	10.8333	12.8333
Completed schooling as of IQ test date	1.3094	.7036	0	3
Completed schooling as of achievement test date	4.0940	1.0400	0	6
Household income (lagged)	5.4759	.5189	4.5511	9.8669
Urban (averaged, time of child's 2nd birthday and 1991-92 survey)	.7356	.4268	0	1
Population density (log, averaged)	8.6589	1.5952	4.5642	11.1956
Price of kerosene (log, averaged)	.8725	.3209	-.0594	1.5009
Price of bananas (log, averaged)	-1.5713	.1975	-2.4487	-1.0186
Price of corn (log, averaged)	.9167	.1545	.4322	1.1842

Table 2 illustrates that achievement tests (Math and English) were administered at the time when all of the sample were still in primary school. The non-verbal intelligence (IQ) test was administered several years before that when most of the sample had yet very few schooling, 1.3 years on average. For that reason the IQ test might be an attractive proxy for an individual's unobserved ability.

Table 3. Summary Statistics of Time-Variant Variables

Variable	1990 Mean (Std. Dev.)	1996 Mean (Std. Dev.)	2002 Mean (Std. Dev.)	2004 Mean (Std. Dev.)
Household size	6.9511 (2.3427)	7.1302 (2.4768)	6.9119 (2.7924)	6.4074 (2.7205)
Family business	0.3468 (0.4506)	0.4425 (0.4968)	0.5094 (0.5000)	0.4003 (0.4901)
Household income (log)	5.9486 (0.5531)	5.9382 (0.7642)	6.2006 (0.8188)	5.8784 (1.0666)
Household income net of individual's (log)	–[6]	–	6.1087 (0.8732)	5.6415 (1.2248)
Caretaker's household	0.9344 (0.2476)	0.9173 (0.2756)	0.8476 (0.3595)	0.7488 (0.4338)
Age (by the beginning of school year *t*)	6.6609 (0.2759)	12.6609 (0.2759)	18.6609 (0.2759)	20.6591 (0.2758)
Completed schooling (by the beginning of school year *t*)	0.0096 (0.0975)	4.9723 (1.2350)	8.9945 (2.5119)	9.5751 (2.8671)
Attended *elementary* school during the year *t*	0.9545 (0.2132)	0.9066 (0.2912)	0.0365 (0.1879)	–[7]
Attended *high* school during the year *t*	–	1.0000[8] (0.0000)	0.1793 (0.3838)	0.0378 (0.1907)
Attended *college* during the year *t*	–	–	0.7757 (0.4175)	0.4803 (0.5000)
Successfully completed the grade, if in *elementary* school that year	0.8338 (0.3724)	0.9394 (0.2387)	0.8571 (0.3780)	–
Successfully completed the grade, if in *high* school that year	–	0.8918 (0.3108)	0.8021 (0.3995)	0.8919 (0.3148)
Successfully completed the grade, if in *college* that year	–	–	0.8652 (0.3419)	0.9148 (0.2796)
Working for pay	–	–	0.7486 (0.4340)	0.7969 (0.4025)
Working experience (in years)	–	–	1.1771 (1.1950)	3.0983 (1.5770)
Log of the hourly wage rate	–	–	2.5798 (.9477)	2.9915 (.7060)
Local wage rate for unskilled labor	–	–	15.6800 (6.9304)	–[9]
Urban	0.7356 (0.4411)	0.7306 (0.4437)	0.7184 (0.4499)	–

[6] This variable (as well as some variables below) is used in modeling "working for pay," which is modeled starting from 1997, and therefore does not have nonmissing observations prior to 1997.

[7] Unless otherwise noted, here and below the variable is missing if it is irrelevant for the year *t*, e.g., no one was in high school in 1990, etc.

[8] 1.0 means that all of those who were eligible to go to high school that year (i.e., all who completed elementary school by 1997) did go to school during the school year 1997.

[9] As noted in Appendix A, community characteristics for years 2003-2005 were proxied by the data from the 2002-2003 survey.

Table 3 adds another dimension to the analysis of the descriptive statistics. An average household size appears to be fairly large throughout the surveys, over 6 people in a household. A substantial fraction of the sample is involved in a family business, the number ranges from 35% in 1990 to about 50% in 2002.

The numbers of years of working experience immediately reveal that our sample represents young wage workers – with slightly over a year of working experience, on average, at the time of the 2002-2003 survey and with slightly more than three years of experience at the time of the 2005 survey.

Table 4. Summary Statistics of Some Time-Variant Variables (all years)

Variable	Obs	Mean	Std. Dev.
Attended *elementary* school	11256	0.8523	0.3549
Attended *high* school (conditional on completion of elementary school)	10618	0.6009	0.4897
Attended *college* (conditional on completion of high school)	2705	0.7146	0.4517
Successfully completed the grade, *elementary* school	11400	0.9220	0.2682
Successfully completed the grade, *high* school	6380	0.8839	0.3204
Successfully completed the grade, *college*	1933	0.8665	0.3402

Table 4 along with some variables in Table 3 provides information on school attendance and school completion by educational group. At this point it is worth providing more details on the educational system in the Philippines. Basic education consists of six years of primary school and four years of secondary school; obtaining a university degree normally takes an additional four to five years. Under the Philippine Constitution, both primary and secondary education are free in public schools. However, the proportion of secondary schools that are public has been considerably smaller, especially in rural areas.[10] Also, while primary education is mandatory, secondary education is voluntary in the Philippines.

For the last few decades, the Philippines have gone through a rapid economic development. The Cebu region exemplifies that transition. This region has been undergoing a transition from agriculture and low-skill manufacturing to a service and technology oriented economy, with substantial population growth as well as rapid economic growth. Six of the top ten products produced in Cebu are high technology (e.g., semiconductors, electronic watches, etc.). This is the type of transition that one can expect many other developing countries to experience in the next few decades.

Such an accelerated economic development in the Philippines has been associated with educational expansion. As a result, the Philippines have achieved one of the highest school enrollment rates, especially in primary schools, among less developed countries. For example, during school year 1990/1991, when most of our sample entered school, the net enrollment rate in primary schools was 95.3 percent (1991 Philippine Development Report 1992). These gains, however, have been offset by low school completion rates. The proportion of students enrolled at the beginning grade who reached the final grade of primary school at the end of the required number of years of study in year 1990/1991, for instance, was 68.2 percent (1991 Philippine Development Report 1992). Dropping out of school and grade repetition account for this low rate. About 40 percent of our sample repeated a grade at least once. Despite the fact that almost all of the individuals in our sample enrolled in school at some point, the proportion of students who reached the final grade of primary school at the

[10] In 1997/1998, for instance, public primary schools accounted for 92.3 percent of total primary enrollments, while public secondary schools accounted for only 72.0 percent of total secondary school enrollments (Behrman, Deolalikar, and Soon 2002).

end of the required number of years was only 69.5 percent. Seventeen percent of the sample never made it to high school. Of those who went to high school, 26.3 percent did not finish by age nineteen.

This naturally raises several questions. What factors affect youths' decision to drop out? Are individuals with lower innate ability more likely to drop out of school than people with higher ability? If so, what can be done to keep the low-ability dropouts in school longer? More importantly, would this additional schooling benefit individuals in the labor market? In other words, do we see a significant return to schooling when we look at their wages? Does this return differ by an individual's ability? These are some of the questions I seek to answer in this work. Knowing these answers should provide important lessons for policymakers in many developing countries that will experience similar economic changes over the coming decades.

CHAPTER IV
MODEL

Overview

The model is developed to answer the questions posed in the previous section. It can be divided into three parts, corresponding to school grade progression, test scores, and labor market outcomes. All of the outcomes are modeled as functions of unobserved ability. The intuition behind modeling innate ability is simple. An individual's innate ability is never observed. Any cognitive test (either achievement or intelligence) is only a proxy for innate ability. It is always unclear how good such a proxy is. Generally, test scores are affected by, among other factors, the amount of acquired schooling at the time the tests are taken.[11] The semiparametric approach that I use to control for an individual's innate ability allows me to avoid such problems. This approach is based on the methodology developed by Hansen, Heckman, and Mullen (2004). I specify a one-factor model, where an unobserved factor enters all outcomes of interest. The inclusion of the unobserved factor as a determinant of cognitive achievement test scores and IQ test scores provides a reason to label the unobserved factor as "ability." It is important to note, however, that "unobserved ability" as used in the dissertation only refers to the collection of unobserved characteristics that impact each of the modeled outcomes.

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[11] Hansen, Heckman, and Mullen (2004), for example, estimate that one year of schooling increases the AFQT score, on average, between 2.79 and 4.2 percentage points.

The only dependence among all outcomes comes from a common unobserved ability. All of the equations are estimated simultaneously using full-information maximum likelihood (FIML) with Gauss-Hermite quadrature approximation for the unobserved ability, which is assumed to follow a standard normal distribution. The normality assumption is relaxed later on. Below, the model is outlined in greater detail.

School Grade Progression

The school grade progression part of the model serves two purposes. First, it helps to identify factors that affect an individual's decision to attend school and to successfully complete each year. I model both attendance and successful completion since, despite high enrollment rates, as previously noted, we observe substantial dropping out in the Philippines, as well as subsequent school reentry, and grade repetition. These phenomena are common in developing countries in general; to the best of my knowledge, however, none of the previous studies addressed the problem of grade repeats and school reentry at the individual level.

The second purpose of the school grade progression part is to control for the endogeneity of schooling – all of the schooling outcomes are modeled as functions of unobserved ability, which reflects the fact that more able individuals, generally, choose to acquire more schooling.

Within each educational level (primary school, secondary school, and tertiary education), progression through school grades is modeled by two binary outcomes. They represent the decisions and behavior of each individual and his/her family with respect to schooling every year.[12] First, a person must decide whether to enroll in school (variable *ATTND*) and then each individual has an opportunity to successfully finish a grade (variable *SUCSS)*. The variable *SUCSS* is modeled if and only if the person attended school that school year, i.e., if the variable *ATTND* is equal to one. *SUCSS* captures dropping out as well as failing to advance to the next grade.

In terms of economic behavior, each individual maximizes his/her utility subject to the budget constraint. The resulting subsequent lifetime indirect utility from attending school during school year *t* is:

$$V_t(ATTND_t = 1) = U_t(ATTND_t = 1) + \beta E\left[V_{t+1}(ATTND_t = 1)\right] + \varepsilon_{t,1}$$

Lifetime indirect utility from not attending school during school year *t* is:

$$V_t(ATTND_t = 0) = U_t(ATTND_t = 0) + \beta E\left[V_{t+1}(ATTND_t = 0)\right] + \varepsilon_{t,0},$$

where $\varepsilon_{t,1}$ and $\varepsilon_{t,0}$ represent preference shocks and are assumed to be independently and identically distributed as Type I extreme value distribution. It follows that an individual decides to enroll in school if and only if the difference in the indirect utilities is greater than zero. The latent variable $ATTND_t^*$ measures this difference in utilities:

$$ATTND_t^* \equiv U_t(ATTND_t = 1) + \beta E\left[V_{t+1}(ATTND_t = 1)\right] + \varepsilon_{t,1} - U_t(ATTND_t = 0) - \beta E\left[V_{t+1}(ATTND_t = 0)\right] - \varepsilon_{t,0}$$

Similar logic applies to the successful completion of the grade, $SUCSS_t^*$, and all other discrete outcomes in this model. For primary school, I model *ATTND* for each person starting with the year after the first school entry, conditional on completed schooling as of the time of that decision. The first school entry is modeled as a separate outcome.

[12] Since the attendance and completion rates across the three groups are different, there is no need for modeled effects to be constant across these groups. I allow the schooling outcome parameters to differ across the three educational groups (grades 1-6, grades 7-10, grade 11 and above).

I approximate the latent indexes $ATTND^*$ and $SUCSS^*$ as:

$$ATTND^*_{it} = \gamma_{ATD}(1 - ATTND_{i,t-1}) + \phi_{ATD} ATTND_{i,t-1}(1 - SUCSS_{i,t-1}) + \alpha'_{ATD} X_i + \beta'_{ATD} Z_{it} + \varphi'_{ATD} C_{it} + \gamma_{ATD} S_{it} + \delta_{ATD} f_i + \xi_{it}$$

$$SUCSS^*_{it} = \gamma_{SUC}(1 - ATTND_{i,t-1}) + \phi_{SUC} ATTND_{i,t-1}(1 - SUCSS_{i,t-1}) + \alpha'_{SUC} X_i + \beta'_{SUC} Z_{it} + \varphi'_{SUC} C_{it} + \gamma_{SUC} S_{it} + \delta_{SUC} f_i + \zeta_{it}$$

The terms $\gamma_{ATD}(1 - ATTND_{i,t-1})$ and $\phi_{ATD} ATTND_{i,t-1}(1 - SUCSS_{i,t-1})$ are included to capture costs associated with the decisions to repeat a grade and to reenter school, respectively. γ_{ATD} represents the effect of not attending school the previous school year and ϕ_{ATD} represents the effect of failing the grade attended during the previous school year. Two similar terms are included in $SUCSS^*_{it}$ to reflect the fact that successfully completing a grade might be easier if the person repeats the grade and that successfully completing a grade might be harder if the person was out of school for some time. The vector X_i represents individual characteristics including age, sex, and a low birth weight dummy as a health measure. The vector Z_{it} consists of family background variables including household income, household size, family business dummy, parental education, and caretaker's household dummy. The vector C_{it} includes community characteristics including urban/rural dummy, population density, food prices, and school quality characteristics. The variable S_{it} represents the amount of successfully completed schooling by the beginning of school year *t*. The variable f_i stands for unobserved ability. The error terms (ξ_{it} and ζ_{it}) are independent of each other and logistically distributed.

Entering School on Time

Initial school entry is modeled as a separate outcome. For simplicity, it is chosen to be a binary outcome – on time vs. late entry to school, with "on time" meaning "entered school by age 7.5." Note that "on time" entry controls for the attendance of the first year in school. The latent index specification is:

$$N_i^* = \alpha_N' X_i + \beta_N' Z_{it-1} + \varphi_N' C_{it-1} + \theta_N f_i + \omega_i ,$$

where subscript "*t*-1" stands for using lagged values (from the time the child was 2 years old) of the variables. Community variables are constructed as the averages of community characteristics from the time the child was 2 years old and 1991-1992 survey. Lagged and averaged characteristics are used for two reasons. One is the fact that sending the child to school is a complex decision, likely to be affected by the past as well as the present. The second reason is to provide additional identification: the variation in the exogenous characteristics at the time of the child's 2nd birthday is different from the present. This is crucial since "on time" entry is at the very beginning of school grade progression and acquired schooling enters in all subsequent outcomes. Aggregate primary school quality characteristics from the 1994-1995 survey are used as a proxy for primary school quality in the area at the time the decision is made to send the child to school. Aggregate school quality characteristics are constructed by computing averages of school quality characteristics across local schools within a certain area using geographical coordinates of schools (for more details, see Zayats 2004).

Test Scores

Three cognitive achievement tests (Math, English, Cebuano) were administered during the 1994-1995 follow-up survey. For the purpose of our analysis, Math and English test scores are used. All children who were surveyed took the tests independent of schooling status. Additionally, the Philippines Non-Verbal Intelligence Test ("IQ test" for simplicity) developed by Guthrie, Tayag, and Jimenez (1977), was administered in the 1991-1992 and 1994-1995 surveys. The IQ test is comparable to Raven's Coloured Progressive Matrices, which are heavily used in empirical research on developing countries as a measure of innate ability. I use the IQ test scores from the 1991-1992 survey, since at that time only a fraction of the sample was already in school. Test scores are modeled similar to Hansen, Heckman, and Mullen (2004), who in their turn extend the factor analysis model used in psychometrics. The k^{th} test score is modeled as

$$T_{k,i} = \beta_k' X_{k,i} + \mu_k(s_i) + \lambda_k(s_i) f_i + \varepsilon_{k,i}(s_i) \qquad k = 1 \text{ (Math)}, 2 \text{ (English)}, 3 \text{ (IQ)}$$

$X_{k,i}$ includes all exogenous regressors (individual, parental, community, and school characteristics) and s_i measures completed education as of the time of the test. $\mu_k(s_i)$ is a level effect of schooling that is uniform across unobserved ability levels. The effect of unobserved ability on test scores can vary by completed schooling at the time of the test, and it is given by $\lambda_k(s_i)$. Both f and $\varepsilon(s)$ are assumed to be independent and have zero means. $\mu_k(s_i)$ is further parameterized as $\mu_k(s_i) = \alpha_k S_i$. A more flexible specification would be a second- or third-degree polynomial, e.g., $\alpha_{1,k} S_i + \alpha_{2,k} S_i^2 + \alpha_{3,k} S_i^3$, but linearity is not very restrictive given that all schooling variation at the time of testing is within primary school only. $\lambda_k(s_i)$ is similarly specified as $\lambda_k(s_i) = \rho_{0,k} + \rho_{1,k} S_i$.

After providing specification for our test score equations it might be worth emphasizing the importance of ability controls in the wage equation by providing a brief illustration:

Suppose that the equation for log of wages is:

$$\ln W_i = \beta_1' X_i + \beta_2 S_i + \beta_3 f_i + \varepsilon(W_i),$$

where X represents all the relevant regressors except schooling and ability. Given this specification, the causal effect of a unit increase in schooling is β_2.

Since f is unobserved it is common in empirical research to proxy f by test scores, T, to avoid ability bias arising from the correlation between f and S. Solving out for f using the test score equation (1):

$$\begin{aligned}\ln W &= \beta_1' X + \beta_2 S + \beta_3 \left(\frac{T_k(s) - \beta_k' X_k - \mu_k(s) - \varepsilon_k(s)}{\lambda_k(s)}\right) + \varepsilon(W) \\ &= \beta_1' X + \beta_2 S - \frac{\beta_3}{\lambda_k(s)} \beta_k' X_k - \frac{\beta_3 \mu_k(s)}{\lambda_k(s)} + \frac{\beta_3}{\lambda_k(s)} T_k(s) + \varepsilon(W) - \frac{\beta_3}{\lambda_k(s)} \varepsilon_k(s)\end{aligned}$$

Two problems emerge: 1) $\frac{\beta_3}{\lambda_k(s)} \varepsilon_k(s)$ is correlated with $T_k(s)$ as long as $\varepsilon_k(s) \neq 0$,

2) even if $\varepsilon_k(s) = 0$, i.e. $T_k(s)$ is a perfect proxy for f, additional S-dependent terms are present in the equation due to the fact that schooling determines test scores, and the estimated marginal effect of schooling on wages, $\hat{\beta}_2$, will be biased unless both $\mu_k(s)$ and $\lambda_k(s)$ are

constants, that is unless schooling has neither direct effect on test scores nor indirect effect via manifest ability. Our specification allows us to eliminate these types of biases.

Earnings

Modeling returns to schooling involves two outcomes. One is the selection into work for pay after leaving school. It resolves the endogeneity of the experience in the wage equation. I assume that working for pay contributes to human capital accumulation only if an individual is out of school. Therefore, for each individual, the experience in the wage regression is the number of years she/he worked for pay while not attending school. The second outcome is a wage equation destined to provide the estimates of the return to schooling.

Wages are initially modeled as of the time of the 2002-2003 survey, when approximately thirty percent of the sample were still in school. Later on I look as well at the wages as of the time of the 2005 survey. The analysis of wages is limited to those individuals who are not in school by the time of the 2002-2003 survey, so selection into work is modeled explicitly only for those who are out of school. I model the work decisions, for those not in school, starting from the school year 1997/1998,[13] when most of the sample were thirteen years of age:

$$R_{it}^{*} = \alpha_R' X_{it} + \beta_R' Z_{it} + \varphi_R' C_{it} + \psi_R' L_{it} + \delta_R f_i + \xi_{it}$$

where R_{it}^{*} is a latent index for whether person i is a wage worker during school year t; L_{it} includes local labor market variables such as the average wage in the area.

Wages are modeled by specifying the equation for the logarithm of hourly wage rate. Several specifications are used. I start with a separate Mincer-type equation, which is

[13] For the school year 1996/1997, only nineteen people reported working for pay while being out of school.

routinely used in the literature on returns to schooling, $\ln W_i = \alpha_0 + \alpha_1 S_i + \alpha_2 exper_i + \xi_i$. I do not include the quadratic in experience due to very young age of the workers. In this specification, the assumption that the only cost of additional schooling is forgone wages will yield α_1 as the private rate of return to schooling.

The preferred specification allows i) the rate of return to education to vary across individuals by unobserved ability and ii) unobserved ability to affect the wages directly. This specification is:

$$\ln W_i = \alpha_w' X_i + \varphi_w' C_{i,2002} + \gamma_w S_i + \eta_w S_i \cdot f_i + \delta_w f_i + \xi_{it}$$

Other variables in the equation are used to capture the formation of human capital besides schooling and ability, as well as to control for observed heterogeneity in, for instance, local labor markets.

Likelihood Function

The individual likelihood after integrating out unobserved ability is the following:

$$\begin{aligned}
&L_i(N=n, T_1=t_1, ..., T_3=t_3, S_T=s_T, S=s, R_m=r_m, ..., R_M=r_M, \ln W=w) = \\
&= \sum_{k=1}^{K} \pi_k \Big\{ \; \Pr(N=0 \mid f_{i,k})^{1-N} \Pr(N=1 \mid f_{i,k})^{N} \cdot \\
&\cdot \prod_{j=year_after_1st_entry}^{sch.year_2002} \left[\begin{array}{l} \left(\Pr(ATTND_j=1 \mid f_{i,k}) \Pr(SUCSS_j=1 \mid f_{i,k})^{SUCSS_j} \Pr(SUCSS_j=0 \mid f_{i,k})^{(1-SUCSS_j)}\right)^{ATTND_j} \cdot \\ \cdot \Pr(ATTND_j=0 \mid f_{i,k})^{1-ATTND_j} \end{array} \right] \cdot \\
&\cdot f_1(t_1 \mid f_{i,k}) \cdot f_2(t_2 \mid f_{i,k}) \cdot f_3(t_3 \mid f_{i,k}) \cdot \prod_{m=start_work}^{M} \left[\Pr(R_m=0 \mid f_{i,k})^{1-R_m} \Pr(R_m=1 \mid f_{i,k})^{R_m} \right] \cdot f_w(\ln W=w \mid f_{i,k})^{R_M} \quad \Big\},
\end{aligned}$$

where K is the number of points of support chosen for the Gauss-Hermite quadrature, π_k is the probability weight that the unobserved ability f takes on the mass point f_k. The sample likelihood is given by the product of the individual likelihoods.

Identification

Hansen, Heckman, and Mullen (2004) prove nonparametric identification of unobserved ability and the identification of the model in a static version of this model. The factor structure assumption for the unobserved ability and the concept of "measurable separability" are key to the identification. The latter, in their model, boils down to having individuals with different amounts of schooling at the time tests are taken. Heckman and Navarro (2005) provide a detailed proof of semiparametric identification for more general dynamic discrete choice models in which agents sequentially update the information on which they act. The outcomes are allowed to be mixed discrete-continuous.

Additionally, the analysis contains numerous time-varying exogenous variables. These include an urban community dummy, local food prices, school characteristics and local wage rates. The studies by Bhargava (1991), Mroz and Surette (1998), and Mroz and Savage (forthcoming) show that the time dimension for the exogenous time-varying instruments like these provides many more identification conditions than one might achieve by simply counting the number of contemporaneous exogenous variables excluded from an equation of interest. As an example, consider school characteristics. In 1992, variation in these characteristics has a direct impact on schooling outcomes. Similarly, variation in 1990 has a direct impact on 1990 outcomes. Because of the timing of decision-making, however, the 1990 school characteristics do not have a direct effect on 1992 outcomes except through the accumulated stock of human capital as of 1992. As a consequence, the 1990 characteristics are, theoretically, instruments for human capital stock observed in 1992. This logic certainly applies to other time-varying exogenous variables used in the analysis. Hence, there are numerous instruments available. This provides implicit exclusion restrictions, i.e., additional multiple identifications, to our model. In addition, treating migration as exogenous gives us even more variation in exogenous characteristics.

CHAPTER V
RESULTS

The model is estimated using FORTRAN with analytic first derivatives, in conjunction with the GQOPT optimization library. The first part of the analysis involves surveys only up to the 2002-2003 survey. The number of mass points used for Gauss-Hermite quadrature is 15 (further increase in the number of quadrature points did not improve the likelihood function). The estimates are reported in Appendix B

In each of our outcomes, impact of the unobserved factor operates in the direction one would expect unobserved ability to operate. The estimates suggest that boys enter school later than girls. Conditional on gender, children with lower ability enter school at a later age (Table 14). The same applies to the children with poor health as measured by the child's height at the time of his/her second birthday. The latter is in agreement with findings of Glewwe, Jacoby, and King (2001), even though I do not control for the endogeneity of a child's health in the model.

As can be seen from Tables 15-17, children with lower ability face lower probabilities of attending school. They are also much more likely to drop out of school at all three levels of education (Tables 18-20), with the effect of lower ability diminishing at higher levels of education. For example, one standard deviation decrease in unobserved ability implies a 7.5 percentage point higher probability of dropping out of elementary school, a 6.7 percentage point higher probability of dropping out of high school, and a 4.7 percentage point higher probability of dropping out of college.[14]

A key question is whether we can keep the low-ability dropouts in school longer. More importantly, would this additional schooling benefit individuals in the labor market? The answers to these questions lie in the wage equation: if the return to schooling is large in absolute terms, then the counterfactual additional schooling would certainly, on average, pay off for school dropouts. However, if the return is small, then additional resources spent on making this subgroup of population stay longer in school might be wasteful, at least for the low-ability subgroup. In this respect, our estimates from the wage equations are informative. While standard Mincer-type wage regression (Table 22) yields a 4.5 percentage point return per additional year of schooling (which is in broad agreement with Schady 2003), our model reveals that the introduction of unobserved ability and controlling for the endogeneity of acquired schooling reduces the estimated return by almost 2 percentage points, down to 2.7 (I allow returns to schooling to vary by ability by introducing the ability-schooling interaction, but the corresponding estimate is essentially zero). In other words, results suggest a presence of an omitted ability bias in the conventional estimates of the return to schooling. At the same time, the estimated coefficient on unobserved ability is 8 (although it is statistically insignificant). This implies that one would have to acquire about three additional years of education to compensate for one standard deviation lower innate ability in terms of labor market returns, ceteris paribus.

Looking at average marginal effects, improving school quality appears to increase achievement test scores. These effects, however, are quite small. Decreasing the local pupil-

[14] These numbers, as well as all other estimates for discrete outcomes (Tables 14-21), represent average marginal effects (i.e., marginal effects are computed for each individual and then averaged across the sample).

teacher ratio, for example, by one standard deviation, 5.19, is expected to increase Math test scores by only .32 score points, or less than one tenth of the standard deviation. Lower pupil-teacher ratio yields higher rates of elementary school completion, but the effect is similarly small. A one standard deviation decrease in the pupil-teacher ratio is expected to increase the elementary school completion rate by .8 percentage points. Surprisingly, the fraction of women with primary education and the fraction of women with more than primary education in each community (proxies for high school quality) have only small effects on the outcomes of interest. Looking at the effects of low birth weight, it is worth noting that low birth weight seems to hurt children at early stages of education, as reflected by lower test scores and lower probability of completing primary school. However, this effect virtually disappears later on. Higher family income appears to benefit both attendance and completion of elementary school, and it strongly affects high school and post-secondary school attendance.

The above discussion is based on the analysis of average marginal effects, and these do not reflect all of the complex relationships among our outcomes. To provide a more comprehensive assessment, I make a series of policy simulations by: 1) doubling household income in all time periods; 2) increasing the mother's education by one standard deviation, i.e., by 3.29 years of education; 3) assigning low birth weight to everyone in the sample; or 4) decreasing local pupil-teacher ratio by one standard deviation, i.e., by 5.19. The approach to implementing simulations is standard: a whole life-cycle to age at the time of the 2002-2003 survey is generated for each individual using estimated structural parameters of the model based on the specified policy change. The standard errors on the effects are estimated using a parametric bootstrap with 50 iterations. The resulting effects of policy changes on major outcomes of interest are reported below in Table 5.

The effects are qualitatively similar to the previously discussed average marginal effects, with the increase in the mother's education producing the largest effect on the outcomes. For instance, while increasing the mother's education raises the probability of successfully completing elementary school by 2.1 percentage points, doubling household income in all time periods leads to only a .6 percentage point increase in the rate of successful elementary school completion. It is difficult, however, to compare the effects to each other since each of them implies different costs behind it. It is much easier from policymaking perspective, for instance, to decrease the class size in schools than to increase parental education.

Table 5. Policy simulation results

Outcome	Doubling household income	Increasing mother's education	Assigning low birth weight to everyone	Decreasing local pupil-teacher ratio
Entered school on time	0.0186 (0.0172)[15]	0.0552 (0.0081)	0.0079 (0.0059)	-0.0214 (0.0135)
Attended *elementary* school	0.0107 (0.0036)	0.0357 (0.0045)	0.0020 (0.0021)	0.0061 (0.0043)
Attended *high* school	0.0093 (0.0058)	0.0248 (0.0052)	-0.0009 (0.0026)	-0.0065 (0.0075)
Attended *college*	0.0172 (0.0108)	0.0247 (0.0109)	-0.0014 (0.0050)	0.0020 (0.0129)
Successfully completed the grade, *elementary* school	0.0063 (0.0029)	0.0213 (0.0029)	0.0017 (0.0012)	0.0049 (0.0030)
Successfully completed the grade, *high* school	-0.0029 (0.0046)	0.0158 (0.0030)	-0.0011 (0.0019)	-0.0011 (0.0049)
Successfully completed the grade, *college*	0.0053 (0.0167)	0.0324 (0.0178)	-0.0033 (0.0054)	-0.0044 (0.0221)
Math test scores	0.3539 (0.1872)	2.2841 (0.1659)	0.2042 (0.0923)	0.3145 (0.2832)
English test scores	0.6955 (0.1685)	2.4074 (0.1857)	0.1440 (0.0830)	0.4168 (0.2580)
Completed schooling as of 2002	0.1339 (0.0324)	0.5213 (0.0405)	0.0189 (0.0233)	0.0187 (0.0539)
Log of the hourly wage rate	0.0089 (0.0091)	0.0156 (0.0161)	0.0025 (0.0073)	0.0003 (0.0073)

[15] Standard errors are in parentheses. The standard errors are estimated using parametric bootstrap with 50 iterations.

When discussing the results, especially from the wage equation, several limitations should be noted. Our sample represents very young wage workers, about nineteen years old at the time of the 2002-2003 survey. So early in their careers some of them may exhibit unusual behavior, confounding the effects of schooling and ability. For example, some high-ability individuals might choose to stay out of school and take low-paying jobs to get more experience. Also, as was previously pointed out, a significant fraction of our sample was still in school at the time of the 2002-2003 survey. We, potentially, do not observe the entire range of completed schooling and, perhaps, ability. In order to help resolve these limitations I supplement the analysis with the most recent data from the 2005 survey. Several other important extensions are carried out in the next section.

CHAPTER VI

EXTENSIONS

Relaxing normality assumption

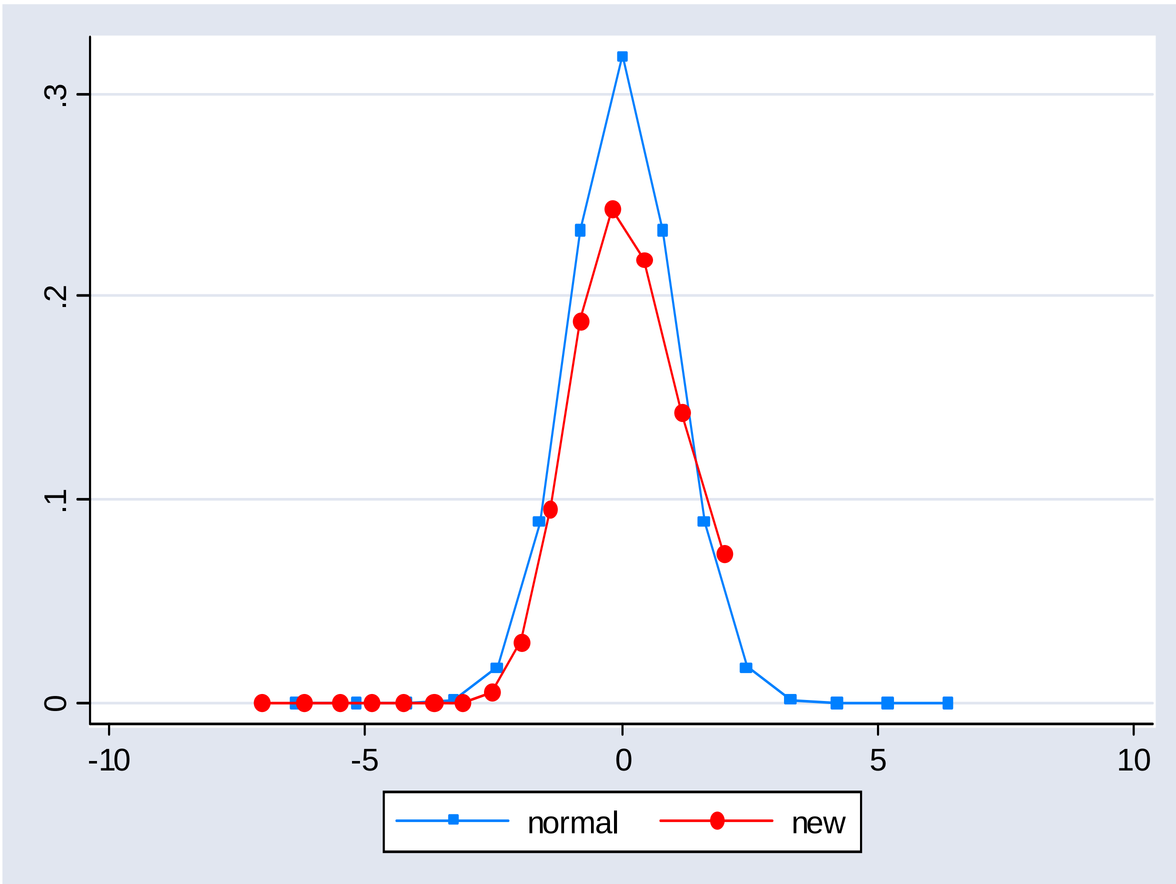
In the above specification the unobserved ability was assumed to follow standard normal distribution. The true distribution of the unobserved ability, however, is unknown and does not have to be normal. The main question here is whether the results are sensitive to the distributional assumptions about the unobserved ability.

I relax the normality assumption by estimating the probability weights for the fixed mass points of the unobserved distribution. A new probability weight, $\pi^*(l)$, is introduced:

$$\pi^*(l) = \frac{e^{\left(\ln \pi(l) + \theta_1 \cdot h(l) + \theta_2 \cdot h(l)^2 + \theta_3 \cdot h(l)^3\right)}}{\sum_{l=1}^{L} e^{\left(\ln \pi(l) + \sum_{k=1}^{3} \theta_k \cdot h(l)^k\right)}},$$

where $\pi(l)$ is a Gauss-Hermite probability weight that corresponds to the *l*-th Gauss-Hermite mass point, $h(l)$ is the *l*-th Gauss-Hermite mass point. If coefficients θ_1, θ_2, θ_3 are equal to zero the specification reduces to the normality. In other words, the model with normality assumption is nested in the new specification. Hence, we can use the likelihood ratio test to test the normality assumption. I estimated the model with new specification. Both distributions are displayed in Figure 1 below.

Figure 1. Relaxing normality: two distributions of unobserved ability[16]



Even though the graph of the estimated distribution appears to have shape somewhat similar to the standard normal distribution the likelihood ratio test strongly rejects the normality assumption implying that the new more flexible specification is preferred. More important is, however, whether the results substantively change when the distributional

[16] Probabilities are plotted against corresponding mass points. "Normal" corresponds to the distribution of the unobserved ability in the specification with normality assumption. "New" corresponds to the distribution of the unobserved ability in the new specification where probability weights are estimated within the model. The "new" distribution is normalized to have zero mean and variance one to be comparable to standard normal.

assumption is relaxed. Surprisingly, they do not. The results appear to be robust to relaxing the distributional assumption for the unobserved ability.

Adding data from the 2005 survey

The most recent survey allows us to supplement our analysis with more complete schooling and labor market trajectories. This is important since at the time of the 2002-2003 survey our sample represents very young wage workers, about nineteen years old, with slightly more than a year of working experience, on average. So early in their careers some of them may exhibit unusual behavior, confounding the effects of schooling and ability and contributing to large standard errors of schooling and ability coefficients in the wage equation.

Some of the descriptive statistics for the 2005 data are reported in a previously discussed Table 3. For instance, as of the time of the 2005 survey individuals have, on average, more working experience, 3.1 years, compared to 1.2 years in the 2002 survey.

Similar to previous analyses the model is estimated in FORTRAN. The number of mass points used is seven (further increase in the number of quadrature points did not improve the likelihood function). The estimation results are reported in Tables 23-36.

Unlike the results from the 2002-2003 data, unobserved ability coefficient and the interaction term as well as the schooling coefficient become statistically significant in the wage equation (Table 26). The estimated coefficient on the interaction of unobserved ability and schooling implies that the return to education now depends on an individual's unobserved ability. An individual's unobserved ability, however, is no longer assumed to follow standard normal distribution. Table 36 presents implied probabilities along with corresponding mass points. Since the mean of the distribution is -0.86 the return to education for an individual with an average ability is estimated to be 4.59 percentage points (6.074-0.86*1.721) which is fairly close to 4.27 percentage points from the Mincer-type regression (Table 37). A one standard deviation higher ability increases the return by 2.65 percentage points (1.54*1.72). Signs on the direct effect of unobserved ability and the interaction of the ability with schooling in the wage equation suggest that the sign and the magnitude of the cumulative effect of an individual's ability on wages depend on the level of an individual's ability as well as the amount of completed schooling.

A seemingly strange result in the wage equation is a negative effect of working experience. The sign is robust to the model specification, it is negative in any of the specifications discussed in this work including basic Mincer-type wage regression. In an attempt to resolve this issue I constructed two experience variables, "experience as of the time of the 2002-2003 survey" and "any additional experience acquired since the 2002-2003 survey (as of the 2005 survey)". This, however, did not change the estimated effect of working experience – both variables had virtually the same effect in terms of the magnitude and the sign. Including only "experience as of the time of the 2002-2003 survey" in the wage equation yielded no changes either. Unfortunately, I have no explanation to why the working experience has a negative effect in the wage equation.

The estimates from the rest of the equations suggest results qualitatively very similar to the previous analysis. This should not be surprising since the 2005 survey provided more data only on earnings and two additional years in the schooling trajectories.

Polynomial in unobserved ability and conditional density estimation (CDE)

In order to provide more flexible controls for the unobserved ability a second-degree polynomial in the unobserved ability is used in each equation. The new squared term has statistically significant estimated effects in most of the equations. The likelihood ratio test accepts new richer specification.

In addition to the polynomial in unobserved ability I adopt conditional density estimation (CDE) approach proposed by Gilleskie and Mroz (2004). This approach allows to relax functional form and distributional assumptions for continuous outcomes. I use the CDE approach in the specification of the wage equation. I partition the distribution of wages into ten discrete cells, i.e. deciles, and model the probability of an advance to a higher, discretized wage level through the logit hazard rate model.

The results are reported in Tables 38-50. The number of mass points used for the distribution of the unobserved ability in the estimation is 11. The implied probabilities are reported in Table 51. The average marginal effects for the CDE specification are reported in Table 49. The return to education appears to be only 2.9 percentage points in the CDE specification.

The rest of the equations reveal results that appear to be similar to what we have previously found. Namely, boys enter school later than girls. They also perform worse at the cognitive achievement tests. Children with lower ability are much more likely to drop out of school at all three levels of education. The test scores appear to be strongly affected by the amount of completed schooling at the time of the test. For that reason whenever such a test is used as a proxy for an individual's ability it will necessarily be picking up some of the schooling effect.

Given the nonlinear nature of the estimation framework, however, and complex relationships among the outcomes it is difficult to interpret most of the estimates in a meaningful way other than via a series of simulations. I make a series of policy simulations by: 1) doubling household income in all time periods; 2) increasing the mother's education by one standard deviation, i.e., by 3.29 years of education; or 4) decreasing local pupil-teacher ratio by one standard deviation, i.e., by 5.19. The approach to implementing simulations is the same as previously: a whole life-cycle to the age at the time of the 2005 survey is generated for each individual using estimated structural parameters of the model based on the specified policy change. The standard errors on the effects are being estimated using a parametric bootstrap and will be reported during the defense. The resulting effects of policy changes on major outcomes of interest are reported in Table 6.

The estimates from Table 6 appear to be very similar to the results from Table 5. All of the effects in Table 6 appear to be fairly small. Even ignoring potential costs associated with each policy change and comparing the effects to each other, the largest increase in the amount of completed schooling is only 0.8. Similarly, the rates of successful school completion are hardly affected by the simulated changes suggesting, perhaps, that in a country with relatively high primary school enrollment and completion rates, like the Philippines, policies oriented toward the achievement of universal primary education might need to be more refined than just increasing educational expenditures.

Table 6. Policy simulation results

Outcome	Doubling household income	Increasing mother's education	Decreasing local pupil-teacher ratio
Entered school on time	0.014117 (0.0144)	0.0560 (0.0083)	-0.0201 (0.0154)
Attended *elementary* school	0.0160 (0.0051)	0.0516 (0.0056)	0.0025 (0.0050)
Attended *high* school	0.0106 (0.0070)	0.0453 (0.0071)	-0.0088 (0.0080)
Attended *college*	-0.0013 (0.0092)	0.0369 (0.0072)	-0.0114 (0.0146)
Successfully completed the grade, *elementary* school	0.0050 (0.0026)	0.0207 (0.0029)	0.0037 (0.0025)
Successfully completed the grade, *high* school	-0.0040 (0.0038)	0.0158 (0.0033)	-0.0022 (0.0053)
Successfully completed the grade, *college*	-0.0036 (0.0080)	0.0198 (0.0062)	-0.0117 (0.0130)
Math test scores	0.2492 (0.1972)	2.2751 (0.1651)	0.0555 (0.2522)
English test scores	0.5589 (0.1841)	2.4123 (0.1538)	0.1955 (0.2445)
Completed schooling as of 2005	0.1340 (0.0566)	0.8002 (0.0508)	-0.0831 (0.0760)
Log of the hourly wage rate	0.0045 (0.0035)	0.0276 (0.0058)	-0.0049 (0.0043)

Nonlinear effects of schooling

In all of the above analyses we implicitly assumed that return to education is the same across all three levels of education, i.e., primary school, high school and college. As evidenced by the existing literature on the returns to schooling such an assumption might be too strong. In order to relax the linearity in schooling we adopt the following specification:

[17] Standard errors are estimated via parametric bootstrap with 50 iterations.

$$\ln W_i = \alpha' X_i + \gamma\, S_i + \eta\, [D6_i (S_i - 6)] + \delta\, [D10_i (S_i - 10)] + \xi_i ,$$

where S_i is the amount of completed schooling, $D6_i$ and $D10_i$ are dummy variables for those who have completed *at least* 6 and 10 years of schooling, respectively, $D6_i(S_i - 6)$ is an interaction term between the $D6_i$ dummy and $(S_i - 6)$, $D10_i(S_i - 10)$ is an interaction term between the $D10_i$ dummy and $(S_i - 10)$. In this specification the mean rate of return to primary education is given by the coefficient γ, the mean rate of return to high school is given by the sum of the coefficients γ and η, the mean rate of return to college education is given by the sum of the coefficients γ, η and δ.

The model is estimated with the above specification for the wage equation using the FIML, with a 2nd degree polynomial in unobserved ability and a 3rd degree polynomial in probability parameters that determine probability weights. Results for a wage equation only are reported below in Table 7. Even though none of the schooling coefficients is statistically significant the likelihood-ratio test suggests that the two additional coefficients are jointly significant, new more flexible specification is preferred. The schooling coefficients suggest considerable nonlinearity of the returns to schooling. Taking into account the interaction of schooling and unobserved ability, the mean rate of return to primary education for an individual with average ability is estimated to be very close to zero, 0.13 percentage points (-0.88+1.01). The mean rate of return to high school for an individual with an average ability is estimated to be 3.01 percentage points (-0.88+2.88+1.01). The mean rate of return to college education for an individual with an average ability is estimated to be 8.63 (-0.88+ +2.88+5.62+1.01).

Table 7. Log of Hourly Wage Rate Equation, Nonlinear in Schooling

Variable	Estimate	Standard error	t-statistic
Male	0.24856	0.04702	5.286
Age	0.11629	0.07256	1.603
Experience	-0.03939	0.01907	-2.065
Completed schooling	*-0.00881*	*0.02849*	*-0.309*
$D6\ (S-6)$	*0.02877*	*0.04185*	*0.688*
$D10\ (S-10)$	*0.05622*	*0.03445*	*1.632*
Urban	-0.10584	0.07551	-1.402
Population density (log)	0.05141	0.02276	2.259
Local wage rate for unskilled labor	-0.00159	0.00307	-0.519
Constant	0.04808	1.55108	0.031
f (unobserved ability)	-0.02347[18]	0.05514	-0.426
f^2 (unobserved ability, squared)	-0.00616	0.00585	-1.053
*f*S* (schooling-ability interaction)	0.00688	0.00644	1.069

OLS vs. FIML

It is a valid question to ask whether specifications simpler than the proposed simultaneous equations framework can do as well as our preferred specification. While we have already compared some of our results to Mince-type wage regression, Table 8 below provides a much more comprehensive comparison. Rows 1-5 represent several variations of the classical Mincer-type wage regression, from basic, most popular specification,(1), to the one with spline functions and IQ variable as a proxy for an individual's unobserved ability, (5). Rows 6-10 represent a simple OLS regression with extra explanatory variables in addition to basic Mincer-type specification, the set of regressors is identical to the one we use

[18] The distribution of the unobserved ability is estimated to have mean 1.47 and variance 3.40.

in our FIML specification. Rows 11-12 represent full-information maximum likelihood specifications, first with linearity.

Table 8. Various Specifications of Wage Regressions: OLS and FIML

	Schooling (S)	**D6*(S-6)**	**D10*(S-10)**	**IQ[19] or *f***	**Interaction of IQ/*f* and schooling**
(1) Mincer-type, linear in S	**.043[20] (.011)**	—	—	—	—
(2) 'Mincer', linear in S, with IQ	**.039 (.011)**	—	—	**.046 (.022)**	—
(3) 'Mincer', with IQ and IQ*S	**.045 (.011)**	—	—	-.098 (.063)	**.017 (.007)**
(4) 'Mincer', spline in S	-.007 (.027)	.049 (.037)	**.072 (.024)**	—	—
(5) 'Mincer', spline in S, with IQ and IQ*S	.008 (.029)	.027 (.037)	**.068 (.025)**	-.013 (.071)	.007 (.008)
(6) Type 2 OLS, linear in S	**.038 (.011)**	—	—	—	—
(7) Type 2, linear in S, with IQ	**.032 (.011)**	—	—	**.056 (.023)**	—
(8) Type 2, with IQ and IQ*S	**.039 (.011)**	—	—	-.075 (.064)	**.016 (.007)**
(9) Type 2, spline in S	-.008 (.027)	.047 (.037)	**.069 (.025)**	—	—
(10) Type 2, spline in S, with IQ and IQ*S	.005 (.029)	.026 (.037)	.063 (.025)	.001 (.072)	.007 (.008)
(11) FIML, wages linear in S	**0.061 (0.017)**	—	—	**-0.126[21] (0.054)**	**0.017 (0.005**
(12) FIML, spline in S	0.013 (0.049)	0.030 (0.043)	0.055 (0.037)	-0.023[22] (0.089)	0.007 (0.009)

[19] IQ test scorers are normalized to have mean zero and variance one for corresponding regressions in this Table.

[20] Estimates in bold are statistically significant under conventional 5% significance level.

[21] The distribution of the unobserved ability is estimated to have the mean of -0.86 and the variance 2.38.

[22] The distribution of the unobserved ability is estimated to have the mean of -1.70 and the variance 1.54.

in schooling imposed and then with spline functions in schooling. In both of FIML specifications I used a 1st degree polynomial in unobserved ability to ease comparison to OLS regressions in Table 8.[23] To make better sense of the estimates in Table 8 I computed the corresponding rates of return to education by educational level for an individual with an average ability. They are presented in Table 9. As can be seen from the tables, when linearity

Table 9. Interpreting Results From Table 8: Mean Rates of Return to Education, by Educational Level, for an individual with average ability (wherever appropriate).

	Rate of return to primary school	**Rate of return to high school**	**Rate of return to college education**
(1) Mincer-type, linear in S	4.3	4.3	4.3
(3) ‘Mincer’, with IQ and IQ*S	4.5	4.5	4.5
(4) ‘Mincer’, spline in S	-0.7	4.2	11.4
(5) ‘Mincer’, spline in S, with IQ and IQ*S	0.8	3.5	10.3
(6) Type 2 OLS, linear in S	3.8	3.8	3.8
(8) Type 2, with IQ and IQ*S	3.9	3.9	3.9
(9) Type 2, spline in S	-0.8	3.9	10.8
(10) Type 2, spline in S, with IQ and IQ*S	0.5	3.1	9.4
(11) FIML, wages linear in S	4.6	4.6	4.6
(12) FIML, spline in S	-0.1	3.1	8.6

[23] In other words, row 11 results are equivalent to the wage equation estimates reported in Appendix C. Row 12 differs from Table 7 specification only in the degree of polynomial for the unobserved ability, this difference does not, however, change estimated rates of return (that will become obvious in the next table).

in schooling is imposed ‘Mincer’-type regression yields schooling coefficients very close to what the FIML gives us (compare (1) or (3) to (11)). Linear wage regression, however, appear to be severely misspecified, rates of return to education appear to be nonlinear. When spline functions are introduced the Mincer-type regressions inflates the estimated returns by at least 19% for college education, 13% for high school and by at least 600% for primary school. Type 2 specification, in which we use a broader range of regressors than in the Mincer-type, when paired with IQ variable produces the set of estimated rates of return that are much closer to our preferred specification (compare (10) to (12)) by introducing only 9% bias for college education, 0% for high school and 600% for primary school.

CHAPTER VII

CONCLUSION

Using rich data from the Cebu Longitudinal Health and Nutrition Survey, I analyze the role of an individual's unobserved innate ability in explaining school attendance and completion, and early labor market outcomes of young Filipino adults.

I find that children with lower innate ability enter school at a later age, complete fewer years of school, and are more likely to drop out of school at all levels of education. From a policy making perspective, I find that enhanced conventional school inputs, such as pupil-teacher ratios, do little to keep young children in school. My results suggest that in a country with relatively high primary school enrollment and completion rates, like the Philippines, policies oriented toward the achievement of universal primary education might need to be more refined than just increasing educational expenditures. A series of policy changes, unfortunately, did not reveal any sound instruments that could significantly improve schooling and labor market outcomes of the individuals in the Philippines. Policy simulations, however, suggest a noticeable intergenerational effect of higher amount of completed education. For instance, a one standard deviation increase in mother's education is associated with a 0.8 increase in the amount of completed education for her children.

With respect to labor market outcomes of school dropouts in the Philippines, I find that the returns to education, after controlling for ability, are smaller in the Philippines than in most of developing countries which is in agreement with existing literature. In the analysis of returns to education a standard Mincer-type regression appears to be misspecified. Results reveal significant heterogeneity in the returns to schooling by an individual's ability. Rates of return to education appear to be strongly nonlinear. Our preferred estimates suggest that the mean rate of return to primary education for an individual with average ability is close to zero, -0.1 percentage points; the mean rate of return to high school for an individual with average ability is 3 percentage points; the mean rate of return to college education for an individual with average ability is 8.6 percentage points.

APPENDIX A: Constructed Variables

The variable "*Entered school on time*" is equal to one if a child entered school at age less than 7.5 years old, it is zero otherwise. "*Low birth weigh*" is equal to one if the weight of a child at birth was 2.5 kilograms or less, zero otherwise. "*Age as of*" represents the age of a person at the beginning of the school year. The school year starts in June in the Philippines. "*Completed schooling at t*" represents the number of successfully completed grades by school year *t*.

School quality characteristics that I use are measures aggregated from individual-level school measures. The reason for doing this is the fact that individual school quality measures cannot be constructed for everyone in the sample, but only for those who attended a "primary only" type of school (as opposed to "primary and high school in one" or "high school only"). Although a "primary only" type of school is predominant in Cebu (around 87-90 percent of all schools), I did not want to lose a portion of the sample. Two measures are used for primary school: pupil-teacher ratio and public school dummy. They are constructed based on the school questionnaires administered during the 1994-1995 survey and on a supplemental 1996 survey.

None of the CLHNS data contain high school characteristics. To resolve that issue, I have merged 2000 census data from the Philippines at the barangay (community) level with my sample by barangay of residence. Such measures as "*Fraction of women with primary education in barangay*" and "*Fraction of women with more than primary education in barangay*" were constructed to proxy for the quality of high schools in the areas of residence.

The *household income* variable represents the average household income per week. It is calculated as the sum of three sources of income: 1) resources generated within and by the household (home gardening, income in kind, remittances, pensions, rent savings, etc.); 2) individual earnings (wages, piecework, fishing, self-employment); and 3) group earnings (livestock and farming).

All the pecuniary measures (like *household income* and *food prices*) were deflated to January 1983 pesos.

For all dynamic variables, like *household and community characteristics*, the data are assigned in the following way: years 1990-1993[24] use the data from the 1991-1992 survey, years 1994-1996 use the data from the 1994-1995 survey, years 1997-1999 use the data from the 1998-1999 survey, years 2000-2002 use the data from the 2002-2003 survey, years 2003-2005 use the data from the 2005 survey. The only exception is community characteristics for years 2003-2005. As of now the community data from the 2005 survey has not been processed yet. For that reason I used community data from the 2002-2003 survey for years 2003-2005.

School grade progression

The variables ATTND and SUCSS are created for each educational subgroup. Modeling of ATTND_elementary starts with the year after the first school entry, conditional on completed schooling as of the time of that decision; ATTND_high has a nonmissing value starting with the year right after the year when the last grade of primary school was completed; ATTND_college is modeled starting with the year right after the year when the last grade of high school was completed.

Earnings

<u>2002-2003 survey:</u> In the final sample, 1,781 reported working, of whom 1,333 were working for pay. Only 1,234 were out of school at the time of the 2002-2003 survey. In the analysis of earnings, we limit the sample to only those who reported both working and being out of school by the time of the 2002-2003 survey, that is 1,179 people. Out of these 1,179, wage workers comprise 931. Five people are dropped as outliers in the hourly wage rate distribution (these five reported hourly wages above 400 pesos, while the 99th percentile had 250 pesos per hour). That leaves us with 926 wage workers (509 men and 417 women). Hourly wage rate was computed using available information on: 1) reported earnings per day, 2) reported number of days working per week, and 3) reported number of hours working per week. For those who reported “no regular workday” as their number of working days per week, it is assumed they worked five days a week (48 individuals).

[24] The year sequence starts from 1990 because only twenty-two people attended school in year 1989 (once again, all references to years are references to school years, e.g., “year 1990” means “school year 1990/1991”).

2005 survey: Wage workers comprise 1219. Four people are dropped as outliers in the hourly wage rate distribution (these four reported hourly wages above 450 pesos, while the 99th percentile had 250 pesos per hour). That leaves us with 1215 wage workers (665 men and 550 women).

APPENDIX B: Estimates

Table 10. Math Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	2.1125	0.2749	7.6830
Age as of test date	2.8786	0.4892	5.8850
Male	-3.2162	0.4313	-7.4570
Low birth weight	-1.5214	0.6314	-2.4090
Caretaker’s household	0.7527	0.6759	1.1140
Mother’s education (log)	5.1670	0.4991	10.3530
Family business	0.3655	0.3603	1.0140
Household size	-0.1839	0.0781	-2.3560
Household income (log)	0.4162	0.2479	1.6790
Urban	3.3400	0.7728	4.3220
Price of bananas	-22.9137	8.5506	-2.6800
Price of corn	-0.7767	1.1067	-0.7020
Price of kerosene	2.1595	1.7458	1.2370
Population density (log)	-1.0676	0.2455	-4.3490
Local pupil-teacher ratio	-0.0621	0.0468	-1.3290
Fraction of public schools in the area	-1.1960	4.2673	-0.2800
Constant	-9.3178	10.4155	-0.895
f (unobserved ability)	2.9237	0.7358	3.973
*f*S* (schooling-ability interaction)	1.2277	0.1708	7.186

N=1,953, $\sigma_{\varepsilon} = 4.80$

Table 11. English Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	0.9808	0.2647	3.705
Age as of test date	3.3837	0.4735	7.146
Male	-3.8373	0.4105	-9.348
Low birth weight	-1.1679	0.6023	-1.939
Caretaker's household	0.3564	0.6466	0.551
Mother's education (log)	6.0434	0.4502	13.425
Family business	-0.6126	0.346	-1.771
Household size	-0.2962	0.0731	-4.052
Household income (log)	1.0106	0.2441	4.14
Urban	2.4438	0.7637	3.2
Price of bananas	-5.8483	8.8165	-0.663
Price of corn	-0.211	1.0005	-0.211
Price of kerosene	4.6883	1.6753	2.799
Population density (log)	-0.5747	0.2261	-2.542
Local pupil-teacher ratio	-0.0841	0.0505	-1.664
Fraction of public schools in the area	-2.5295	4.1817	-0.605
Constant	-29.0479	9.3420	-3.109
f (unobserved ability)	1.9474	0.6806	2.861
*f*S* (schooling-ability interaction)	1.4139	0.1526	9.265

N=1,953, $\sigma_{\varepsilon} = 4.42$

Table 12. IQ Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	1.3248	0.2721	4.869
Age as of test date	-4.0188	0.5861	-6.857
Male	-0.348	0.2926	-1.189
Low birth weight	-0.7279	0.4124	-1.765
Caretaker’s household	0.4923	0.5217	0.944
Mother’s education (log)	2.8393	0.3501	8.11
Family business	-0.0525	0.2974	-0.176
Household size	-0.2305	0.0622	-3.707
Household income (log)	0.7222	0.2983	2.421
Urban	0.5586	0.5388	1.037
Price of bananas	-6.7527	3.7945	-1.78
Price of corn	0.2456	0.4849	0.506
Price of kerosene	0.13	0.1982	0.656
Population density (log)	0.1329	0.1667	0.798
Local pupil-teacher ratio	-0.0028	0.0334	-0.084
Fraction of public schools in the area	1.326	2.915	0.455
Constant	55.8985	6.6202	8.444
f (unobserved ability)	3.804	0.314	12.114
*f*S* (schooling-ability interaction)	-0.8788	0.2072	-4.242

N=1,949, $\sigma_{\varepsilon} = 5.17$

Table 13. Log of Hourly Wage Rate

Variable	Estimate	Standard error	t-statistic
Male	0.3877	0.07	5.537
Age	0.1345	0.1157	1.163
Experience	0.0186	0.0356	0.524
Completed schooling	0.0267	0.0232	1.153
Urban	0.0071	0.1196	0.06
Population density (log)	0.007	0.0371	0.189
Local wage rate for unskilled labor	-0.0084	0.0051	-1.653
Constant	-0.3009	2.1626	-0.139
f (unobserved ability)	0.0805	0.1235	0.652
*f*S* (schooling-ability interaction)	-0.0008	0.0135	-0.06

N=918, $\sigma_{\varepsilon} = 0.92$

Table 14. Entered School on Time

Variable	Av. Marg. Effect	t-statistic
Male	-0.0478	-2.41
Caretaker's household	0.0004	0.01
Low birth weight	-0.0482	-1.638
Height of the child	1.0761	4.368
Household income (lagged)	0.0276	1.268
Mother's education (log)	0.1476	6.841
Family business	-0.0402	-1.846
Urban (averaged across time)	-0.1140	-3.007
Population density (log, averaged)	0.0311	2.763
Price of kerosene (log, averaged)	-0.0855	-2.139
Price of bananas (log, averaged)	0.0653	1.178
Price of corn (log, averaged)	-0.1392	-1.72
Local pupil-teacher ratio	0.0037	1.681
Fraction of public schools in the area	0.2703	1.41
f (unobserved ability)	0.0586	5.026

N=1,963

Table 15. "Did individual *i* attend ELEMENTARY school during school year *t*?"

Variable	Av. Marg. Effect	t-statistic
Missed school last year	-0.0929	-23.126
Failed last grade	-0.0477	-11.715
Completed schooling as of t	-0.0069	-4.27
Age as of t	-0.0113	-9.12
Male	-0.0073	-2.039
Low birth weight	-0.0042	-0.988
Caretaker's household	0.0050	1.155
Mother's education (log)	0.0213	5.68
Family business	0.0028	0.892
Household size	-0.0019	-3.311
Household income (log)	0.0050	2.024
Urban	0.0028	0.499
Price of bananas	-0.0433	-1.31
Price of corn	0.0185	2.943
Price of kerosene	-0.0013	-0.284
Population density (log)	0.0008	0.446
Local pupil-teacher ratio	-0.0004	-1.311
Fraction of public schools in the area	-0.0184	-0.563
f (unobserved ability)	0.0206	8.584

N=11,489, N of individuals=1,953

Table 16. “Did individual *i* attend HIGH school during school year *t*?”

Variable	Av. Marg. Effect	t-statistic
First year of high school	-0.1467	-13.535
Missed school last year	-0.2777	-25.284
Failed last grade	-0.2235	-20.06
Completed schooling as of t	-0.1008	-19.882
Age as of t	-0.0351	-7.272
Male	-0.0113	-1.535
Low birth weight	-0.0077	-0.746
Caretaker’s household	0.0276	2.792
Mother’s education (log)	0.0412	4.707
Family business	0.0041	0.603
Household size	-0.0034	-2.648
Household income (log)	0.0142	2.542
Urban	-0.0041	-0.285
Price of bananas	0.0741	1.059
Price of corn	-0.0009	-0.038
Price of kerosene	-0.0300	-2.302
Population density (log)	-0.0064	-1.284
Local pupil-teacher ratio	0.0002	0.305
Fraction of public schools in the area	-0.0876	-1.359
Fraction of women with primary education	-0.3306	-3.394
Fraction of women with more than primary	-0.0341	-0.664
f (unobserved ability)	0.0204	4.01

N=8,638, N of individuals=1,736

Table 17. "Did individual *i* attend COLLEGE during school year *t*?"

Variable	Av. Marg. Effect	t-statistic
First year of college	0.2268	4.484
Missed school last year	-0.2173	-4.993
Failed last grade	-0.3461	-7.97
Completed schooling as of t	0.0610	2.17
Age as of t	-0.0402	-2.496
Male	-0.0121	-0.743
Low birth weight	0.0163	0.583
Caretaker's household	0.0312	1.349
Mother's education (log)	0.0401	1.872
Family business	-0.0138	-0.867
Household size	-0.0035	-1.176
Household income (log)	0.0264	2.27
Urban	0.0302	1.105
Price of bananas	0.0169	0.077
Price of corn	0.0143	0.158
Price of kerosene	-0.0242	-0.556
Population density (log)	0.0081	0.553
Local pupil-teacher ratio	-0.0005	-0.28
Fraction of public schools in the area	0.1575	1.114
Fraction of women with primary education	-0.3131	-0.682
Fraction of women with more than primary	-0.3555	-1.403
f (unobserved ability)	0.0089	0.847

N=1,178, N of individuals=586

Table 18. "Did individual *i* successfully complete the grade during school year *t*, ELEMENTARY school?"

Variable	**Av. Marg. Effect**	**t-statistic**
Missed school last year	-0.0602	-9.221
Failed last grade	-0.0113	-1.542
Completed schooling as of t	0.0031	0.718
Age as of t	0.0010	0.368
Male	-0.0507	-7.923
Low birth weight	-0.0192	-2.204
Caretaker's household	0.0161	1.853
Mother's education (log)	0.0630	8.438
Family business	0.0026	0.49
Household size	-0.0044	-3.865
Household income (log)	0.0127	2.845
Urban	0.0127	1.305
Price of bananas	-0.0819	-1.347
Price of corn	0.0220	2.765
Price of kerosene	0.0001	0.033
Population density (log)	0.0008	0.26
Local pupil-teacher ratio	-0.0012	-1.826
Fraction of public schools in the area	0.0931	1.485
f (unobserved ability)	0.0748	14.971

N=12,176, N of individuals=1,957

Table 19. “Did individual *i* successfully complete the grade during school year *t*, HIGH school?”

Variable	Av. Marg. Effect	t-statistic
First year of high school	-0.0234	-1.218
Missed school last year	0.0075	0.346
Failed last grade	-0.0866	-7.048
Completed schooling as of t	0.0247	2.512
Age as of t	-0.0082	-1.215
Male	-0.1158	-10.637
Low birth weight	0.0056	0.383
Caretaker’s household	0.0573	4.259
Mother’s education (log)	0.0691	5.491
Family business	0.0186	2.103
Household size	-0.0001	-0.055
Household income (log)	0.00005	0.006
Urban	-0.0364	-1.862
Price of bananas	-0.0248	-0.288
Price of corn	-0.0115	-0.386
Price of kerosene	-0.0084	-0.528
Population density (log)	-0.0006	-0.09
Local pupil-teacher ratio	0.0001	0.104
Fraction of public schools in the area	0.2408	2.717
Fraction of women with primary education	0.0281	0.178
Fraction of women with more than primary	0.0523	0.624
f (unobserved ability)	0.0671	10.147

N=6,451, N of individuals=1,731

Table 20. "Did individual *i* successfully complete the grade during school year *t*, COLLEGE?"

Variable	Av. Marg. Effect	t-statistic
First year of college	-0.0650	-0.131
Missed school last year	-0.1576	-2.02
Failed last grade	0.0588	0.47
Completed schooling as of t	-0.0090	-0.018
Age as of t	0.0857	1.829
Male	-0.0795	-2.345
Low birth weight	0.0464	0.689
Caretaker's household	0.0877	1.559
Mother's education (log)	0.1061	2.212
Family business	0.0133	0.405
Household size	-0.0035	-0.537
Household income (log)	0.0070	0.29
Urban	-0.0719	-0.99
Price of bananas	0.0902	0.213
Price of corn	-0.0632	-0.433
Price of kerosene	0.0096	0.133
Population density (log)	0.0254	0.915
Local pupil-teacher ratio	0.0011	0.255
Fraction of public schools in the area	0.1293	0.446
Fraction of women with primary education	0.0907	0.132
Fraction of women with more than primary	0.1467	0.454
f (unobserved ability)	0.0467	1.972

N=811, N of individuals=545

Table 21. Working for Pay During the Year *t*

Variable	Av. Marg. Effect	t-statistic
Age as of t	0.1169	13.426
Male	0.0291	2.144
Low birth weight	0.0465	2.411
Mother's education (log)	-0.0712	-5.211
Family business	-0.0831	-6.122
Household size	0.0037	1.614
Household income net of individual's (log)	-0.0286	-3.539
Urban	-0.0060	-0.226
Price of bananas	0.6305	3.747
Price of corn	0.1605	3.182
Price of kerosene	0.0455	1.939
Population density (log)	-0.0007	-0.074
Local wage rate for unskilled labor as of t	0.0015	1.452
Local pupil-teacher ratio	0.0007	0.547
Fraction of public schools in the area	0.3655	2.882
Fraction of women with primary education	-0.0994	-0.577
Fraction of women with more than primary	0.0583	0.669
f (unobserved ability)	-0.0096	-1.324

N=3,898, N of individuals=1,454

Table 22. Mincer-type Log Wage Regression

Variable	Estimate	Standard error	t-statistic
Male	.4057	.0628	6.46
Experience	.0258	.0301	0.86
Completed schooling	.0447	.0143	3.13
Constant	1.9696	.1511	13.03

N=918, σ_{ε} = 0.92, R^2 =0.04

APPENDIX C: Estimates, supplementing with the 2005 survey

Table 23. Math Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	3.11492	0.37769	8.247
Age as of test date	2.27098	0.49756	4.564
Male	-3.04256	0.4332	-7.024
Low birth weight	-0.99129	0.66148	-1.499
Caretaker's household	1.14632	0.68061	1.684
Mother's education (log)	4.89109	0.53859	9.081
Family business	0.62614	0.37129	1.686
Household size	-0.19333	0.08121	-2.381
Household income (log)	0.22211	0.26476	0.839
Urban	3.39628	0.80304	4.229
Price of bananas	-25.8751	9.14074	-2.831
Price of corn	0.04114	1.16724	0.035
Price of kerosene	1.891	1.76208	1.073
Population density (log)	-1.03714	0.25299	-4.1
Local pupil-teacher ratio	-0.02382	0.04882	-0.488
Fraction of public schools in the area	-0.62886	4.53253	-0.139
Constant	-4.21461	10.89893	-0.387
f (unobserved ability)	1.84322	0.52379	3.519
*f*S* (schooling-ability interaction)	0.78696	0.13427	5.861

Table 24. English Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	2.14434	0.37537	5.713
Age as of test date	2.73246	0.48767	5.603
Male	-3.77085	0.4176	-9.03
Low birth weight	-0.6899	0.62435	-1.105
Caretaker's household	0.95332	0.66066	1.443
Mother's education (log)	5.74045	0.47724	12.028
Family business	-0.47278	0.35945	-1.315
Household size	-0.28491	0.07634	-3.732
Household income (log)	0.81043	0.25827	3.138
Urban	2.59129	0.78464	3.303
Price of bananas	-9.69458	9.34356	-1.038
Price of corn	0.10469	1.04911	0.1
Price of kerosene	4.15973	1.75858	2.365
Population density (log)	-0.58657	0.2379	-2.466
Local pupil-teacher ratio	-0.06253	0.05108	-1.224
Fraction of public schools in the area	-1.46062	4.42113	-0.33
Constant	-21.7146	9.86754	-2.201
f (unobserved ability)	1.03949	0.49645	2.094
*f*S* (schooling-ability interaction)	0.94294	0.12608	7.479

Table 25. IQ Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	0.78263	0.38547	2.03
Age as of test date	-4.26682	0.59916	-7.121
Male	-0.41946	0.30457	-1.377
Low birth weight	-0.43979	0.42766	-1.028
Caretaker’s household	0.59344	0.55004	1.079
Mother’s education (log)	2.67701	0.37108	7.214
Family business	-0.02996	0.31368	-0.096
Household size	-0.28207	0.06502	-4.338
Household income (log)	0.71683	0.31705	2.261
Urban	0.39075	0.56902	0.687
Price of bananas	-7.02879	3.97768	-1.767
Price of corn	0.22643	0.50342	0.45
Price of kerosene	0.12219	0.20257	0.603
Population density (log)	0.19194	0.17526	1.095
Local pupil-teacher ratio	0.0087	0.03444	0.253
Fraction of public schools in the area	1.51734	3.04717	0.498
Constant	60.01885	7.04429	8.52
f (unobserved ability)	2.57793	0.24422	10.556
*f*S* (schooling-ability interaction)	-0.65841	0.14383	-4.578

Table 26. Log of Hourly Wage Rate

Variable	Estimate	Standard error	t-statistic
Male	0.24952	0.04695	5.314
Age	0.11914	0.07186	1.658
Experience	-0.03753	0.01846	-2.033
Completed schooling	0.06074	0.01682	3.611
Urban	-0.099	0.07424	-1.334
Population density (log)	0.04974	0.02265	2.196
Local wage rate for unskilled labor	-0.00162	0.00309	-0.525
Constant	-0.48365	1.5542	-0.311
f (unobserved ability)	-0.12613	0.0544	-2.318
*f*S* (schooling-ability interaction)	0.01721	0.00521	3.305

Table 27. Entered School on Time

Variable	Estimate	Standard error	t-statistic
Constant	-1.01075	1.86116	-0.543
Male	-0.34491	0.1329	-2.595
Caretaker's household	0.04698	0.25344	0.185
Low birth weight	-0.25978	0.19807	-1.312
Height of the child	7.10745	1.60757	4.421
Household income (lagged)	0.12619	0.14492	0.871
Mother's education (log)	0.94564	0.14058	6.727
Family business	-0.31539	0.14678	-2.149
Urban (averaged across time)	-0.89463	0.25443	-3.516
Population density (log, averaged)	0.22647	0.07583	2.987
Price of kerosene (log, averaged)	-0.60661	0.27147	-2.235
Price of bananas (log, averaged)	0.56948	0.37626	1.514
Price of corn (log, averaged)	-0.76513	0.54104	-1.414
Local pupil-teacher ratio	0.02249	0.01515	1.485
Fraction of public schools in the area	2.039	1.29063	1.58
f (unobserved ability)	0.2454	0.05047	4.863

Table 28. "Did individual *i* attend ELEMENTARY school during school year *t*?"

Variable	Estimate	Standard error	t-statistic
Constant	8.38027	1.87944	4.459
Missed school last year	-3.58737	0.15046	-23.843
Failed last grade	-1.80821	0.15667	-11.542
Completed schooling as of t	-0.18207	0.05846	-3.114
Age as of t	-0.47338	0.04625	-10.234
Male	-0.25653	0.14007	-1.831
Low birth weight	-0.05034	0.16749	-0.301
Caretaker's household	0.18151	0.16722	1.085
Mother's education (log)	0.71608	0.1421	5.039
Family business	0.20936	0.12272	1.706
Household size	-0.0653	0.02299	-2.841
Household income (log)	0.18093	0.09633	1.878
Urban	0.07424	0.22471	0.33
Price of bananas	-2.36825	1.32831	-1.783
Price of corn	0.44235	0.24398	1.813
Price of kerosene	0.00381	0.17782	0.021
Population density (log)	0.0386	0.06519	0.592
Local pupil-teacher ratio	-0.00428	0.01104	-0.388
Fraction of public schools in the area	-0.82912	1.31639	-0.63
f (unobserved ability)	0.45686	0.06653	6.867

Table 29. “Did individual *i* attend HIGH school during school year *t*?”

Variable	Estimate	Standard error	t-statistic
Constant	21.78741	1.70868	12.751
First year of high school	-1.70687	0.12841	-13.292
Missed school last year	-3.57008	0.11572	-30.85
Failed last grade	-2.82595	0.13407	-21.078
Completed schooling as of t	-1.24543	0.05865	-21.235
Age as of t	-0.47393	0.03689	-12.849
Male	-0.07221	0.08781	-0.822
Low birth weight	-0.07892	0.11958	-0.66
Caretaker’s household	0.38258	0.11217	3.411
Mother’s education (log)	0.53889	0.1051	5.127
Family business	0.10599	0.08032	1.32
Household size	-0.02665	0.01415	-1.883
Household income (log)	0.11983	0.05876	2.039
Urban	-0.04498	0.17808	-0.253
Price of bananas	0.30584	0.82268	0.372
Price of corn	0.05867	0.28379	0.207
Price of kerosene	-0.30697	0.14258	-2.153
Population density (log)	-0.07917	0.05662	-1.398
Local pupil-teacher ratio	0.00554	0.00884	0.627
Fraction of public schools in the area	-1.82412	0.73907	-2.468
Fraction of women with primary education	-3.15619	1.15965	-2.722
Fraction of women with more than primary	-0.20294	0.63772	-0.318
f (unobserved ability)	0.1663	0.0365	4.556

Table 30. "Did individual *i* attend COLLEGE during school year *t*?"

Variable	Estimate	Standard error	t-statistic
Constant	16.17487	2.99355	5.403
First year of college	0.87195	0.1995	4.371
Missed school last year	-2.9783	0.21613	-13.78
Failed last grade	-3.67108	0.24662	-14.885
Completed schooling as of t	-0.11558	0.08152	-1.418
Age as of t	-0.56391	0.07332	-7.692
Male	-0.2866	0.11669	-2.456
Low birth weight	-0.07053	0.18173	-0.388
Caretaker's household	0.43284	0.17899	2.418
Mother's education (log)	0.60936	0.15559	3.917
Family business	0.17996	0.1206	1.492
Household size	-0.01511	0.02559	-0.591
Household income (log)	0.02179	0.06421	0.339
Urban	0.41393	0.23791	1.74
Price of bananas	-1.71997	1.66515	-1.033
Price of corn	-0.15955	0.62587	-0.255
Price of kerosene	-0.14834	0.31336	-0.473
Population density (log)	-0.15241	0.09576	-1.592
Local pupil-teacher ratio	0.00641	0.01575	0.407
Fraction of public schools in the area	-0.80286	1.06062	-0.757
Fraction of women with primary education	-3.29603	2.86844	-1.149
Fraction of women with more than primary	-1.01037	1.60393	-0.63
f (unobserved ability)	0.14385	0.04983	2.887

Table 31. "Did individual *i* successfully complete the grade during school year *t*, ELEMENTARY school?"

Variable	Estimate	Standard error	t-statistic
Constant	-0.7936	1.65524	-0.479
Missed school last year	-1.12957	0.126	-8.965
Failed last grade	-0.38693	0.14264	-2.713
Completed schooling as of t	0.06885	0.07369	0.934
Age as of t	0.01385	0.04737	0.292
Male	-0.90979	0.11568	-7.865
Low birth weight	-0.27676	0.16686	-1.659
Caretaker's household	0.29133	0.16528	1.763
Mother's education (log)	1.18331	0.13961	8.476
Family business	0.03849	0.10341	0.372
Household size	-0.07455	0.02206	-3.38
Household income (log)	0.17682	0.08594	2.058
Urban	0.29712	0.18624	1.595
Price of bananas	-1.64969	1.17803	-1.4
Price of corn	0.44735	0.15358	2.913
Price of kerosene	-0.00429	0.07467	-0.057
Population density (log)	0.01403	0.05851	0.24
Local pupil-teacher ratio	-0.01844	0.01216	-1.516
Fraction of public schools in the area	1.98163	1.19014	1.665
f (unobserved ability)	0.86525	0.07064	12.248

Table 32. "Did individual *i* successfully complete the grade during school year *t*, HIGH school?"

Variable	Estimate	Standard error	t-statistic
Constant	-3.19785	2.22097	-1.44
First year of high school	-0.16103	0.19692	-0.818
Missed school last year	-0.13214	0.19931	-0.663
Failed last grade	-0.88248	0.13079	-6.748
Completed schooling as of t	0.22766	0.09382	2.427
Age as of t	-0.01746	0.05627	-0.31
Male	-1.10589	0.10775	-10.263
Low birth weight	0.03099	0.14134	0.219
Caretaker's household	0.6105	0.13192	4.628
Mother's education (log)	0.67267	0.1236	5.442
Family business	0.15454	0.09093	1.7
Household size	-0.0016	0.01855	-0.086
Household income (log)	-0.03331	0.06821	-0.488
Urban	-0.51226	0.20799	-2.463
Price of bananas	-0.52471	0.87984	-0.596
Price of corn	0.17297	0.30086	0.575
Price of kerosene	-0.13479	0.15898	-0.848
Population density (log)	0.04847	0.06911	0.701
Local pupil-teacher ratio	0.00512	0.01183	0.432
Fraction of public schools in the area	2.42789	0.92323	2.63
Fraction of women with primary education	1.09003	1.57299	0.693
Fraction of women with more than primary	0.77761	0.85866	0.906
f (unobserved ability)	0.42181	0.04988	8.456

Table 33. "Did individual *i* successfully complete the grade during school year *t*, COLLEGE?"

Variable	Estimate	Standard error	t-statistic
Constant	-2.61024	3.51923	-0.742
First year of college	-0.04694	0.29425	-0.16
Missed school last year	-0.38392	0.29076	-1.32
Failed last grade	0.43907	0.48787	0.9
Completed schooling as of t	0.49942	0.16145	3.093
Age as of t	0.04272	0.09711	0.44
Male	-0.29731	0.16116	-1.845
Low birth weight	-0.12738	0.28756	-0.443
Caretaker's household	0.54951	0.25761	2.133
Mother's education (log)	0.58487	0.21598	2.708
Family business	0.15446	0.15992	0.966
Household size	0.01762	0.03089	0.57
Household income (log)	-0.04249	0.09797	-0.434
Urban	0.02373	0.34231	0.069
Price of bananas	-0.25002	2.20672	-0.113
Price of corn	-1.42072	0.67395	-2.108
Price of kerosene	-0.17336	0.34938	-0.496
Population density (log)	-0.09366	0.1298	-0.722
Local pupil-teacher ratio	0.02524	0.02048	1.232
Fraction of public schools in the area	-1.62356	1.47843	-1.098
Fraction of women with primary education	3.43858	3.43454	1.001
Fraction of women with more than primary	1.76213	1.62844	1.082
f (unobserved ability)	0.22384	0.06394	3.501

Table 34. Working for Pay During the Year *t*

Variable	Estimate	Standard error	t-statistic
Constant	-12.9635	1.09862	-11.8
Age as of t	0.487	0.02165	22.497
Male	0.16401	0.05491	2.987
Low birth weight	0.15571	0.07887	1.974
Mother's education (log)	-0.30736	0.0549	-5.598
Family business	-0.37279	0.05699	-6.542
Household size	0.02246	0.00949	2.366
Household income net of individual's (log)	-0.13686	0.02981	-4.591
Urban	-0.08089	0.10239	-0.79
Price of bananas	2.30577	0.64855	3.555
Price of corn	0.86752	0.19772	4.388
Price of kerosene	0.3594	0.09383	3.83
Population density (log)	0.04339	0.03846	1.128
Local wage rate for unskilled labor as of t	0.00363	0.00418	0.868
Local pupil-teacher ratio	0.005	0.00506	0.987
Fraction of public schools in the area	2.05069	0.51353	3.993
Fraction of women with primary education	0.01711	0.72687	0.024
Fraction of women with more than primary	0.38545	0.36024	1.07
f (unobserved ability)	-0.01807	0.02019	-0.895

Table 35. Parameters Defining Probability Weights

Variable	Estimate	Standard error	t-statistic
θ_1	-0.35472	0.09634	-3.682
θ_2	0.30232	0.02838	10.654
θ_3	0.00018	0.00631	0.028

Table 36. Implied Probabilities[25]

Mass points	Probabilities
-3.75044	.0780248
-2.366759	.208829
-1.154405	.2923748
0	.2470966
1.154405	.1289738
2.366759	.0391427
3.75044	.0055584

[25] Mass points and corresponding probabilities from the table imply the mean of the distribution to be equal to -0.86 and the variance 2.38.

Table 37. Mincer-type Log Wage Regression (as of the 2005 survey)

Variable	Estimate	Standard error	t-statistic
Male	.2470	.0420	5.88
Experience	-.0427	.0106	-2.45
Completed schooling	.0427	.0143	4.01
Constant	2.5989	.1536	16.92

N= 1215, σ_{ε} = 0.68, R^2 = 0.07

APPENDIX D: Estimates, specification includes data from the 2005 survey, CDE specification

Table 38. Math Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	2.18445	0.23148	9.437
Age as of test date	2.09395	0.47389	4.419
Male	-2.66783	0.37531	-7.108
Low birth weight	-0.84493	0.57965	-1.458
Caretaker’s household	0.97861	0.61476	1.592
Mother’s education (log)	4.7781	0.45787	10.435
Family business	0.52985	0.34799	1.523
Household size	-0.11214	0.07371	-1.521
Household income (log)	0.20748	0.24831	0.836
Urban	3.33722	0.723	4.616
Price of bananas	-17.109	8.66475	-1.975
Price of corn	-0.84108	1.08883	-0.772
Price of kerosene	3.3216	1.75877	1.889
Population density (log)	-1.12482	0.22967	-4.898
Local pupil-teacher ratio	-0.01261	0.04296	-0.294
Fraction of public schools in the area	-3.66975	3.80116	-0.965
Constant	-7.07441	10.15863	-0.696
f (unobserved ability)	3.54512	0.43349	8.178
f^2 (unobserved ability squared)	0.84796	0.04898	17.311
*f*S* (schooling-ability interaction)	0.39619	0.09541	4.153

Table 39. English Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	0.95941	0.20427	4.697
Age as of test date	2.49932	0.43988	5.682
Male	-3.41452	0.35982	-9.49
Low birth weight	-0.65376	0.54637	-1.197
Caretaker's household	0.7899	0.62201	1.27
Mother's education (log)	5.73284	0.44615	12.85
Family business	-0.5395	0.33319	-1.619
Household size	-0.21286	0.06895	-3.087
Household income (log)	0.78481	0.24597	3.191
Urban	2.62567	0.7223	3.635
Price of bananas	-0.60473	8.40629	-0.072
Price of corn	-0.84046	0.98902	-0.85
Price of kerosene	5.64818	1.72862	3.267
Population density (log)	-0.70414	0.2216	-3.178
Local pupil-teacher ratio	-0.04813	0.04467	-1.078
Fraction of public schools in the area	-4.38272	3.77675	-1.16
Constant	-23.1019	9.07288	-2.546
f (unobserved ability)	3.08587	0.38221	8.074
f^2 (unobserved ability squared)	0.94404	0.04677	20.186
*f*S* (schooling-ability interaction)	0.49648	0.08095	6.133

Table 40. IQ Test Scores

Variable	Estimate	Standard error	t-statistic
Completed schooling as of test date	1.04677	0.24173	4.33
Age as of test date	-3.35711	0.54275	-6.185
Male	-0.27795	0.2579	-1.078
Low birth weight	0.02195	0.39632	0.055
Caretaker’s household	0.42202	0.50784	0.831
Mother’s education (log)	2.39864	0.29923	8.016
Family business	-0.17237	0.2707	-0.637
Household size	-0.23761	0.0575	-4.132
Household income (log)	0.81328	0.26772	3.038
Urban	-0.01154	0.46035	-0.025
Price of bananas	-5.21439	3.17807	-1.641
Price of corn	0.04846	0.42844	0.113
Price of kerosene	0.15633	0.17541	0.891
Population density (log)	0.25546	0.14212	1.797
Local pupil-teacher ratio	-0.00306	0.02873	-0.106
Fraction of public schools in the area	-0.42015	2.61866	-0.16
Constant	51.32728	6.24039	8.225
f (unobserved ability)	2.58942	0.1925	13.452
f^2 (unobserved ability squared)	-0.11728	0.0359	-3.266
*f*S* (schooling-ability interaction)	-0.43525	0.11551	-3.768

Table 41. Entered School on Time

Variable	Estimate	Standard error	t-statistic
Constant	-1.21481	1.87979	-0.646
Male	-0.3157	0.13369	-2.361
Caretaker’s household	0.02835	0.25076	0.113
Low birth weight	-0.223	0.20034	-1.113
Height of the child	6.94476	1.62058	4.285
Household income (lagged)	0.14233	0.14586	0.976
Mother’s education (log)	0.91609	0.13906	6.588
Family business	-0.33051	0.14837	-2.228
Urban (averaged across time)	-0.93739	0.25638	-3.656
Population density (log, averaged)	0.22814	0.07599	3.002
Price of kerosene (log, averaged)	-0.60164	0.27028	-2.226
Price of bananas (log, averaged)	0.61432	0.38251	1.606
Price of corn (log, averaged)	-0.70429	0.54763	-1.286
Local pupil-teacher ratio	0.02153	0.01535	1.403
Fraction of public schools in the area	1.84718	1.30316	1.417
f (unobserved ability)	0.25097	0.05186	4.84
f^2 (unobserved ability squared)	0.01192	0.01769	0.674

Table 42. "Did individual *i* attend ELEMENTARY school during school year *t*?"

Variable	Estimate	Standard error	t-statistic
Constant	7.68035	1.87807	4.089
Missed school last year	-3.53563	0.14985	-23.594
Failed last grade	-1.80972	0.15458	-11.707
Completed schooling as of t	-0.11741	0.05427	-2.164
Age as of t	-0.51332	0.04473	-11.476
Male	-0.19306	0.13634	-1.416
Low birth weight	-0.09268	0.15952	-0.581
Caretaker's household	0.17632	0.16792	1.05
Mother's education (log)	0.65989	0.13875	4.756
Family business	0.20726	0.12813	1.618
Household size	-0.05843	0.02311	-2.529
Household income (log)	0.17752	0.09824	1.807
Urban	0.06841	0.22576	0.303
Price of bananas	-2.1659	1.31224	-1.651
Price of corn	0.3741	0.24353	1.536
Price of kerosene	0.04228	0.17888	0.236
Population density (log)	0.02923	0.06459	0.453
Local pupil-teacher ratio	-0.00117	0.01053	-0.111
Fraction of public schools in the area	-0.82312	1.32523	-0.621
f (unobserved ability)	0.48975	0.07484	6.544
f^2 (unobserved ability squared)	0.10949	0.01788	6.125

Table 43. "Did individual *i* attend HIGH school during school year *t*?"

Variable	Estimate	Standard error	t-statistic
Constant	21.59043	1.7124	12.608
First year of high school	-1.70289	0.12968	-13.132
Missed school last year	-3.55274	0.11683	-30.408
Failed last grade	-2.82234	0.13457	-20.972
Completed schooling as of t	-1.23714	0.05947	-20.804
Age as of t	-0.48219	0.03711	-12.995
Male	-0.05105	0.08748	-0.584
Low birth weight	-0.09267	0.12105	-0.766
Caretaker's household	0.37442	0.11179	3.349
Mother's education (log)	0.53206	0.10418	5.107
Family business	0.10782	0.08164	1.321
Household size	-0.02548	0.01432	-1.78
Household income (log)	0.12031	0.05923	2.031
Urban	-0.03954	0.1788	-0.221
Price of bananas	0.32103	0.82906	0.387
Price of corn	0.04668	0.28374	0.165
Price of kerosene	-0.30486	0.14373	-2.121
Population density (log)	-0.09057	0.05664	-1.599
Local pupil-teacher ratio	0.00618	0.00885	0.698
Fraction of public schools in the area	-1.87239	0.74877	-2.501
Fraction of women with primary education	-3.14761	1.16871	-2.693
Fraction of women with more than primary	-0.16434	0.64292	-0.256
f (unobserved ability)	0.1666	0.03788	4.398
f^2 (unobserved ability squared)	0.04594	0.01034	4.444

Table 44. “Did individual *i* attend COLLEGE during school year *t*?”

Variable	Estimate	Standard error	t-statistic
Constant	15.98374	3.02216	5.289
First year of college	0.86905	0.20045	4.335
Missed school last year	-2.97816	0.21759	-13.687
Failed last grade	-3.67068	0.24856	-14.767
Completed schooling as of t	-0.11849	0.08208	-1.444
Age as of t	-0.5628	0.07381	-7.625
Male	-0.27987	0.11779	-2.376
Low birth weight	-0.06653	0.18433	-0.361
Caretaker’s household	0.43498	0.17934	2.426
Mother’s education (log)	0.60955	0.15498	3.933
Family business	0.18178	0.12065	1.507
Household size	-0.01315	0.02572	-0.511
Household income (log)	0.0193	0.06466	0.298
Urban	0.41663	0.23887	1.744
Price of bananas	-1.75116	1.688	-1.037
Price of corn	-0.18646	0.63088	-0.296
Price of kerosene	-0.14512	0.31458	-0.461
Population density (log)	-0.15236	0.09598	-1.587
Local pupil-teacher ratio	0.00648	0.01594	0.407
Fraction of public schools in the area	-0.83433	1.07404	-0.777
Fraction of women with primary education	-3.27376	2.87981	-1.137
Fraction of women with more than primary	-1.02833	1.60915	-0.639
f (unobserved ability)	0.14503	0.06291	2.305
f^2 (unobserved ability squared)	0.02753	0.0223	1.234

Table 45. "Did individual *i* successfully complete the grade during school year *t*, ELEMENTARY school?"

Variable	Estimate	Standard error	t-statistic
Constant	-1.86058	1.57492	-1.181
Missed school last year	-1.09271	0.12443	-8.782
Failed last grade	-0.42614	0.14382	-2.963
Completed schooling as of t	0.15197	0.0703	2.162
Age as of t	-0.0413	0.04492	-0.919
Male	-0.79952	0.10442	-7.657
Low birth weight	-0.28231	0.13963	-2.022
Caretaker's household	0.28004	0.15784	1.774
Mother's education (log)	1.08552	0.13022	8.336
Family business	0.01483	0.10076	0.147
Household size	-0.05894	0.02077	-2.838
Household income (log)	0.17692	0.08269	2.139
Urban	0.25445	0.17443	1.459
Price of bananas	-1.21895	1.16904	-1.043
Price of corn	0.42342	0.15165	2.792
Price of kerosene	0.00177	0.07246	0.024
Population density (log)	0.00133	0.05526	0.024
Local pupil-teacher ratio	-0.01559	0.01036	-1.504
Fraction of public schools in the area	1.60639	1.07619	1.493
f (unobserved ability)	0.93614	0.07092	13.199
f^2 (unobserved ability squared)	0.17121	0.01645	10.407

Table 46. "Did individual *i* successfully complete the grade during school year *t*, HIGH school?"

Variable	Estimate	Standard error	t-statistic
Constant	-3.61291	2.18769	-1.651
First year of high school	-0.16519	0.19705	-0.838
Missed school last year	-0.12059	0.19963	-0.604
Failed last grade	-0.8744	0.1311	-6.67
Completed schooling as of t	0.24503	0.0939	2.61
Age as of t	-0.03648	0.05609	-0.65
Male	-1.05239	0.10341	-10.177
Low birth weight	0.02646	0.13639	0.194
Caretaker's household	0.58061	0.13095	4.434
Mother's education (log)	0.64446	0.11917	5.408
Family business	0.15389	0.09085	1.694
Household size	0.00176	0.01818	0.097
Household income (log)	-0.0295	0.06828	-0.432
Urban	-0.49527	0.20835	-2.377
Price of bananas	-0.4992	0.87919	-0.568
Price of corn	0.13826	0.30003	0.461
Price of kerosene	-0.13272	0.1584	-0.838
Population density (log)	0.04021	0.0685	0.587
Local pupil-teacher ratio	0.00538	0.01156	0.466
Fraction of public schools in the area	2.35878	0.88578	2.663
Fraction of women with primary education	1.03575	1.56597	0.661
Fraction of women with more than primary	0.69609	0.85193	0.817
f (unobserved ability)	0.42225	0.04379	9.643
f^2 (unobserved ability squared)	0.08204	0.0142	5.778

Table 47. "Did individual *i* successfully complete the grade during school year *t*, COLLEGE?"

Variable	Estimate	Standard error	t-statistic
Constant	-2.97235	3.52024	-0.844
First year of college	-0.04542	0.2938	-0.155
Missed school last year	-0.39659	0.29092	-1.363
Failed last grade	0.43508	0.49643	0.876
Completed schooling as of t	0.49482	0.16227	3.049
Age as of t	0.04648	0.09792	0.475
Male	-0.28147	0.16201	-1.737
Low birth weight	-0.11729	0.29024	-0.404
Caretaker's household	0.55147	0.25912	2.128
Mother's education (log)	0.58362	0.21606	2.701
Family business	0.1537	0.16231	0.947
Household size	0.01949	0.0311	0.627
Household income (log)	-0.0421	0.09864	-0.427
Urban	0.02684	0.33972	0.079
Price of bananas	-0.2957	2.19673	-0.135
Price of corn	-1.44783	0.6756	-2.143
Price of kerosene	-0.1635	0.34981	-0.467
Population density (log)	-0.09298	0.1294	-0.719
Local pupil-teacher ratio	0.02577	0.02059	1.252
Fraction of public schools in the area	-1.68854	1.47477	-1.145
Fraction of women with primary education	3.47217	3.44168	1.009
Fraction of women with more than primary	1.72758	1.63553	1.056
f (unobserved ability)	0.2332	0.06713	3.474
f^2 (unobserved ability squared)	0.02877	0.0224	1.284

Table 48. Working for Pay During the Year *t*

Variable	Estimate	Standard error	t-statistic
Constant	-12.4765	1.1007	-11.335
Age as of t	0.462	0.02171	21.278
Male	0.14566	0.0542	2.688
Low birth weight	0.1338	0.07703	1.737
Mother's education (log)	-0.30423	0.05472	-5.56
Family business	-0.32502	0.05658	-5.745
Household size	0.03156	0.00942	3.349
Household income net of individual's (log)	-0.14769	0.03069	-4.813
Urban	-0.08521	0.10324	-0.825
Price of bananas	2.24186	0.64472	3.477
Price of corn	0.81286	0.19745	4.117
Price of kerosene	0.36202	0.09129	3.966
Population density (log)	0.04928	0.0381	1.294
Local wage rate for unskilled labor as of t	-0.0007	0.00413	-0.17
Local pupil-teacher ratio	0.00617	0.00505	1.222
Fraction of public schools in the area	2.24148	0.50257	4.46
Fraction of women with primary education	-0.20235	0.71978	-0.281
Fraction of women with more than primary	0.32889	0.37021	0.888
f (unobserved ability)	-0.03106	0.02159	-1.439
f^2 (unobserved ability squared)	-0.02139	0.00691	-3.096

Table 49. Log of Hourly Wage Rate, CDE specification. Reporting average marginal effects for all regressors except for the unobserved ability terms.

Variable	Av. Marginal Effect	Std. error
Male	0.0847	0.0214[26]
Age	0.1053	0.0468
Experience	-0.0206	0.0077
Completed schooling	0.0293	0.0073
Urban	-0.0467	–
Population density (log)	0.0314	–
Local wage rate for unskilled labor	-0.0003	–

[26] The standard errors are estimated via parametric bootstrap with 50 iterations.

Table 50. Parameters Defining Probability Weights

Variable	Estimate	Standard error	t-statistic
θ_1	0.7629	0.07848	9.72
θ_2	0.2645	0.01466	18.038
θ_3	-0.0591	0.00574	-10.292

Table 51. Implied Probabilities[27]

Mass points	Probabilities
-5.188001	.0385228
-3.936167	.0112604
-2.865123	.0139281
-1.876035	.0310303
-.928869	.0822841
0	.1934869
.928869	.3088073
1.876035	.2488818
2.865123	.0684083
3.936167	.0033828
5.188001	7.17e-06

[27] Mass points and corresponding probabilities imply the mean of the distribution to be equal to 0.54 and the variance 2.97.

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