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Cognitive Skills and Youth Labor Market Outcomes

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Abstract

This paper provides new cross-country evidence on the impact of cognitive skills, as measured by international achievement tests, on subsequent youth employment outcomes. In our initial analysis, we find that high average scores are strongly associated with increases in school enrollment and large reductions in the incidence of unemployment, with slightly stronger effects for women. Higher scores also correlate with a larger share of youth employed in wage and salaried jobs, outside of agriculture, and to some extent in higher status occupations, but these findings are less robust. Conditional on average test scores, greater within-cohort dispersion lead to reduced school attendance and increased employment at young ages, perhaps reflecting the less precise signal value of further formal educational attainment in the presence of large quality differences. In specifications including both educational attainment and measured test scores, test scores have stronger effects on unemployment, but attainment is also strongly predictive of employment and some measures of job quality. We conclude that while increasing education quality can play a central role in improving youth employment outcomes, increasing attainment remains an important and complementary objective to foster the creation of better jobs for youth. However, preliminary extensions to the existing analysis using data from additional countries and years suggest much more important effects of test scores on measures of job quality, such as wage and non-agricultural employment, than on employment, enrollment, unemployment, or labor force participation.

1. Introduction

Youth employment outcomes are a large and growing concern worldwide. Youth unemployment rates are consistently greater than those of adults, reaching up to 50 percent among the poor in Latin America.[1] The issue is particularly pressing in the aftermath of the recent financial crisis, which young workers bore the brunt of in both developed and developing countries.[2] Rough estimates, for example, suggest that youth aged 16 to 25 lost 17 million jobs worldwide in 2009, corresponding to a one percent drop in the share of young people employed (ILO, 2011). Limited job opportunities for youth, at least in OECD countries, can lead to increases in crime[3], and have potentially lasting effects on the economic well-being of the most affected cohorts.[4] Moreover, youth frustration with stagnant job opportunities amidst rising levels of educational attainment is perceived to be a driving factor behind the 2011 Arab spring uprisings in Tunisia and Egypt.[5] In several countries, rising youth unemployment has threatened to "create a lost generation of the disaffected, unemployed, or underemployed."[6]

A growing consensus believes that a major part of the solution lies in improving the quality of education and young people's cognitive skills, rather than increasing the mere quantity of schooling.[7] The recent focus on cognitive skills contrasts with earlier studies' attention to other factors that determine youth employment outcomes, such as demographic structure, general labor market conditions, or stringent labor regulation.[8] This recent emphasis on skills and education quality is based primarily on two types of evidence. The first is a longstanding literature that finds that individual variation in cognitive skills is a strong determinant of positive adult outcomes in various countries.[9] Partly, these relationships reflect the role of non-cognitive skills or traits, such as motivation and conscientiousness, which are correlated with cognitive skills and important additional inputs into both achievement test scores and labor market outcomes.[10]

More recently, a second body of evidence has emerged documenting the close link between cognitive test scores and growth outcomes at the country level. One influential set of growth estimates finds a strong positive relationship between countries' average test score between 1960 and 2000, and their average rate of GDP growth during the same period, with test scores dominating measures of educational attainment as predictors of growth (Hanushek and Kimko,

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1 Attanasio et. al (2008).
2 See for example OECD (2011) and Bell and Blanchflower (2010) for OECD countries, and Cho and Newhouse (2010) for non-OECD countries.
3 See Fougere et al (2009) and Lin (2008) for evidence from France and the US.
4 See for example, Oreopoulos et al (2008), Kahn (2010), and Bell and Blanchflower (2011).
5 Campante and Chor (2012).
6 Coy (2011).
7 See for example Jimenez, et al (2012).
8 Korenman and Neumark (2000) and O'Higgins (2003) conclude that while the size of the youth cohort has a substantial effect on youth unemployment rates, the effects of general labor conditions are stronger. Meanwhile, Bertola et al (2007) and Montenegro and Pages (2004) focus on the influence of institutions on youth employment.
9 These are reviewed in Hanushek and Woessman (2008).
10 Bowles, Gintis, and Osborne (2001), Borghans et al (2008), and Cunha and Heckman (2008).

2000; Hanushek and Woessman, 2008).[11] A comprehensive survey of both types of evidence declares that this constitutes "strong evidence that the cognitive skills of a population have powerful effects on individual earnings, the distribution of income, and economic growth." As a result, improving cognitive skills is claimed to be "THE key issue" in promoting economic development, and would presumably also improve youth employment outcomes.[12]

If cognitive skills are in fact a major constraint to improving youth employment outcomes, public strategies to address youth unemployment should place greater emphasis on developing these skills. For example, developing country governments may prioritize spending or technical assistance to improve education and/or early childhood health and nutrition. Targeted second-chance interventions designed to boost the skills and job readiness of early dropouts or working age adults also have the potential to increase both cognitive and non-cognitive skills.

It is far from clear, however, that focusing on cognitive skills is the most effective strategy to improve youth employment opportunities, for two reasons. First, subsequent analysis has raised concerns about the primacy of cognitive skills and education quality over the quantity of education in driving growth (Breton, 2011). More importantly, no analysis has directly examined directly whether youth in countries with higher measured skills enjoy better labor market outcomes. It is therefore premature to conclude that improving youths' cognitive skills is certain to improve their labor market outcomes.

This paper contributes new evidence towards better understanding the role of measured cognitive skills in creating better jobs for youth. We first revisit the cross-country analysis of growth originally presented in Hanushek and Woessman (2008). We confirm that average test scores are highly correlated with growth in the original sample of countries. This strong positive correlation is sharply reduced, however, when the analysis is limited to the more recent time period from 1990 to 2010 and several additional countries added to the analysis.[13] Furthermore, faster-growing countries in the last decade experienced faster improvements in reading scores over the past decade. This is consistent with economic growth causing cognitive skills to improve, perhaps by providing parents and children with stronger incentives to acquire these skills. Overall, these findings raise two concerns: For some countries, high levels of cognitive skills may not be sufficient to ignite growth, and that the strong correlation between measured cognitive skills and contemporaneous growth rates in many countries reflects joint causality.

Second and more importantly, we utilize data from up to 315 tested cohorts in 67 countries to estimate the relationship between cognitive skills and subsequent youth labor market outcomes. Average scores on achievement tests are matched to aggregate labor market outcomes for

[11] These estimates were first presented in Hanushek and Kimko (2000) and further elaborated in Hanushek and Woessman (2008, 2011).
[12] Hanushek and Woessman (2008).
[13] These are countries, many of which are in Eastern Europe and Central Asia, that were excluded from the 1960-2010 analysis because of the unavailability of GDP data from 1960.

cohorts with sufficient education to be eligible for the test. Cohorts are matched based on country, gender, and age. Data on test scores are taken from three main sources: First, we use data from the OECD's Programme for International Student Assessment (PISA) tests, administered beginning in 2000. The second source of data is the Trends in International Math and Science Study (TIMSS), which was first administered in 1997. Finally, we use a published meta-dataset of available test scores developed in Altinok and Murseli (2006) (A-M). This meta-dataset incorporates several tests, including both the PISA and TIMSS, as well as the International Assessment of Educational Progress (IAEP), the Analysis Programme of the CONFEMEN Education Systems (PASEC), the International Association for the Evaluation of Educational Achievement (IEA), those conducted by the Latin American Laboratory for the Assessment of Educational Quality (LLECE) and those conducted by the Southern and Eastern African Consortium for the Measurement of Educational Quality (SACMEQ). Unlike the PISA and TIMSS exams, which are administered to 9th graders, the Altinok and Murseli aggregate contains tests administered at a variety of grade levels, and importantly, includes a broader set of countries, including many more countries from the developing world.

The most striking and robust finding is that, after controlling for predetermined country characteristics such as past per capita GDP and youth employment outcomes, cohorts with higher test scores are substantially more likely to be enrolled in school and significantly less likely to be unemployed. In most cases, the strong inverse relationship between test scores and future unemployment is robust to the inclusion of country fixed effects, indicating that countries that experienced more rapid improvements in test scores also experienced greater reduction in youth unemployment rates. We also find some indication of improvements in job quality with higher test scores, conditional on working. Higher scores are associated with a significantly greater likelihood that young workers, especially males, are employed outside the agricultural sector and in a wage job. Neither of these findings is robust to the inclusion country effects, suggesting that it may take decades for improvements in cognitive skills to alter countries' comparative advantage towards more productive jobs for youth. There is also some indication that higher scores may be associated with another measure of job quality, based on occupation. Overall, the results bolster the case that interventions that improve education quality and measured cognitive skills would reduce youth unemployment while increasing school enrollment, and eventually lead to better jobs for youth, with potentially important cumulative effects on future incomes and growth.

A secondary finding considers the role of test scores relative to that of years of education in determining labor market outcomes. Average years of education remains similarly predictive of several labor market outcomes when including test scores as an additional regressor, in contrast to Hanushek and Kimko (2000) and Hanushek and Woessman's (2008) finding that only cognitive skills are predictive of growth rates in joint regressions.[14] The continued importance of

[14] See Hanushek and Kimko (2000) and Hanushek and Woessman (2008).

years of education in the presence of test scores is more consistent with Breton's (2011) finding that in alternative specifications better motivated by dynamic models of growth, both years of education and cognitive skills or test scores are predictive of growth. We conclude that both education quality, as measured by performance on international assessments, and average educational attainment are important determinants of youth outcomes in labor markets.

Finally, we turn to measures of test score inequality and examine whether changes in the dispersion of test scores, holding mean scores constant, affect youth labor market outcomes. The results indicate that more unequal PISA test scores are associated with lower rates of school attendance, higher rates of employment, and among these employed, and employment in more productive sectors.[15] This likely reflects a non-linear relationship between cognitive skills and school enrollment, which could arise if the returns to education decline especially rapidly at the low end of the test distribution.[16] Increased dispersion could also contribute to reduced school enrollment due to asymmetric information in labor markets. Increasing the variance of test score performance within cohorts would make observed educational attainment a less informative measure to potential employers, reducing the labor market return to additional schooling. In this case, efforts to improve poor performing schools and to achieve more uniformity in standards may have important long-term payoffs by increasing attainment.

One caveat is that preliminary extensions to the analysis to include additional countries and years do not show the same patterns described above. While the existing analysis shows the strongest evidence for effects of test scores on employment, school enrollment, and unemployment, analysis including an additional set of countries and years suggests much more important effects on measures of job quality, such as wage employment and non-agricultural employment.[17] In contrast the newer data show little evidence for significant effects of test scores on youth unemployment.

The next section revisits the analysis of growth and cognitive skills originally presented in Hanushek and Woessman (2008), making the case that a more nuanced analysis, and an analysis of intermediate outcomes, is needed to more convincingly make the link between cognitive skills and growth. Section 3 presents a model of job search where cognitive skills affect search parameters and job finding. Section 4 discusses the test score data and labor market outcome data used in the remainder of the paper, as well as the empirical methods. Section 5 discusses the estimates of average effects of test scores, effects by gender and income, and robustness checks. Section 6 examines effects of the dispersion in cognitive skills, as measured by the dispersion in individual test scores. Section 7 concludes.

[15] The strong association between dispersion and sectoral productivity appears to be an anomaly, as dispersion has no apparent effect on agricultural employment, wage employment, or

[16] Low-scoring students may also be less likely to afford to continue to university.

[17] These new results are based on the newest draft version 3.3 of the International Income Distribution Database (I2D2), rather than 2,0. Version 3.3 is still under revision and notably may still contain errors in the labor force indicators of interest here, particularly in measures of current enrollment.

2. Growth and Cognitive Skills Revisited

This section revisits the relationship between cognitive skills and growth, by focusing on the relationship between test scores and subsequent growth, and by looking at growth since 1990 and examining a larger set of countries.

We use the country average cognitive skill measure from Hanushek and Woessman (2008), which is based on 12 different exams administered between 1964 and 2003. This measure is calculated for 69 countries, and does not vary over time. This measure increases rapidly in per capita GDP (Figure 1), although relatively few low-income countries are represented in the sample.

A central problem with this measure is that many of the tests included are administered during the 1990s and after—after growth has been realized. Therefore, the relationship between these cognitive skill measures based on those test scores potentially reflect past growth. Given the possibility of joint causality, it is perhaps unsurprising that, conditional on GDP and average years of schooling in 1960, that country average growth rates between 1960 and 2000 are highly correlated with country cognitive score measures from the same period.

First, we replicate the strong correlation between average growth and average test score reported in Hanushek and Woessman (2009). Because we consider extend the time period to run through 2010 instead of 2000, we find a slightly weaker relationship (Table 1, column 2). Of the 69 countries for which cognitive skill measures are available, 24 lack GDP data from 1960, and 45 remain in the regression.

Next, in order to consider more recent changes, we narrow the window of growth that we examine to growth between 1990 and 2010. The coefficient on country cognitive score, although still large, becomes statistically insignificant, conditioning on GDP in 1990 and average years of schooling in 1990. This largely confirms the finding that the strong relationship between growth and average skills is robust to examining a more recent period (Hanushek and Woessman, 2009)

This strong correlation is not robust, however, to the addition of new countries. Because we consider a more recent period, GDP data from the base year are available for 24 additional countries. These are largely comprised of post-communist countries. We find that the point estimate on country cognitive score drops dramatically in value upon the inclusion of these additional countries, and becomes statistically insignificant.

In addition, looking at a specific standardized test over time, there is suggestive evidence that economic growth improves reading scores, supporting the argument that the direction of causality runs from growth to cognitive skills. Countries that grew faster between 2000 and 2009 improved more on their PISA reading scores during the same period. Test participants were arguably too young to contribute to growth over those nine years, implying that the direction of causality runs from growth to skills.

We draw two main conclusions from this. First, the strong correlation between test scores and growth becomes significantly weaker when adding a wider set of countries. In part, this may reflect the unique experience of Eastern Europe, in which a relatively skilled population made a sudden transition to a market economy. Regardless, it casts some doubt on the strength of the relationship between growth and skills. Second, there is suggestive evidence support the notion that skills increase more in faster in rapidly growing countries. This is consistent with youth in more rapidly growing counties being more exposed to information, and having greater financial incentive to study. Despite the strong within-country evidence documenting individual returns to skills, the cross-country evidence is far less convincing that interventions to increase performance on standardized tests will necessarily promote growth.

Despite the fundamental importance of growth, it is inherently difficult to link it to improvements in cognitive skills. This is largely because improvements in students' test scores may not impact the overall economy for several decades. We therefore turn our attention to youth labor market outcomes, which tend to be realized within ten years of taking the test. Because of this relatively short lag, it is feasible to link test scores from the 1990's and early 2000's to subsequent youth employment outcomes, mitigating the possibility that skills are responding to economic growth. Linking test scores to employment outcomes, relative to GDP growth, offers two additional advantages: First, labor market outcomes can be observed for those youth with sufficient education to be eligible for the test. Second, effects of cognitive skills can be separately estimated for men and women.

3. A Model of Job Search and Cognitive Skills

Before examining the empirical evidence, it is useful to set out a theoretical framework to demonstrate how cognitive skills may affect unemployment duration and job quality. Following Rogerson, Shimer and Wright (2005), we develop a continuous time search theoretic model of the labor market where the search frictions determining job finding and the probability of separation. In our model, these search frictions vary with θ, a parameter indexing cognitive skills.

As in the standard set of search models, a worker accepts a job offer if it exceeds her reservation wage ω_R, and rejects it and remains unemployed if it does not. Once a worker has accepted a job, she receives wage ω each period, discounted at rate r. She faces a probability of separation each period of λ, leading to an effective discount rate of $\lambda + r$. This problem can be described by the set of Bellman equations:

$$rW(\omega) = \omega + \lambda[U - W(\omega)]$$

$$rU = b + \alpha \int_0^\infty max\{0, W(\omega) - U\} dF(\omega)$$

where b is the per period wage outside of the labor market, α is the arrival rate of new offers, $W(\omega)$ is the lifetime utility of accepting the wage offer ω, U is the utility of rejecting the offer and continuing to the next period, and $F(\omega)$ is the probability distribution of wage offers.

To capture the effect of increase in the mean of the cognitive skills distribution, we allow both the arrival rate of job offers α as well as the probability of separation to vary with the index of cognitive skills, θ:

$$rW(\omega) = \omega + \lambda(\theta)[U - W(\omega)]$$

$$rU = b + \alpha \int_0^\infty max\{0, W(\omega) - U\} dF(\omega)$$

The separation probability is decreasing in cognitive skills, because more productive workers, besides contributing to economic growth, will be more likely to be retained during a downturn.

In this set up, it is possible to solve for the reservation wage ω_R as a function of cognitive skills θ:

$$\omega_R = b + \frac{\alpha}{\lambda(\theta) + r} \int_{\omega_R}^\infty [1 - F(\omega)] d\omega$$

The expression for the average duration of unemployment spells is:

$$D_U = \frac{1}{\alpha[1 - F(\omega_R)]}$$

The expression for the average duration of employment spells, in contrast, is:

$$D_E = \frac{1}{[1 - \lambda(\theta)]}$$

The unemployment rate as a function of cognitive skills θ will then be equal to the average percentage of time that individuals spend unemployed, conditional on cognitive skills θ:

$$Unemployment\ rate = \frac{D_U}{D_U + D_E} = \frac{\dfrac{1}{\alpha[1 - F(\omega_R)]}}{\dfrac{1}{\alpha[1 - F(\omega_R)]} + \dfrac{1}{[1 - \lambda(\theta)]}}$$

$$= \frac{1}{1 + \dfrac{\alpha[1 - F(\omega_R)]}{[1 - \lambda(\theta)]}}$$

For analytical tractability, we assume a uniform distribution of wage offers along the interval $[0, \overline{\omega}]$ and solve for the unemployment rate as a function of parameters:

$$F(\omega_R) = \frac{1}{\overline{\omega}}\omega_R = \frac{b + \dfrac{\alpha}{\lambda(\theta) + r}(\overline{\omega} - 1)}{\overline{\omega} + \dfrac{\alpha}{\lambda(\theta) + r}(\overline{\omega} - 1)} 1 - F(\omega_R) = \frac{\overline{\omega} - b}{\overline{\omega} + \dfrac{\alpha}{\lambda(\theta) + r}(\overline{\omega} - 1)}$$

$$Unemployment\ rate = \frac{1}{1 + \dfrac{\alpha}{[1 - \lambda(\theta)]}\left[\dfrac{\overline{\omega} - b}{\overline{\omega} + \dfrac{\alpha}{\lambda(\theta) + r}(\overline{\omega} - 1)}\right]}$$

By inspection, if $b < \overline{\omega} < 1$, as θ increases and $\lambda(\theta)$ decreases, the unemployment rate drops (see Appendix for full derivation), implying lower unemployment rates among individuals with higher cognitive skills.

A similar result can be obtained by assuming that search frictions (as parameterized by the arrival rate of offers α) decrease with cognitive skills, leading to a higher arrival rate of offers. This could result from two possibilities. The first is that improved cognitive skills increases productivity. If youth are partly able to signal this increased productivity through additional educational attainment, job interviews or personal networks, increased skills could directly raise demand for their labor. A second complementary possibility is that greater levels of cognitive skills (and non-cognitive skills) in an economy facilitates effective job search. This could occur if cognitive skills increase the use of communication technology, or help reduce isolation and broaden social networks. This could be another mechanism through which increases in average skills would reduce unemployment.

In this model we have no explicit parameters measuring job quality or match quality, but could view the average wage as a proxy for job quality. The average wage is determined by the distribution of wages above the reservation threshold, and is given by:

$$\omega = \int_{\omega_R}^{\overline{\infty}} f(\omega) d\omega$$

$$= \int_{\omega_R}^{\overline{\omega}} \frac{1}{\overline{\omega}} d\omega$$

$$= \frac{1}{\overline{\omega}} (\overline{\omega} - \omega_R)$$

$$= \frac{\overline{\omega} - b}{\overline{\omega} + \frac{\alpha}{\lambda(\theta) + r} (\overline{\omega} - 1)}$$

If cognitive skills increase the rate of job offers, this will increase the reservation wage and therefore job quality. If $b < \overline{\omega} < 1$, the average wage, the best indicator of job quality observable in this model, is increasing in cognitive skills θ if either λ is a diminishing function of θ or if α is increasing in

In sum, raising the mean level of cognitive skills in a standard job-search model could lower unemployment rates and raise employment rates both by decreasing the likelihood of separation once a job has been acquired, and by increasing either the quantity or quality of new job offers. The former could occur as employers learn more about workers' cognitive skills, and are less likely to separate from more skilled workers. Meanwhile, young workers with high average skill could receive more offers, either because they are partially able to signal their ability, or because they are more effective in searching for jobs. In either case, skilled workers would have a greater selection of offers to choose from and would also be expected to find a higher quality job.

4. Data and Methodology

4.1 Data

Our measures of cognitive skills in this analysis are derived from country average scores in international assessments that are meant to be comparable across countries. Test score data analyzed in this paper are available from two main sources.

Average test scores by country, year and grade level for the OECD's PISA and the TIMSS are obtained from the World Bank's Education Statistics (Edstats) database. The PISA, which was administered in 2000, 2003, 2006 and 2009, tests skills in mathematics, reading, and science. The TIMSS, administered in 1995, 1999, 2003, 2007 and 2011, tests skills in mathematics and sciences.

In addition, we use data from a published, standardized compilation of test scores made available by Altinok and Murseli (2006). Their meta-dataset includes data from the PISA and TIMSS, as well as older and more regionally focused examinations such as the International Assessment of Educational Progress (IAEP), the Program on the Analysis of Education Systems (PASEC), the International Assessment of Educational Progress (IEA), the Latin American Laboratory for the Evaluation of the Quality of Education (LLECE), and the Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ). However, unlike the PISA and the TIMSS, the A-M data on test scores is not disaggregated by gender.

Data from national censuses and labor market surveys, compiled in the World Bank's International Income Distribution Database (I2D2), are used to measure labor market outcomes for the cohorts for which we have relevant test score outcome data.[18]

Cohorts or cells are defined based on country, birth year, and gender. We examine average labor market outcomes at this cell level. Outcomes are measured only for youth age 15-24 with a minimum education level to be eligible for the test—so for the PISA and TIMSS, youth that completed the 9th grade.

To measure cohort labor market outcomes, we also include youth that are one year older and younger than the exact cohort that took the test. This ensures sufficient data on outcomes, as there are small samples in which few respondents have graduated high school. Outcome data are available for employment status, enrollment, wage, productivity, occupational status, and industry of employment.

[18] The I2D2 is a standardized collection of household and labor force surveys from a wide set of countries. An earlier version of the data is described in Montenegro and Hirn (2009). Earlier versions of these data have also been used in selected other studies (Clemens, et al, 2009, King et al, 2010).

We also examine very rough indicators of sectoral productivity data based on output and employment numbers made available through the World Bank's World Development Indicators database. Productivity estimates are available for the agriculture, industry and service sectors. These sectoral productivity data are available for very few countries, and thus the productivity results should be taken with appropriate caution.

Linking the test score data to the I2D2 data on labor market outcomes, we are able to match test scores for between 34 and 61 countries to labor market outcome data (Table 2, column 1), or for between 128 and 257 cohorts to labor market outcome data (Table 2, column 2).[19] Finally, we obtain additional controls for country characteristics from the International Labour Organization's Key Indicators of the Labour Market (KILM) database. We use their imputed estimates of youth labor force participation and youth unemployment rates by gender for 1991.[20] Finally, we also include a measure of natural resource dependence, the share of gross domestic product from natural resources in 1990, from the World Bank's World Development Indicators database, as an additional control. This addresses potential concerns that dependence on natural resources could lead to poor test performance and high rates of youth unemployment.

4.2 Methodology

We divide the data into cells based on cohort and age, and in our main analysis, impose a condition for inclusion in the sample that youth attained a sufficient amount of schooling to be eligible for the test when it was administered.

We then estimate the relationship between average labor market outcomes and average test scores (S), controlling for age, gender, the log of per capita GDP in 1990, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, the share of GDP in natural resources in 1990, a linear time tend, and a vector of region dummies[21]:

$$\bar{Y}_{c,t} = \beta_1 \cdot Score_c + \beta_2 \cdot Age_{c,t} + \beta_3 \cdot Gender_c + \theta \cdot X_c + \gamma \cdot t + \varepsilon_C$$

Where c indexes cohort, which is defined based on country, age, and gender. C indexes country and t year that the labor market data is observed. X is a vector of the four predetermined country characteristics from the early 1990's.

[19] Cohorts in this case are defined by gender, birth year, and country.
[20] The KILM contains imputed estimates using the Global Economic Trends model, which imputes labor market outcomes separately by age group and gender based on regional models with country fixed effects and GDP growth rates.
[21] Countries are classified in regions according to World Bank classifications, and high-income countries comprise a separate region.

For each of the three test score datasets (PISA, TIMSS, and Altinok-Murseli), we examine the following employment outcomes: whether or not an individual is currently employed, whether or not an individual is currently a student, whether or not an individual is currently a non-student, whether or not an individual is currently employed, and whether or not an individual is unemployed, conditional on being active in the labor force. We also examine whether or not individuals are currently working in agriculture, a measure of occupational status, whether or not individuals are currently in wage employment, and estimates of the productivity of individuals' sectors of employment (based on employment and output estimates from country-level WDI data).

As an important robustness check, we introduce country fixed effects into the specification:

$$\bar{Y}_{c,t} = \beta_1 \cdot Score_{c,t} + \beta_2 \cdot Age_{c,t} + \beta_3 \cdot Gender_c + \gamma \cdot t + \delta_C + \varepsilon_C$$

We then examine these estimates separately for men and for women. Because test scores may affect labor market outcomes at different levels of development, test scores in another specification are interacted with the log of GDP in 1990, to allow the effect of test scores to vary with income.

$$\bar{Y}_{c,t} = \beta_1 \cdot Score_{c,t} + \beta_2 \cdot Age_{c,t} + \beta_3 \cdot Gender_c + \beta_4 \cdot Score_{c,t} \cdot Log(GDP_{C,1990}) + \theta \cdot X_c + \gamma \cdot t + \delta_C + \varepsilon_C$$

In addition, we examine the effects of test score by income level by restricting estimates to low- and middle-income countries.

We then look at an expanded sample of youth—including those at all levels of education—for two reasons. First, it allows us to check if the results are robust to the sample inclusion criteria. Second, it allows us to compare the coefficients on test scores with those on educational attainment, as measured by average years of schooling. We regress employment outcomes and employment quality indicators on average test scores, cohort average educational attainment, age and age squared, the log of per capita GDP in 1990, the log of per capita GDP in 1990 squared, a control for the year of the survey, year of survey squared, and a vector of region dummies:

$$\bar{Y}_{c,t} = \beta_1 \cdot Score_{c,t} + \beta_2 \cdot Age_{c,t} + \beta_3 \cdot Gender_c + \beta_4 \cdot Educ_{c,t} + \theta \cdot X_c + \gamma \cdot t + \varepsilon_C$$

We assess the robustness of our results to this alternative sample and specification and compare the relative importance of test scores and years of schooling in these specifications.

5. Results

5.1 Average Effects

Matching labor market outcomes to the PISA, we find evidence that higher test scores not only lead to higher rates of continued enrollment, but also improve employment outcomes by lowering unemployment and raising employment quality, as measured by the type of employment (wage, non-wage) and occupational status. In regressions controlling for age, the log of country GDP per capita in 1990, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, the share of GDP in natural resources in 1990, the survey year, gender, and a full set of region indicators, a one standard deviation increase in PISA test scores is associated with a 35.3 percentage point increase in the likelihood of continued enrollment (significant at the 1 percent level), a 22.3 percentage point reduction in youth idleness (significant at the 5 percent level), and an unemployment ratio (unemployed youth as a share of the youth population) that is 5.3 percentage points lower (significant at the 1 percent level). Most strikingly, we find that conditional on employment, a one standard deviation increase in PISA test scores is associated with a 11.4 percentage point increase in the likelihood of being in wage employment for youth (significant at the 5 percent level), and a 2.7 percentage point increase in the likelihood of being in a high-status occupation. While we do find strong and significant effects of test scores on unemployment ratios and rates, wage employment, and the share of youth in agricultural employment, we find no evidence for effects on the total share employed (potentially due to prolonged school enrollment) or the remaining two indicators of employment quality, agricultural employment and sectoral productivity.

Similarly, when matching labor market outcomes to TIMSS test score data, we find evidence that higher test scores lower unemployment ratios and rates and conditional on being employed, decrease the likelihood of employment in the agricultural sector. An approximately one-standard deviation increase in TIMSS test scores is associated with an unemployment ratio that is 3.7 percentage points lower (marginally significant at the 5 percent level), and an unemployment ratio that is 3.5 percentage points lower (significant at the 5 percent level), again controlling for age, the log of country GDP per capita in 1990, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, the share of GDP in natural resources in 1990, the survey year, gender, and a full set of region indicators. In similar regressions with indicators of employment quality as the outcomes, we find that the likelihood of agricultural employment is 3.3 percentage points lower in countries with TIMSS scores that one standard deviation higher (significant at the 5 percent level). We find no statistically significant relationships between TIMSS scores and other measures of employment quality (wage employment rates, estimates of sectoral productivity, and measures of occupational status).

Finally, when considering the Altinok-Murseli meta-dataset of test scores, which includes the largest set of countries but for a heterogeneous set of examinations, we find that higher test scores are associated with a statistically significant and large increase in enrollment, coupled with a statistically significant decline in employment, a marginally significant decrease in youth idleness, and a significant decline in unemployment ratios. A one standard deviation increase in test scores in sample is associated with a 5.1 percentage point decline in employment at these ages (statistically significant at the 1 percent level), which given a 13.5 percentage point increase in school enrollment (significant at the 1 percent level) and a 5.6 percentage point decline in youth idleness (marginally significant at the 10 percent level) is potentially a positive outcome. We also find that a one standard deviation increase in test scores is associated with a 2.7 percentage point decrease in unemployment ratios (significant at the 1 percent level). Increases in test scores in the Altinok-Murseli database are associated with a 3.3 percentage point decline in the likelihood of employment in the agricultural sector (significant at the 1 percent level) and a 5.4 percentage point increase in the likelihood of wage employment (significant at the 5 percent level), but are not statistically significantly associated with improvements in the remaining indicators of employment quality.

Our results, showing that increases in test scores are strongly and significantly associated with continued enrollment, are broadly consistent with early evidence from studies tracking individual students who were administered the PISA in Canada and elsewhere (reference from Hanushek and Woessman handbook chapter), whose primary early conclusion is an association between higher PISA test scores at the individual level and continued enrollment, as measured by progression into higher education (include references from Hanushek footnote here and discuss).

5.2 Effects by Gender and Income

PISA scores show strong effects on employment outcomes for both men and women, with if anything slightly stronger and more significant effects on enrollment rates and employment outcomes for women than for the population in general, significantly raising enrollment while lowering employment rates, and lowering rates of idleness and unemployment ratios among female youth. When we restrict the analysis to girls and women, a one standard deviation increase in PISA scores among female test-takers is associated with a large 41.5 percentage point increase in the probability of continued enrollment (significant at the 1 percent level), and a related 10.8 percentage point decrease in the likelihood of working (significant at the 5 percent level) at these ages. Increases in PISA scores lead to more moderate, but still large, increases in enrollment for men, with a one standard deviation increase in test scores associated with a 24.0 percentage point increase in school enrollment (marginally significant at the 10 percent level). The results on reduced unemployment in the full sample appear in both the sample of men and women as well, as a one-standard deviation increase in PISA test scores in the sample of girls and women is associated with a 6.0 percentage point decrease in the unemployment ratio (significant at the 5 percent level) and a 4.9 percentage point decrease (significant at the 5 percent level) for men, perhaps partially reflecting decreases in labor force participation at these young ages. In contrast, we find smaller point estimates on test scores in the regressions for men-only, and no statistically significant relationships between higher PISA test scores and improved employment outcomes or continued enrollment.

When looking at employment quality, we find reductions in the rate of agricultural employment and increases in wage employment associated with higher PISA test scores for men. A one standard deviation increase in test scores for men is associated with a 5.3 percentage point reduction in the likelihood of employment in the agricultural sector conditional on employment (marginally significant at the 10 percent level), and a large 18.1 percentage point increase in the likelihood of wage employment conditional on being employed (significant at the 1 percent level). We find no statistically significant relationship between PISA scores and employment quality for women.

TIMSS test scores are more strongly associated with improved employment outcomes for women than for men. When estimating the effects of test scores on employment outcomes for women, we find that a one standard deviation increase in test scores would lead to a 5.0 percentage point reduction in the unemployment ratio (significant at the 1 percent level), and a 4.9 percentage point reduction in the unemployment rate (marginally significant at the 10 percent level).

We find no results for either women or men on other measures of employment quality, using TIMSS scores as a measure of cognitive skills or educational quality.

Results using scores from the Altinok-Murseli database are similarly strong for women and men on enrollment and employment outcomes. A one standard deviation increase in test scores for women is associated with a 15.0 percentage point increase in school enrollment (significant at the 1 percent level), and a related 4.2 percentage point reduction in working (significant at the 5 percent level). Increases in test scores in this database are also associated with significant reductions in youth idleness for women (8.2 percentage points, significant at the 5 percent level), and reductions in the unemployment ratio for women as well (2.5 percentage points, significant at the 1 percent level). For men, a one standard deviation increase in scores is similarly associated with a 5.9 percentage point decrease in rates of working (significant at the 1 percent level), a 11.6 percentage point increase in the likelihood of school enrollment at these ages (significant at the 1 percent level), and a 2.9 percentage point reduction in the unemployment ratio (significant at the 1 percent level).

Results from this database show improvements in measures of job quality for both men and women. A one standard deviation increase in test scores is associated with a 4.9 percentage point reduction in the likelihood of employment in agriculture for men (significant at the 1 percent level), a 6.0 percentage point increase in the likelihood of wage employment for men (significant at the 5 percent level), and a 4.9 percentage point increase in the likelihood of wage employment for women (significant at the 5 percent level).

When analyzing the potential effects of test scores by income, we find that the estimated positive effects of test scores on employment outcomes are spread across the income distribution. First, restricting estimates to a sample of low- and middle-income countries, we find estimates that are largely consistent with our previously reported results for all countries in both magnitudes and significance, showing that the estimated positive effects of test scores on employment are not driven by the tail of high-income countries, or by a rough comparison of high-income to lower-income countries, but also reflected in the distribution of outcomes among low- and middle-income countries.

In the sample excluding high-income countries, according to the World Bank classification, a one standard deviation increase in PISA test scores leads to a 28.3 percentage point increase in school enrollment, significant at the 5 percent level, as well as a related 12.7 percentage point decrease in the probability that youth are working at these ages, significant at the 5 percent level, and a 5.7 percentage point reduction in unemployment ratios, likely reflecting a reduction in labor force participation at young ages. Similarly, a one standard deviation increase in TIMSS test scores is associated with a 4.7 percentage point reduction in unemployment ratios (significant at the 1 percent level) and a 4.2 percentage point reduction in unemployment rates (marginally significant at the 10 percent level).

An exception to this general pattern of robustness is that the results using test scores from the Altinok-Murseli database are not robust to the exclusion of high-income countries. The weak results derived from the Altinok and Murseli (2006) database for this subsample may reflect the fact that there may be too much heterogeneity across tests included in the database, and that scores may not be sufficiently standardized across tests. Tests differ widely in content and difficulty, with some oriented towards measuring specific practical competencies (such as the IALS), others more tailored to measure achievement related to academic curricula, such as the TIMSS and the LLECE, and still others intended to be more classic achievement tests to measure progress in basic subject areas such as math and reading, such as the PISA. Many tests are designed to be comparable across countries within a round, but not specifically designed to allow comparisons across administrations in different years. Differences in the sample of countries participating in these assessments further makes the standardization of scores across tests a challenging task, and early estimates using our own standardization of scores across tests yielded similarly weak results. We continue to include the analysis of the Altinok and Murseli meta-dataset of test scores here though, as it covers the largest set of countries and cohorts, and produces results consistent with those for the PISA and TIMSS in the full sample.

When interacting test scores linearly with income, we find that effects on working, schooling, and idleness are stronger for lower income countries, while effects on unemployment, especially unemployment rates, appear to be generally stronger for higher income countries (results not shown).

Allowing effects to vary nonlinearly with income, we find suggestive evidence for a different pattern of effects, with effects on most employment outcomes for all tests larger in high income countries, and effects on employment quality outcomes larger in lower income countries (Figures 1a, 1b, and 1c). An exception to this is employment and PISA test scores.

5.3 Robustness Checks and Effects on Educational Attainment

To test the robustness of our results to the construction of our sample, we then repeat our analysis including a broader sample of youth, rather than restricting our analysis of labor market outcomes to those youth who had completed sufficient education to be eligible for the relevant assessments. We also use this broader sample to look at average years of education as an outcome, and furthermore to compare the explanatory power of years of education and of test scores in regressions including both education and test scores as right hand side variables.

We find similar effects of test scores in regressions in this broader sample, including average years of education as an additional right hand side variable. Higher PISA and TIMSS scores are again associated with statistically and economically significantly higher rates of school enrollment and lower rates of working at these ages, with a one standard deviation increase in test scores associated with between a 7.3 percentage point and 19.6 percentage point decrease in employment (significant at the 1 percent level, all three tests), and a 14.5 percentage point to 44.3 percentage point increase in school enrollment (significant at the 1 percent level, PISA and Altinok-Murseli). Higher scores are also associated with lower unemployment ratios and rates, with a standard deviation increase in test scores leading to either a 8.4 percentage point reduction in unemployment ratios (PISA, significant at the 1 percent level) or a 3.3 percentage point reduction in unemployment ratios (Altinok-Murseli, significant at the 1 percent level), and a 2.4 to 2.9 percentage point reduction in unemployment rates (TIMSS and Altinok-Murseli, marginally significant at the 10 percent level). Higher test scores from all three sources (PISA, TIMSS, Altinok-Murseli) are associated with a significantly lower likelihood of employment in the agricultural sector, as before. Higher test scores from the PISA and Altinok-Murseli databases are associated with significant increases in the likelihood of wage employment, conditional on working.

When comparing test scores and average years of education, both are similarly often predictive of labor market outcomes, and similarly economically and statistically significant in regressions of labor market outcomes.

Average years of education remains similarly predictive of labor market outcomes when including test scores as an additional control variable, in contrast to Hanushek and Kimko (2000) and Hanushek and Woessman's (2008) specifications finding that only cognitive skills are predictive of growth rates in joint regressions, and more consistent with Breton's (2011) finding that in alternative specifications better motivated by dynamic models of growth, both years of education and cognitive skills or test scores are predictive of growth. We conclude that both the quality of education, as measured by students' performance on international assessments, and average educational attainment drive cross-country differences in youth outcomes in labor markets.

Examining average years of education as a function of test scores and other controls, we find mixed evidence for positive impacts of test scores on educational attainment, somewhat surprising given our earlier results on the effect of higher test scores on continued enrollment. We find that the relationship between test scores and average years of education is only positive and significant when test scores from the PISA database are used; in that case a one standard deviation higher test score is associated with 2.179 additional years of schooling on average (significant at the 1 percent level).

Finally, as an additional check, we test the robustness of our empirical results to the inclusion of country fixed effects, relying on cross-birth cohort, within-country differences in test score performance and employment outcomes to identify the effect of cognitive skills on youth labor markets. We find that the negative and strong relationship between PISA test scores and unemployment ratios and rates is at least partially robust to the inclusion of country fixed effects, but that our results on reductions in working, increases in school enrollment, and decreases in youth idleness are not. A one standard deviation increase in TIMSS test scores is associated with a 13.2 percentage point decrease in the unemployment rate (significant at the 5 percent level), while a one standard deviation increase in test scores in the Altinok-Murseli database is associated with a 2.2 percentage point decrease in unemployment ratios (marginally significant at the 10 percent level) and a 2.4 percentage point decrease in unemployment rates (significant at the 5 percent level). One caveat is that the sample of countries on which we are able to estimate these effects is smaller and higher income than the full sample, as richer countries are more likely to have participated in multiple rounds of testing than lower income countries.

We find that our primary results are robust in specifications excluding additional controls for youth unemployment rates, labor force participation, and natural resources; robust to the inclusion of unemployment measures based on national statistics rather than ILO imputations; and partially robust to the inclusion of higher order polynomial terms in age and log per capita GDP.

5.4 Extensions to Include Additional Countries and Years

We next discuss results based on a newer release of the I2D2 database (version 3.3, released in August 2012). Applying the empirical framework above to the newer data, for the most part we find no consistent evidence for strong effects of test scores on employment, school enrollment, unemployment, or labor force participation among youth. Results from the TIMSS still do suggest marginally significant increases in school enrollment among youth, as a one standard deviation increase in test scores is associated with a 7 percentage point increase in school attendance at these ages. This result is robust to and becomes larger with the inclusion of country fixed effects. In specifications using the Altinok-Murseli database as the source of test-score data, we also still do see evidence for declines in working at young ages, with a one standard deviation increase in test scores associated with a 4 percentage point decrease in employment among youth, which is also robust to the inclusion of country fixed effects.

However, we do find stronger evidence than previously for effects of test scores on job quality, as indicated by wage employment and non-agricultural employment. Looking at PISA scores, a one standard deviation increase in scores is associated with a 16 percentage point increase in wage employment and a 9 percentage point decrease in employment in agriculture, although these effects are not robust to the inclusion of country fixed effects. Using the Altinok-Murseli database, a one standard deviation increase in test scores is associated with a 6 percentage point increase in wage employment and a 4 percent decrease in agricultural employment, and these effects are in fact robust to the inclusion of country fixed effects.

Taken together, the results are suggestive of strong effects on job quality, if not on employment, schooling and other outcomes, although these estimates are subject to revision as corrected versions of the expanded database become available.

6. Inequality in Cognitive Skills and Youth Labor Markets

We next use individual-level test data from the PISA to next assess the relationship between degree of inequality in cognitive skills, as reflected in test-score outcomes, on labor market outcomes for youth.

In a context with imperfect information about employee quality, employers may be hesitant to hire new workers, especially in the presence of employment regulation, and even more so when information problems are particularly severe—when the average quality of workers is low and the dispersion of worker quality conditional on observables, such as educational attainment, is particularly high. In this case, inequality and failures of the educational system, and particularly unobservable differences in education quality, may propagate through youth labor markets and make it more difficult for employers to selectively hire high-quality young employees.

From the item-level PISA data, we construct a measure of average performance, average percentage of items answered correctly, that should roughly correspond to the average PISA score measure used in our primary analysis above. We also construct a measure of test score dispersion, the within-cohort standard deviation in the percentage of items answered correctly.

Regressing our employment and employment quality outcomes on these two measures, as well as our full set of controls, we find that as above, increases in average test performance are associated with significant increases in school enrollment, decreases in youth idleness, decreases in the unemployment ratio, and decreases in the unemployment rate. They are also associated with increases in job quality, as measured by wage employment and occupational status.

Increases in the dispersion of test scores tend to mitigate these effects, with significant decreases in school enrollment and increases in working at young ages. A one percentage point increase in the standard deviation of the percentage of items answered correctly is associated with a 4.2 percentage point reduction in the likelihood of continued enrollment (significant at the 5 percent level), and a 2.3 percentage point increase in the likelihood of working at young ages (marginally significant at the 10 percent level).

Somewhat puzzlingly, however, an increase in the dispersion of test performance is also associated with a statistically significant increase in youth sectoral productivity, conditional on employment. It is possible that when the signal value of continued education decreases, marginal youth who then select into employment are employed in higher productivity sectors, such as manufacturing.

Overall we find that increases in the dispersion of test scores lead to decreases in continued enrollment and increases in working at young ages, perhaps reflecting that increases in the variation in educational quality as evidenced by test scores, particularly at the low end, may decrease the signal value of educational attainment and render working or apprenticeship at young ages more attractive relative to continued formal education.

7. Conclusion

In summary, this paper presents new evidence suggesting that improvements in cognitive skills reduce unemployment, and may improve job quality in the medium term. These results fill in part of the potential causal chain from better education quality, not just quantity, to economic growth and development. In particular, school enrollment rates rise and rates of working and unemployment ratios drop as test score measures of cognitive skills rise. Job quality improves as well, as agricultural employment shares fall and, in some cases, wage employment rates and occupational status rise as cognitive skills increase. The effects of test scores for most outcomes are still present when controlling for educational attainment or restricting attention to low- and middle-income countries, suggesting that the correlations between test scores and youth employment outcomes are not driven solely by differences in educational attainment, or broad contrasts between the labor markets of high-income and low-income countries.

One significant concern for this study, as for all cross-country studies, is that of establishing causality. It is likely that better labor market opportunities raise the returns to skill investment, and thus raise investment in schooling and test scores. Similarly, it is also possible that unobserved factors, such as culture or the level of drive or determination, drive both cross-country differences in test scores and cross-country differences in youth employment. The findings on job quality and enrollment are of particular concern because they are not robust to the inclusion of country effects. This could in part reflect a delayed effect of cognitive skills on labor market structure, as countries' comparative advantage gradually adjusts to increased skills among youth. It is hard to rule out, however, the possibility that the positive relationship between skills and job quality is partly due to joint causality, if for example students have greater incentives to acquire academic skills in economies that are less dependent on agricultural employment. Recent experimental evidence further highlights the possibility that students' efforts to attend school and acquire skills are sensitive to their perceived returns.[22] A second concern is the robustness of the specific conclusions to additional data. Estimates based on a newer release of the database of labor market outcomes fail to show a discernible relationship between cognitive skills and unemployment, but suggest stronger and more robust effects of test scores on job quality..

[22] In a randomized controlled study in India, Jensen (2012) finds that increasing access to jobs in the burgeoning business process outsourcing industry in rural India leads young women 15 to 21 years old at the outset of the study to obtain more schooling and post-school training in English and computer skills, and to delay marriage and childbearing. Similarly, simply providing information about the income returns to education that exceeded students' prior beliefs in the Dominican Republic led to increases in schooling, among both girls and boys (Jensen, 2010).

The strong relationship between test scores and youth employment outcomes suggests highlighting policies in developing countries that can provide incentives or additional educational inputs to boost skills and test scores and thus labor market outcomes and growth. One option to do so is to target employment training programs to youth. Youth training programs, however, often focus on more practical skills for employment, targeting behaviors or vocational training rather than investing in improving basic skills in reading and arithmetic at a later age, assuming that low-scoring youth are already bound for more low-skill or vocational employment. One program in Uganda provided grants to groups of youth to pursue employment training, leading to high rates of enrollment in popular vocational training institutes to pursue trade professions such as tailoring or carpentry (Blattman et al, 2012). An evaluation of the "Jovenes en Accion" program in Colombia found that job training led to large increases in income, and interestingly, increases that were sharply higher for women than for men (Attanasio et al, 2008). The program, which provided three months of in-classroom training and three months of practical on-the-job training to youth in the two lowest socio-economic strata of the population, raised incomes for men by 8 percent and incomes for women by 18 percent. An evaluation of a third program in the Dominican Republic, the "Juventud y Empleo" program, finds modest effects of youth training on earnings, conditional on employment, but no evidence for effects on employment outcomes (Card et al, 2011).

A second policy option would be to support remedial education programs that seek to build basic skills in reading and math, even at later ages. Much of the empirical evidence on the effectiveness of remedial education programs, or on the impact of increases in education quality, comes however from interventions targeted towards younger children. Banerjee et al (2007) find in a randomized evaluation that providing remedial education to elementary school aged children in India initially lagging behind their peers led to significant test score gains.

As emphasized in Banerjee et al (2007), the quest to improve education quality and subsequent real outcomes in developing countries is a daunting task, as quickly scaling up enrollment in a setting of limited resources has led to larger class sizes and lower instructional quality. Our results, however, provide an indication that both increasing attainment and raising instructional quality pay off in the form of better for youth. Furthermore, improving levels of cognitive skills has the additional likely benefit of reducing youth unemployment. Given the significant implications of youth unemployment and job quality for the future working lives of current youth, further investments to improve both the quantity and quality of education are essential.

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Table 1: Growth as a function of cognitive skill measures

Average per capita GDP growth rate	(I) 1960-2000 (published results)	(II) 1960-2010 (attempted replication)	(III) 1990-2010 (H-W sample)	(IV) 1990-2010 (Additional countries)
Country cognitive score	1.541***	1.221***	0.894	0.206
	(0.434)	(0.404)	(0.594)	(0.539)
GDP in initial year	-0.000***	-0.000***	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Years of schooling in initial year	-0.235*	-0.229*	-0.111	-0.386***
	(0.136)	(0.127)	(0.170)	(0.139)
Observations	45	45	45	69
R-squared	0.420	0.428	0.234	0.141

Source: Hanushek, E. A., & Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature*, 46(3), 607–668; Author's calculations

Table 2: Data coverage

Test score source	Number of participating countries	Number of cohorts (country, birth year, and gender) observed	Number of cells (survey years in which cohorts outcomes are observed)
Total			
PISA	41	176	454
TIMSS	34	128	329
Altinok-Murseli (A-M)	67	315	723
Tests in multiple years			
PISA	32	158	436
TIMSS	27	114	315
Altinok-Murseli (A-M)	50	281	689

Note: Cohorts are defined separately by gender. On average countries administered each test roughly twice, to four different cohorts.

Table 3: Countries and test years

Country	PISA	TIMSS	Altinok-Murseli
Albania	2000		
Argentina	2000, 2006		1995, 2000
Armenia		2003	2003
Austria	2000, 2003, 2006		1995, 1999, 2000, 2003
Belarus	2000, 2003, 2006		1999, 2000, 2003
Bulgaria	2000, 2006	1999, 2003	1999, 2000, 2003
Bolivia			1995, 2000
Brazil	2000, 2003, 2006		1991, 1995, 1999, 2000 (2), 2003
Cameroon			2000
Canada	2000	1995, 1999	1991, 1995, 1999, 2000
Chile	2000, 2006, 2009	1999, 2003	1995, 1999, 2000 (2), 2003
Colombia		1995	1995, 1999, 2000
Cyprus		1999, 2003	1991, 1995, 1999, 2000, 2003
Czech Republic	2000, 2003, 2006	1999	1995, 1999, 2000, 2003
Denmark	2000, 2003		1991, 1999, 2000
Dominican Republic			1995
Egypt		2003	2003
Estonia	2006	2003	2003
Finland	2000, 2003	1999	1991, 1999, 2000, 2003
France	2000, 2003		1991, 1999, 2000, 2003
Germany	2000, 2003		1999, 2000, 2003
Ghana		2003	2003
Great Britain	2000, 2003, 2006		1991, 1995, 1999, 2000, 2003
Greece	2000, 2003, 2006		1991, 1995, 1999, 2000, 2003
Honduras			1995
Hungary	2000, 2003	1995, 1999, 2003	1984, 1991, 1995, 1999, 2000, 2003
Iceland	2000, 2003		
Indonesia	2000	1999	1991, 1999, 2000
Iran		1995, 1999, 2003	1995, 1999, 2000, 2003
Ireland	2000, 2003, 2006		1995, 1999, 2000, **2003**
Italy	2000, 2003, 2006	1999, 2003	1991, 1999, 2000, 2003
Jordan		1999	1991, 1995, 1999, 2000
Kenya			2000
Latvia	2000, 2003, 2006	1995, 1999, 2003	1995, 1999, 2000, 2003
Lebanon		2003	2003
Lithuania	2006	1995, 1999, 2003	1999, 2000, 2003
Luxembourg	2000, 2003, 2006		1999, 2000, 2003
Macedonia		1999, 2003	1999, 2000, 2003
Madagascar			1995
Malawi			1995, 2000
Mali			1995
Mauritius			1995, 2000, 2002, 2003
Mexico	2000, 2003, 2006		1995, 1999, 2000 (2), 2003

Moldova		1999, 2003	1999, 2000, 2003
Mozambique			1991
Netherlands	2003	1999, 2003	1991, 1995, 1999, 2000, 2003
Niger			1995
Norway	2003	2003	1991, 1995, 1999, 2000, 2003
Paraguay			1995
Peru	2000		
Philippines		1999, 2003	1984, 1991, 1999, 2000, 2003
Poland	2000, 2003, 2006		1984, 1999, 2000, 2003
Portugal	2000, 2003, 2006		1991, 1995, 1999, 2000, 2003
Romania	2006	1999, 2003	
Russia	2000, 2003	1995, 1999, 2003	1991, 1999, 2000, 2003
Senegal			1995
Slovakia	2003	1995, 1999, 2003	1999, 2000, 2003
Slovenia	2006	1995, 1999, 2003	1995, 1999, 2000, 2003
South Africa		1995, 1999, 2003	1999, 2000, 2002, 2003
Spain	2000, 2003, 2006		1991, 1999, 2000, 2003
Sweden	2000, 2003, 2006	2003	1991, 1999, 2000, 2003
Syria			1991
Thailand	2000, 2003, 2006, 2009	1995, 1999, 2007	1991, 1995, 1999, 2000, 2003
Togo			2000
Tunisia		1999	1995, 1999, 2000
Turkey	2003	1999	1999, 2000, 2003
Uganda			1995, 2000
Uruguay	2003, 2006		2003
United States	2000, 2003	1995, 1999, 2003	1991, 1995, 1999, 2000, 2003
Venezuela			1991, 1995
Zambia			1995
Total test years	**88**	**64**	**204**

Table 4: Descriptive statistics

Variable	N	Mean	Standard Deviation
PISA			
Employed	454	0.364	0.214
Student	454	0.261	0.300
Idle	454	0.291	0.268
Unemployment ratio	454	0.081	0.046
Unemployment rate	387	0.213	0.133
Agricultural employment	346	0.112	0.129
Wage employment	346	0.814	0.171
Occupational status	319	0.048	0.046
Sectoral productivity	176	9.394	1.018
TIMSS			
Employed	329	0.446	0.194
Student	329	0.114	0.230
Idle	329	0.336	0.202
Unemployment ratio	329	0.103	0.060
Unemployment rate	248	0.326	0.200
Agricultural employment	216	0.138	0.146
Wage employment	216	0.768	0.212
Occupational status	196	0.056	0.057
Sectoral productivity	96	9.532	1.076
Altinok-Murseli			
Employed	723	0.437	0.219
Student	723	0.186	0.298
Idle	723	0.294	0.201
Unemployment ratio	723	0.083	0.045
Unemployment rate	669	0.187	0.128
Agricultural employment	641	0.100	0.152
Wage employment	641	0.847	0.221
Occupational status	563	0.079	0.061
Sectoral productivity	283	9.412	1.165

Table 5a: Estimated effect of test score, by employment outcome, PISA

PISA	(I) Employed	(II) Student	(III) Idle	(IV) Unemployment ratio	(V) Unemployment rate
Test score	-0.080	0.353**	-0.223**	-0.053***	-0.026
	(0.056)	(0.132)	(0.095)	(0.016)	(0.040)
Gender	0.057**	-0.167***	0.110***	-0.003	-0.029
	(0.024)	(0.059)	(0.031)	(0.010)	(0.019)
Age	0.076***	-0.033***	-0.051**	0.009***	-0.015***
	(0.010)	(0.011)	(0.019)	(0.002)	(0.005)
Log per capita GDP	0.084***	-0.262***	0.147***	0.030***	-0.008
	(0.029)	(0.059)	(0.032)	(0.007)	(0.021)
Youth unemployment rate by gender, 1991	0.002	-0.016	0.009	0.006***	0.011***
	(0.004)	(0.010)	(0.006)	(0.001)	(0.002)
Youth labor force part. by gender, 1991	0.010**	-0.025***	0.010	0.005***	0.007***
	(0.005)	(0.009)	(0.006)	(0.001)	(0.002)
Natural resource rents to GDP, 1990	0.009	-0.007	-0.005	0.000	-0.003
	(0.007)	(0.010)	(0.008)	(0.001)	(0.003)
R-squared	0.811	0.622	0.669	0.498	0.406
Number of observations	454	454	454	454	387

Note: Regressions also include regional dummies, and a linear time trend. Standard errors clustered on country.

Table 5b: Estimated effect of test score, by employment outcome, TIMSS

TIMSS	(I) Employed	(II) Student	(III) Idle	(IV) Unemployment ratio	(V) Unemployment rate
Test score	-0.013	0.030	0.018	-0.035***	-0.037**
	(0.020)	(0.044)	(0.034)	(0.011)	(0.016)
Gender	0.027**	-0.051**	0.023	0.001	0.025
	(0.013)	(0.024)	(0.022)	(0.007)	(0.019)
Age	0.081***	-0.023	-0.073***	0.016***	-0.003
	(0.009)	(0.019)	(0.023)	(0.002)	(0.004)
Log per capita GDP	0.099***	-0.198***	0.095**	0.003	-0.073***
	(0.023)	(0.049)	(0.041)	(0.007)	(0.017)
Youth unemployment rate by gender, 1991	-0.003	-0.002	-0.002	0.007***	0.013***
	(0.004)	(0.008)	(0.006)	(0.002)	(0.003)
Youth labor force part. by gender, 1991	0.004	-0.007	-0.003	0.006***	0.009***
	(0.004)	(0.008)	(0.006)	(0.002)	(0.003)
Natural resource rents to GDP, 1990	0.008*	-0.029***	0.020**	0.002	0.002
	(0.004)	(0.009)	(0.008)	(0.001)	(0.003)
R-squared	0.910	0.694	0.674	0.589	0.753
Number of observations	329	329	329	329	248

Note: Regressions also include regional dummies, and a linear time trend. Standard errors clustered on country.

Table 5c: Estimated effect of test score, by employment outcome, Altinok-Murseli

Altinok-Murseli	(I) Employed	(II) Student	(III) Idle	(IV) Unemployment ratio	(V) Unemployment rate
Test score	-0.051***	0.135***	-0.056*	-0.027***	-0.019
	(0.016)	(0.042)	(0.033)	(0.007)	(0.012)
Gender	0.022	-0.127***	0.107***	-0.003	-0.034***
	(0.019)	(0.033)	(0.026)	(0.008)	(0.010)
Age	0.054***	-0.021*	-0.037***	0.003**	-0.011***
	(0.003)	(0.011)	(0.010)	(0.002)	(0.002)
Log per capita GDP	0.015	-0.090***	0.063**	0.013***	0.005
	(0.010)	(0.033)	(0.029)	(0.004)	(0.006)
Youth unemployment rate by gender, 1991	-0.007**	0.000	0.001	0.005***	0.016***
	(0.003)	(0.008)	(0.006)	(0.001)	(0.002)
Youth labor force part. by gender, 1991	0.001	-0.010	0.005	0.005***	0.010***
	(0.003)	(0.008)	(0.006)	(0.001)	(0.002)
Natural resource rents to GDP, 1990	0.001	-0.007	0.006	0.001	-0.001
	(0.002)	(0.008)	(0.006)	(0.000)	(0.001)
R-squared	0.816	0.588	0.282	0.264	0.620
Number of observations	723	723	723	723	723

Note: Regressions also include regional dummies, and a linear time trend. Standard errors clustered on country.

Table 6a: Estimated effect of test score, by employment outcome for men

Male youth	(I) Employed	(II) Student	(III) Idle	(IV) Unemployment ratio	(V) Unemployment rate
PISA					
Test score	-0.021	0.240*	-0.171	-0.049**	-0.032
	(0.065)	(0.125)	(0.103)	(0.019)	(0.051)
R-squared	0.854	0.7	0.739	0.487	0.388
Observations	227	227	227	227	206
TIMSS					
Test score	-0.013	0.058	-0.025	-0.020	-0.005
	(0.019)	(0.043)	(0.034)	(0.013)	(0.020)
R-squared	0.923	0.752	0.756	0.593	0.723
Observations	165	165	165	165	135
Altinok-Murseli					
Test score	-0.059***	0.116***	-0.028	-0.029***	-0.015
	(0.012)	(0.034)	(0.030)	(0.010)	(0.014)
R-squared	0.841	0.72	0.439	0.235	0.657
Observations	362	362	362	362	340

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Table 6b: Estimated effect of test score on employment outcomes for women

Female youth	**(I)** Employed	**(II)** Student	**(III)** Idle	**(IV)** Unemployment ratio	**(V)** Unemployment rate
PISA					
Test score	-0.108**	0.415***	-0.251***	-0.060**	-0.022
	(0.050)	(0.132)	(0.088)	(0.024)	(0.054)
R-squared	0.778	0.639	0.642	0.529	0.45
Observations	227	227	227	227	181
TIMSS					
Test score	-0.019	0.060	0.010	-0.050***	-0.049*
	(0.030)	(0.062)	(0.040)	(0.017)	(0.026)
R-squared	0.907	0.681	0.618	0.6	0.787
Observations	164	164	164	164	113
Altinok-Murseli					
Test score	-0.042**	0.150***	-0.082**	-0.025***	-0.022
	(0.018)	(0.040)	(0.037)	(0.009)	(0.018)
R-squared	0.806	0.554	0.235	0.274	0.641
Observations	361	361	361	361	329

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Table 7: Estimated effect of test on employment outcomes including country fixed effects, by gender and test

	(I) Employed	(II) Student	(III) Idle	(IV) Unemployment ratio	(V) Unemployment rate
Pooled					
PISA	0.188	0.240	-0.386*	-0.041	0.059
	(0.136)	(0.186)	(0.220)	(0.036)	(0.093)
TIMMS	-0.139*	-0.308**	0.375**	0.072	-0.132**
	(0.078)	(0.131)	(0.139)	(0.049)	(0.056)
Altinok-Murseli	-0.024	0.019	0.027	-0.022*	-0.024**
	(0.023)	(0.014)	(0.033)	(0.012)	(0.011)
Men					
PISA	0.035	0.325*	-0.354	-0.004	0.178
	(0.159)	(0.169)	(0.263)	(0.044)	(0.149)
TIMMS	-0.227*	-0.463***	0.533***	0.158*	-0.012
	(0.112)	(0.165)	(0.176)	(0.080)	(0.081)
Altinok-Murseli	-0.058***	0.025	0.064**	-0.031*	-0.025**
	(0.020)	(0.016)	(0.029)	(0.017)	(0.012)
Women					
PISA	0.197*	0.183	-0.337	-0.042	0.129
	(0.116)	(0.334)	(0.338)	(0.063)	(0.163)
TIMMS	-0.060	-0.388*	0.370	0.085	-0.166
	(0.124)	(0.217)	(0.271)	(0.067)	(0.110)
Altinok-Murseli	0.001	0.017	-0.007	-0.010	-0.008
	(0.030)	(0.015)	(0.041)	(0.017)	(0.012)

Note: Regressions include age and a linear time trend.

Table 8a: Estimated effect of test score on job quality indicators, by test

	(I) Agricultural employment	(II) Wage employment	(III) High-status occupation	(IV) Sectoral productivity
PISA				
Test score	-0.028	0.114**	0.027*	-0.059
	(0.035)	(0.047)	(0.016)	(0.162)
R-squared	0.810	0.707	0.305	0.983
Observations	346	346	319	176
TIMSS				
Test score	-0.033**	0.009	0.010	0.119
	(0.017)	(0.031)	(0.009)	(0.196)
R-squared	0.642	0.656	0.481	0.99
Observations	216	216	196	96
Altinok-Murseli				
Test score	-0.033***	0.054**	0.000	-0.011
	(0.010)	(0.023)	(0.007)	(0.052)
R-squared	0.73	0.802	0.758	0.987
Observations	641	641	563	283

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Table 8b: Estimated effect of test score on job quality indicators, by test, men

	(I) Agricultural employment	(II) Wage employment	(III) High-status occupation	(IV) Sectoral productivity
PISA				
Test score	-0.053*	0.181***	0.024	-0.012
	(0.029)	(0.041)	(0.018)	(0.185)
R-squared	0.892	0.759	0.275	0.986
Observations	180	180	162	91
TIMSS				
Test score	-0.003	-0.002	0.005	0.082
	(0.019)	(0.029)	(0.018)	(0.226)
R-squared	0.813	0.758	0.620	0.996
Observations	113	113	101	49
Altinok-Murseli				
Test score	-0.049***	0.060**	0.013	0.013
	(0.014)	(0.027)	(0.008)	(0.051)
R-squared	0.779	0.817	0.708	0.989
Observations	322	322	283	142

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Table 8c: Estimated effect of test score on job quality indicators, by test, women

	(I) Agricultural employment	(II) Wage employment	(III) High-status occupation	(IV) Sectoral productivity
PISA				
Test score	-0.013	0.058	0.038	-0.114
	(0.030)	(0.057)	(0.026)	(0.132)
R-squared	0.77	0.668	0.374	0.995
Observations	166	166	157	85
TIMSS				
Test score	-0.027	0.007	-0.003	0.088
	(0.019)	(0.040)	(0.010)	(0.102)
R-squared	0.538	0.577	0.419	0.997
Observations	103	103	95	47
Altinok-Murseli				
Test score	-0.018	0.049**	-0.013	-0.032
	(0.013)	(0.019)	(0.008)	(0.055)
R-squared	0.721	0.799	0.809	0.991
Observations	319	319	280	141

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Table 9: Estimated employment quality outcomes including country fixed effects, by gender and test

	(I) Agriculture	(II) Wage employment	(III) Occupational status	(IV) Sectoral productivity
Pooled				
PISA	0.032	0.009	-0.002	-0.136
	(0.054)	(0.078)	(0.031)	(0.091)
TIMMS	-0.139*	0.206**	-0.009	0.193
	(0.074)	(0.077)	(0.027)	(0.193)
Altinok-Murseli	0.014	-0.005	0.033***	-0.040*
	(0.013)	(0.010)	(0.011)	(0.020)
Men				
PISA	0.022	0.045	-0.006	-0.293***
	(0.074)	(0.109)	(0.040)	(0.057)
TIMMS	-0.029	0.207	-0.067*	0.28
	(0.115)	(0.153)	(0.037)	(0.221)
Altinok-Murseli	0.006	-0.001	0.042***	-0.023***
	(0.009)	(0.012)	(0.012)	(0.007)
Women				
PISA	-0.056	-0.006	0.003	0.022
	(0.082)	(0.155)	(0.064)	(0.047)
TIMMS	-0.074	0.163	-0.067	0.108
	(0.085)	(0.173)	(0.063)	(0.228)
Altinok-Murseli	0.009	0.001	0.018	-0.058
	(0.015)	(0.010)	(0.012)	(0.043)

Note: Regressions include age and a linear time trend.

Table 10: Robustness checks—estimated effects on employment outcomes for all youth, unconditional on education

	(I) Employed	(II) Student	(III) Idle	(IV) Unemployment ratio	(V) Unemployment rate
PISA					
Test score	-0.196***	0.443***	-0.170*	-0.084***	-0.027
	(0.062)	(0.111)	(0.098)	(0.016)	(0.046)
Years of education	0.039*	-0.028	-0.029	0.020***	0.022**
	(0.021)	(0.025)	(0.028)	(0.003)	(0.010)
R-squared	0.857	0.631	0.692	0.629	0.433
Observations	454	454	454	454	407
TIMSS					
Test score	-0.073***	0.005	0.085	-0.017	-0.029*
	(0.021)	(0.060)	(0.053)	(0.011)	(0.017)
Years of education	0.056***	0.035	-0.077**	-0.014***	-0.009
	(0.015)	(0.028)	(0.031)	(0.005)	(0.009)
R-squared	0.92	0.677	0.693	0.614	0.739
Observations	332	332	332	332	267
A-M					
Test score	-0.076***	0.145***	-0.036	-0.033***	-0.024*
	(0.014)	(0.044)	(0.036)	(0.006)	(0.013)
Years of education	0.042***	-0.023	-0.028	0.009***	0.002
	(0.012)	(0.023)	(0.034)	(0.002)	(0.004)
R-squared	0.87	0.596	0.287	0.343	0.589
Observations	752	752	752	752	688

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Table 11: Robustness checks—estimated effects on employment quality for all youth, unconditional on education

	(I) Agriculture	(II) Wage employment	(III) Occupational status	(IV) Sectoral productivity
PISA				
Test score	-0.083**	0.136**	0.016	0.029
	(0.032)	(0.059)	(0.015)	(0.157)
Years of education	-0.009	0.013	0.006	0.022
	(0.007)	(0.009)	(0.004)	(0.018)
R-squared	0.805	0.729	0.311	0.983
Observations	371	371	347	193
TIMSS				
Test score	-0.073***	-0.015	-0.004	0.057
	(0.023)	(0.036)	(0.011)	(0.186)
Years of education	-0.002	0.045**	0.012**	-0.046**
	(0.010)	(0.019)	(0.006)	(0.016)
R-squared	0.684	0.724	0.511	0.992
Observations	235	235	213	106
A-M				
Test score	-0.034***	0.048**	-0.004	0.004
	(0.010)	(0.023)	(0.008)	(0.058)
Years of education	-0.006*	0.023***	0.011***	0.024
	(0.004)	(0.009)	(0.002)	(0.018)
R-squared	0.732	0.81	0.787	0.988
Observations	656	656	578	288

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Table 13: Estimates for all youth, unconditional on education, including country fixed effects

	(I) Employed	(II) Student	(III) Idle	(IV) Unemployment ratio	(V) Unemployment rate
PISA					
Test score	0.176	0.110	-0.218	-0.069*	0.044
	(0.135)	(0.158)	(0.132)	(0.035)	(0.084)
Years of education	0.069***	0.028	-0.125**	0.029***	-0.015
	(0.014)	(0.044)	(0.054)	(0.007)	(0.013)
R-squared	0.897	0.869	0.834	0.749	0.64
Observations	456	456	456	456	407
TIMSS					
Test score	-0.101	-0.187***	0.232***	0.055	-0.128**
	(0.073)	(0.066)	(0.068)	(0.055)	(0.060)
Years of education	0.066***	0.116***	-0.164***	-0.018**	0.012
	(0.021)	(0.031)	(0.036)	(0.008)	(0.016)
R-squared	0.940	0.906	0.863	0.659	0.819
Observations	332	332	332	332	267
A-M					
Test score	-0.027*	0.008	0.041**	-0.022***	-0.022*
	(0.014)	(0.013)	(0.017)	(0.009)	(0.012)
Years of education	0.074***	-0.016	-0.077**	0.019***	-0.009
	(0.020)	(0.012)	(0.032)	(0.002)	(0.010)
R-squared	0.940	0.931	0.826	0.532	0.777
Observations	752	752	752	752	688

Note: Regressions also include age and a linear time trend. Standard errors clustered on country.

Table 14: Estimates for all youth, unconditional on education, including country fixed effects

	(I) Agriculture	(II) Wage employment	(III) Occupational status	(IV) Sectoral productivity
PISA				
Test score	0.120**	-0.070	-0.023	-0.314**
	(0.059)	(0.077)	(0.026)	(0.124)
Years of education	-0.014	0.028	0.001	0.072
	(0.014)	(0.022)	(0.006)	(0.048)
R-squared	0.853	0.801	0.493	0.990
Observations	371	371	347	193
TIMSS				
Test score	-0.119	0.199**	-0.017	0.177
	(0.087)	(0.088)	(0.022)	(0.198)
Years of education	-0.079***	0.039*	0.020*	0.014
	(0.024)	(0.023)	(0.011)	(0.063)
R-squared	0.804	0.879	0.651	0.994
Observations	235	235	213	106
A-M				
Test score	0.015	-0.007	0.034***	-0.041
	(0.011)	(0.014)	(0.012)	(0.024)
Years of education	-0.021***	0.022*	-0.002	0.011
	(0.008)	(0.013)	(0.005)	(0.016)
R-squared	0.902	0.937	0.87	0.998
Observations	656	656	578	288

Note: Regressions also include age and and a linear time trend. Standard errors clustered on country.

Table 15a: Employment outcomes as a function of dispersion in PISA test performance

	(I) Employed	(II) Student	(III) Idle	(IV) Unemployment ratio	(V) Unemployment rate
PISA					
Percentage correct	-0.006	0.016**	-0.008**	-0.002**	-0.005***
	(0.004)	(0.007)	(0.003)	(0.001)	(0.002)
Standard deviation, percentage correct	0.023*	-0.042*	0.015	0.004	0.011
	(0.014)	(0.022)	(0.014)	(0.004)	(0.010)
R-squared	0.856	0.661	0.722	0.491	0.588
Observations	208	208	208	208	175

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Table 15b: Employment quality outcomes as a function of dispersion in PISA test performance

	(I) Agriculture	(II) Wage employment	(III) Occupational status	(IV) Sectoral productivity
PISA				
Percentage correct	-0.001	0.007***	0.003**	0.002
	(0.002)	(0.002)	(0.001)	(0.011)
Standard deviation, percentage correct	-0.001	-0.001	-0.001	0.095***
	(0.005)	(0.008)	(0.007)	(0.028)
R-squared	0.849	0.830	0.390	0.988
Observations	161	161	148	89

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.

Figure 1a: Effects of test scores by GDP, PISA

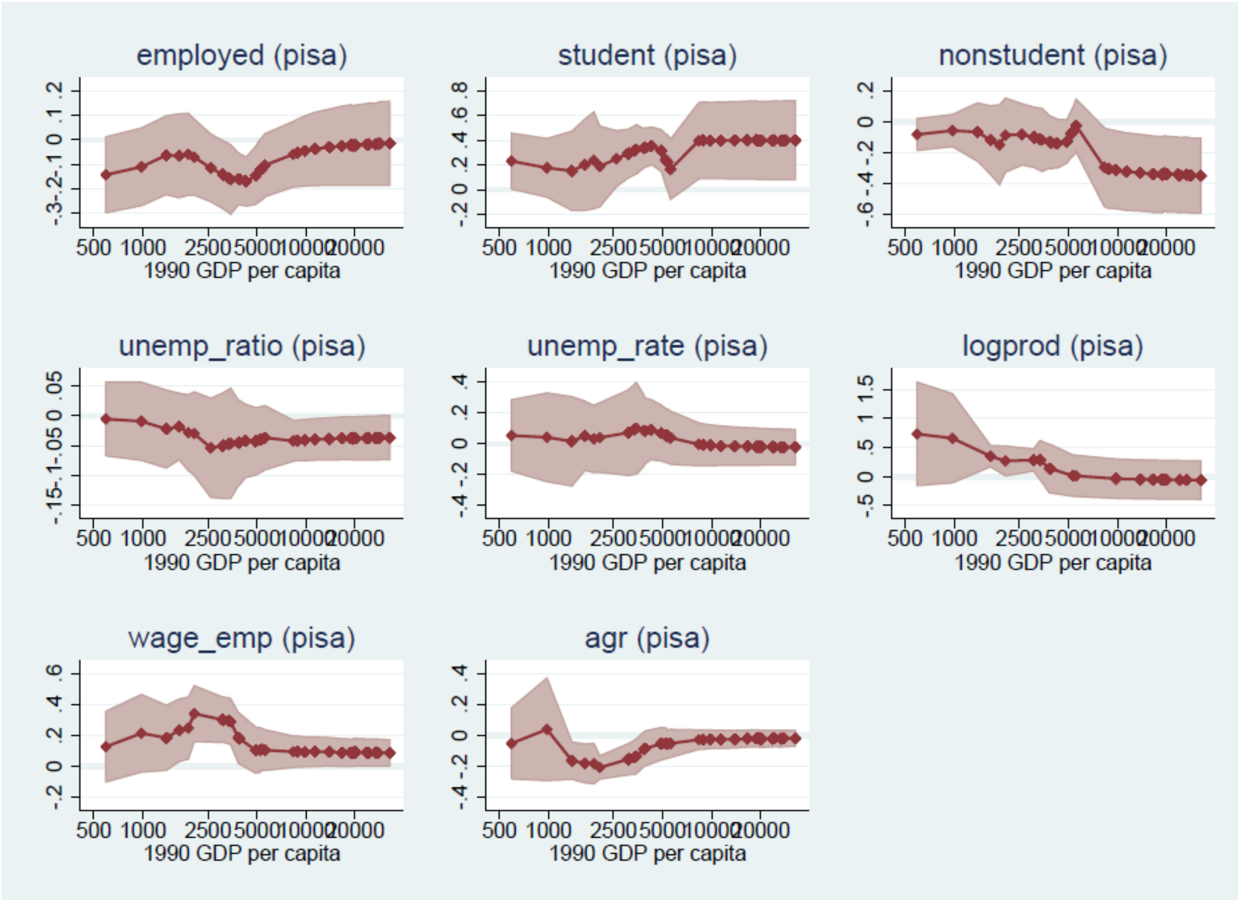


Figure 1b: Effects of test scores by GDP, TIMSS

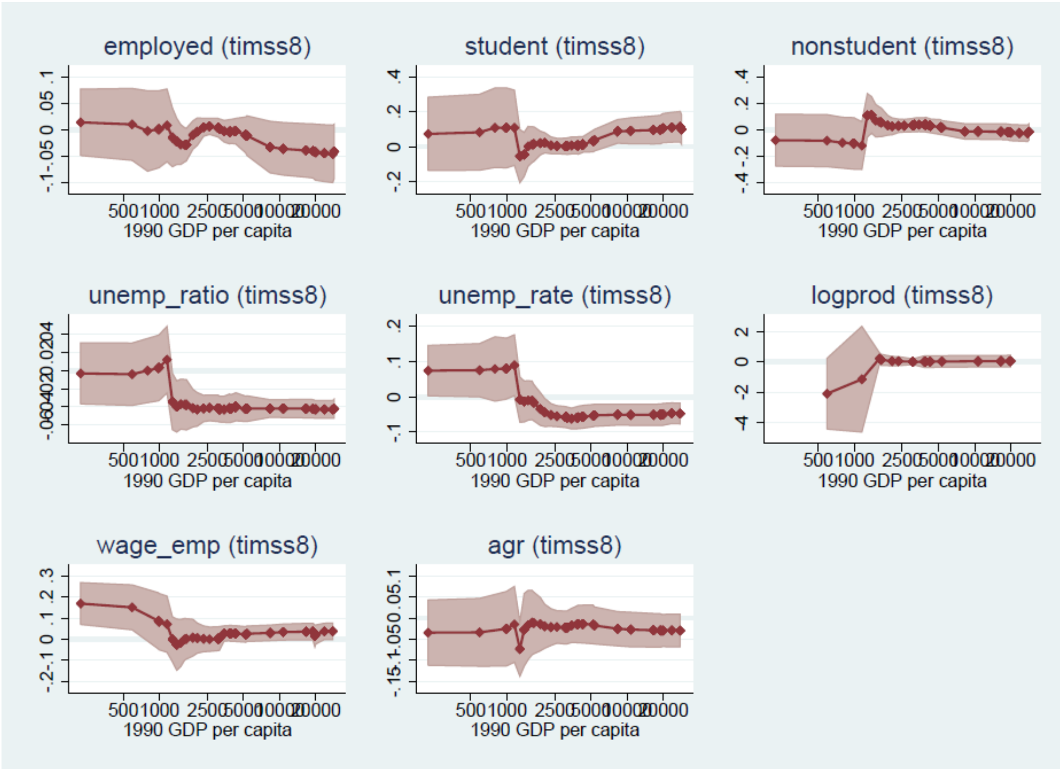
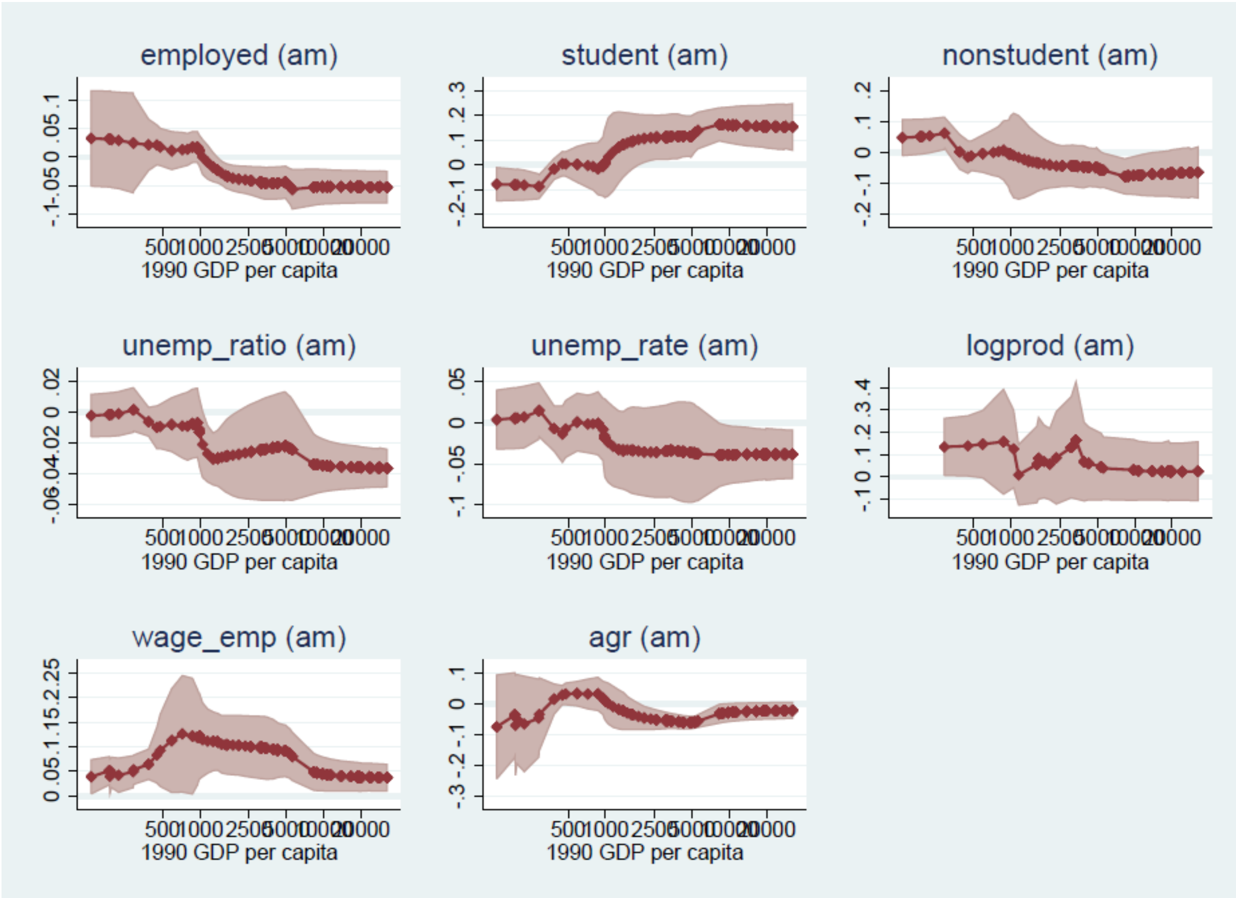


Figure 1c: Effects of test scores by GDP, Altinok-Murseli



Appendix Table 1: Years of education as a function of test scores

	(I) PISA	(II) TIMSS	(III) Altinok-Murseli
Test score	2.179***	0.436	-0.094
	(0.398)	(0.336)	(0.261)
Gender	0.024	0.882***	0.132
	(0.310)	(0.247)	(0.250)
Age	0.499***	0.568***	0.291***
	(0.047)	(0.063)	(0.042)
Log per capita GDP	0.644***	0.414**	0.812***
	(0.191)	(0.197)	(0.126)
Youth unemployment rate by gender, 1991	0.127***	0.182***	0.079***
	(0.032)	(0.042)	(0.024)
Youth labor force part. by gender, 1991	0.104***	0.191***	0.072***
	(0.032)	(0.044)	(0.027)
Natural resource rents to GDP, 1990	0.162***	0.019	0.047***
	(0.034)	(0.037)	(0.018)
R-squared	0.727	0.811	0.676
Number of observations	454	332	752

Note: Regressions also include per capita GDP in 1990, age, youth unemployment rates by gender in 1991, youth labor force participation rates by gender in 1991, natural resource to GDP ratios, regional dummies, and a linear time trend. Standard errors clustered on country.