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Are There Long-Term Benefits from Early Childhood Education in Low- and Middle-Income Countries?

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Abstract: We examine the relationship between participation in early childhood education (ECE) and various long-term outcomes: post-ECE educational attainment, the development of both cognitive and socioemotional skills, and labor market outcomes. The data are from the recent Skills Toward Employability and Productivity surveys of urban adults in 12 low- and middle-income countries. Using OLS regression and propensity score matching techniques, we find suggestive evidence of long-term benefits across countries, as well as mixed evidence within countries. Notably, we find positive and statistically significant associations between ECE participation and post-ECE educational attainment (a mean of 0.9 additional years across countries). We find relatively fewer cases of positive associations between ECE and long-term socioemotional outcomes. The evidence on ECE and labor market outcomes is varied, with positive associations for skill-

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use but weak associations with earnings. Such mixed results suggest that improvements in the quality of ECE programs are necessary for realizing the full range of long-term benefits.
Keywords: Early childhood education; comparative education; education policy; socioemotional skills; cognitive skills

¿Hay beneficios a largo plazo de la educación infantil en países de bajos y medianos ingresos?
Resumen: Examinamos la relación entre la participación en la educación de la primera infancia (ECE) y varios resultados a largo plazo: el logro educativo después de la ECE, el desarrollo de habilidades cognitivas y socioemocionales, y los resultados del mercado laboral. Los datos provienen de las recientes encuestas de Habilidades hacia el Empleabilidad y la Productividad de adultos urbanos en 12 países de ingresos bajos y medianos. Encontramos evidencia sugestiva de beneficios a largo plazo en todos los países, así como evidencia mixta dentro de los países. En particular, encontramos asociaciones positivas y estadísticamente significativas entre la participación de ECE y el logro educativo después de la ECE (una media de 0,9 años adicionales en todos los países). Encontramos relativamente pocos casos de asociaciones positivas entre ECE y resultados socioemocionales a largo plazo. La evidencia sobre ECE y los resultados del mercado laboral es variada, con asociaciones positivas para el uso de habilidades pero asociaciones débiles con los ingresos. Estos resultados mixtos sugieren que las mejoras en la calidad de los programas de ECE son necesarias para realizar toda la gama de beneficios a largo plazo.
Palabras clave: educación de la primera infancia; educación comparada; política educativa; habilidades socioemocionales; habilidades cognitivas

Há benefícios a longo prazo da educação infantil em países de baixa e média renda?
Resumo: Nós examinamos a relação entre a participação na educação infantil (ECE) e vários resultados a longo prazo: o sucesso escolar após a educação infantil, o desenvolvimento de habilidades cognitivas e sócio-emocionais, e os resultados do mercado de trabalho. Os dados são provenientes de pesquisas recentes sobre Competências para Empregabilidade e Produtividade de adultos urbanos em 12 países de baixa e média renda. Encontramos evidências sugestivas de benefícios a longo prazo em todos os países, bem como evidências mistas nos países. Em particular, encontramos associações positivas e estatisticamente significativas entre a participação no ECE e o desempenho educacional após a ECE (uma média de 0,9 anos adicionais em todos os países). Encontramos relativamente poucos casos de associações positivas entre ECE e resultados socioemocionais de longo prazo. A evidência sobre a ECE e os resultados do mercado de trabalho é mista, com associações positivas para o uso de habilidades, mas associações fracas com a renda. Esses resultados mistos sugerem que melhorias na qualidade dos programas de ECE são necessárias para a obtenção de toda a gama de benefícios a longo prazo.
Palavras-chave: educação infantil; educação comparada; política educacional; habilidades sócio-emocionais; habilidades cognitivas

Introduction

Currently, many countries are considering expanding early childhood education (ECE) programs, such as universal preschool, kindergartens, and daycare centers designed to foster cognitive and socioemotional development in children (Behrman & Urzúa, 2013; Campos, 2013; Cascio, 2015; Mostafa & Green, 2013; Nores & Barnett, 2010; OECD, 2012; Sayre, Devercelli, Neuman, & Wodon, 2015; Tatto, 2015; Wotipka, Rabling, Sugawara, & Tongliemnak, 2016). These policy considerations are supported by neuroscience evidence showing that brain synapses develop rapidly during a child's early years, thereby laying the foundation for cognitive and socioemotional functioning for the rest of a child's life (Shonkoff & Phillips, 2000). The ECE expansion efforts are also motivated by growing evidence of the long-term benefits that early childhood programs bring individuals and societies (Heckman, 2011). In this study, we contribute to the evidence base by presenting statistical associations between ECE participation and long-term outcomes using representative samples of urban adults in 12 low- and middle-income countries. By doing so, we provide suggestive evidence of the long-term benefits of ECE participation in these countries.

Our study is motivated by the fact that despite the promise of long-term benefits from investments in early childhood, several commonly noted limitations suggest that the current evidence base has only limited applicability to current decisions surrounding the policy of scaling up ECE in low- and middle-income countries. The first limitation is that the evidence of strong results from early childhood interventions typically comes from high-dosage, holistic early childhood development (ECD) programs, which differ substantially from the ECE programs that low- and middle-income countries are considering scaling (Mostafa & Green, 2013). Indeed, a concern that arises throughout the literature is that lower-quality ECE may *undermine* cognitive and socioemotional development (Cascio, 2015).

Second, most of the evidence comes from high-income countries and therefore may have limited applicability to low- and middle-income countries (Behrman & Urzúa, 2013). Third, some of the evidence is based on a handful of randomized-control trials that had small sample sizes, rather than regionally or nationally representative data that would permit generalizations (Heckman, 2011). Fourth, the populations in existing studies are often targeted and socioeconomically disadvantaged, which raises the question whether similar benefits could be achieved within a general population (Baker, 2011). Finally, the evidence on long-term benefits is limited (Bauer & Schanzenbach, 2016; Garces, Thomas, & Currie, 2002; Ruhm & Waldfogel, 2012). In short, there are doubts as to whether wide scaling-up of ECE participation will yield long-term benefits in low- and middle-income countries.

With this background in mind, we conduct an analysis of the long-term benefits to participation in ECE from these 12 countries: Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Laos, Macedonia, Sri Lanka, Ukraine, Vietnam, and China (Yunnan Province only). We use cross-sectional data from the Skills Toward Employability and Productivity (STEP) Skills Measurement surveys carried out between 2012 and 2014 (Pierre, Sanchez Puerta, Valerio, & Rajadel, 2014), which surveyed adults living in urban areas. For each respondent, we have a self-report of participation in a formally organized ECE facility such as a kindergarten, crèche, daycare, nursery school, or Montessori program prior to entering the formal education system.

The STEP surveys also include retrospective information on the respondent's household socioeconomic characteristics from the time respondents were young members of their households, which permits us to consider a rich set of covariates on childhood circumstances or "social origins." As for long-term outcomes, we consider the quantity of post-ECE schooling, adulthood cognitive skills (specifically, a literacy proficiency assessment), adulthood socioemotional skills or capacities (including self-reported Big Five personality traits, grit, and patience), and labor market outcomes, including self-reported participation, skill-use at work, and earnings.

Methodologically, we use ordinary least squares (OLS) and propensity score matching (PSM) techniques. We acknowledge that rigorous controlled evaluations of individual ECE programs are superior for establishing the causal impact of ECE on long-term outcomes (internal validity; Nores & Barnett, 2010). From a practical perspective, however, we recognize methodologists such as Angus Deaton and Nancy Cartwright (2016) who have argued that observational population-level studies allow one to reach generalizable findings (external validity). In this study, we are able to generalize about the multitude of early childhood programs experienced by the urban residents of the STEP countries.

We find statistical support for and therefore suggestive evidence of some long-term benefits from ECE in most of the low- and middle-income countries considered in this study. Notably, we find strong, positive statistical associations between ECE participation and post-ECE educational attainment in 11 of the 12 countries. In contrast, when we analyze associations between ECE participation and adulthood cognitive and socioemotional skills and labor market outcomes, we find inconclusive evidence of ECE benefits within and across countries. Statistical associations between ECE and long-term outcomes also differ by social origins, but we observe no consistent patterns. To add to the ongoing policy deliberations, we argue that realizing long-term benefits may require better-quality ECE programs than those that have been offered in the past and are currently offered.

A Brief Review of the Quantitative Research on Early Childhood Education

As a field, research on early childhood is large and continues to grow (Pianta, Barnett, Justice, & Sheridan, 2015). Our criteria for selecting the literature for review are as follows. First, we only review quantitative studies.[1] Second, we review literature on programs in low- and middle-income countries, making an exception only for a few seminal programs in high-income countries. Third, we mostly review articles on long-term benefits, although we consider studies that examine short-term cognitive and socioemotional benefits. Fourth, we review studies of large ECE programs that low- and middle-income countries intend to adopt, such as universal ECE and childcare programs. In addition, to highlight the importance of the quality of early childhood interventions, we also review the literature on ECD programs that are designed to foster children's holistic development across physical, cognitive, linguistic, and socioemotional domains from the prenatal stage though transition to primary school.

The literature on truly long-term outcomes of early childhood interventions comes from studies of highly subsidized ECD programs initiated by several European countries in the 1970s, including Denmark, France, and Norway (Cascio, 2015). Children who were part of the first cohort of Norway's relatively high-quality universal childcare program, for example, completed higher levels of education and were less likely to require welfare in their thirties than those who just missed eligibility. Additionally, earnings inequality was reduced among this first cohort, although this was due not to an increase in average earnings but rather to a decrease in earnings for children from households that fell within the upper part of the earnings distribution. Overall, the biggest impacts were observed for children from more disadvantaged backgrounds when measured 30 years later

[1] Our exclusion of the qualitative literature is in no way a dismissal of such literature. Indeed, qualitative research often provides deep insight into aspects of design, implementation, and mechanisms. Our focus on quantitative literature is dictated by space constraints. Nevertheless, some of the literature covered in this study also contain qualitative components (e.g., Stevens & English, 2016).

(Havnes & Mogstad, 2015). It is important to note, of course, that Norway's was a more comprehensive ECD program, rather than providing ECE alone.

Some of the studies on early childhood display a pattern of benefits changing across the life cycle, with most of the positive outcomes demonstrated during the short-term, then fading through adolescence, and finally reemerging somehow in adulthood. Three of the most commonly cited of these studies come from high-quality, high-intensity programs in the United States that targeted disadvantaged children and their families and focused on a broad range of skills: the Abecedarian, Perry, and Nurse-Family Partnership programs (Stevens & English, 2016). The Abecedarian Early Intervention Project, launched in the 1970s in the state of North Carolina, provided 57 low-income, high-risk children with high-quality, intensive, year-round, full-day early childhood intervention and parent engagement, beginning in infancy and continuing for five years. Follow-up studies in 1984 and 2014 demonstrated large and sustained effects on education attainment, employment, and other life outcomes. The Nurse-Family Partnership provides home visits by registered nurses to young, first-time, low-income mothers, beginning during pregnancy and lasting until the child turns two. Three randomized control trials have been conducted on the program since the 1970s, and all have shown large and sustained effects on child and maternal outcomes (Olds et al., 1998). The Perry Preschool Program was a pilot in Michigan in which 58 low-income, high-risk children and their families received eight months of preschool and home visits. Longer-term outcomes included less need for special education services, higher rates of high school completion, improved family planning, higher earnings, higher rates of employment and home ownership, and lower involvement in crime (Heckman, 2011).

In the context of low- and middle-income countries, anything prior to grade 1 is considered ECE (sometimes called kindergarten, preprimary school, or reception, depending on the system). Primary school is typically considered to start at grade 1, which is for children ages 6 or 7, depending on the country. The landmark study, by Gertler et al. (2014), is of a two-year psychosocial intervention in Jamaica that targeted children with reduced growth rates in their human development.[2] In particular, the program targeted 129 growth-stunted children from low socioeconomic backgrounds ages 9 to 24 months in 1986 and 1987. The program was a high-quality, holistic ECD intervention that included parenting and health support. A follow-up 20 years later found that the intervention had increased their earnings by 25%, which was enough to allow them to catch up to a nonstunted comparison group. The intervention was also associated with better self-esteem and lower anxiety and depression. The study also found strong, statistically significant effects on internalizing behaviors, defined by measures of self-esteem, anxiety, and depression.

Other studies from low- and middle-income countries consider ECE participation and shorter-term outcomes (measured at preschool age, elementary school age, or secondary school age). A study of urban children in Montevideo, Uruguay, by Aguilar & Tansini (2012) found that ECE participation was associated with higher test scores and lower grade repetition rates in the first and seventh years of elementary school. In a different study of children in all urban areas of Uruguay, Berlinski, Galiani, & Manacorda (2008) showed that ECE participants had accumulated 0.8 additional years of post-ECE schooling by age 15 and were 27 percentage points more likely to be enrolled in school than siblings who did not participate in ECE. In a study of ECE in Argentina, Berlinski, Galiani, & Gertler (2009) found that ECE participation led to an eight percent increase in average test scores in third grade and greater student self-control as measured by behaviors such as attention, effort, class participation, and discipline.

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[2] Reduced growth or stunted growth is a manifestation of malnutrition and recurrent infections such as diarrhea.

There is also emerging evidence from countries that have scaled up their ECE programs quickly, without sufficient attention to quality, that benefits are not achieved if programs are not of adequate quality. For instance, in South Africa, Grade R (for *r*eception year) was designed to prepare five-year-old children for primary schooling. In 2001, the government introduced a conditional grant to expand access to Grade R for children from low socioeconomic backgrounds. While the country saw an increase to near-universal ECE access by 2015, it faced challenges in ensuring program quality. An evaluation of this effort by Goldman (2014) compared mathematics and literacy scores among students in grades 1 through 6. Goldman found that Grade R participants from homes with higher socioeconomic status had higher scores, but also concluded that Grade R participation did not have a significant impact on learning outcomes in mathematics or literacy for children from the three poorest-wealth quintiles.[3]

Another example of an ECE program that was rapidly expanded is the Literacy Program at the Right Age (PAIC), which was run in Brazil's Ceará State in 2007. Using analytical techniques to compare test-score changes in Ceará and neighboring states, Costa & Carnoy (2015) found that PAIC had positive effects on student achievement in both mathematics and literacy scores from grades 1 through 9. Unlike South Africa's Grade R, gains were observed among PAIC participants from all socioeconomic backgrounds.

In summary, the quantitative studies on ECE programs in low-, middle-, and high-income countries suggest that ECE participation has short-term benefits, although these benefits may vary by program quality and the socioeconomic status of the children. The literature does not report cases of ECE participants having *worse* outcomes than nonparticipants. There is also a lack of studies on ECE participation and long-term outcomes in low- and middle-income countries. Our analysis of the relationship between ECE participation and long-term educational attainment, cognitive skills, socioemotional skills, and labor market outcomes in our 12 selected countries seeks to provide new information to address the knowledge gaps in the early childhood education literature.

Data

The STEP Skills Measurements surveys are a World Bank initiative for addressing the skills of urban adults in select low- and middle-income countries (Pierre et al., 2014). Country participation in the STEP surveys is a function of several factors, including interest, logistics, and funding. In this study, we use all available countries that were included in the initial wave of surveys carried out between March 2012 and July 2014.[4] The selection of these 12 countries is intended to illustrate the economic and regional diversity among countries considered low- or middle-income. According to World Bank classifications in 2014, the only low-income country (defined as having per capita income below $1,046)[5] in our selection is Kenya ($840). The lower-middle-income countries (defined as having per capita incomes from $1,046 to $4,125) are Armenia ($3,720), Bolivia ($2,220), Georgia ($3,280), Ghana ($1,550), Laos ($1,260), Sri Lanka ($2,920), Ukraine ($3,500), and Vietnam ($1,400). The upper-middle-income countries (defined as having per capita incomes from $4,126 to $12,735) include Colombia ($6,990), Macedonia ($4,870), and the Chinese province of Yunnan ($4,435). These countries represent several world regions: Eastern Europe and Central Asia (Armenia, Georgia, Macedonia, and Ukraine), Latin America (Bolivia and Colombia), Sub-Saharan

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[3] As Samuels et al. (2015) acknowledges, the Grade R evaluation was not a randomized control trial. Since the program was already in place, researchers matched participant and nonparticipant students with similar characteristics.

[4] The STEP data are publicly available at: http://microdata.worldbank.org/index.php/catalog/step

[5] In this paper, all references to dollars are to US dollars.

Africa (Ghana and Kenya), South Asia (Sri Lanka), Southeast Asia (Laos and Vietnam), and East Asia (Yunnan).

The STEP survey sampling strategy was designed to ensure that the target population represents at least 95% of the urban working-age population (ages 15 to 64) in each country. Given our interest in the working-age population of men and women, we follow the European Union's practice of using the 20–64 age group to define this population, which also facilitates comparison with the OECD's PIAAC data. To allow comparability of the data collected with other country surveys and to account for country contexts, the STEP surveys use each country's official definition of "urban." This was also essential for protecting the quality of the sample frames. To ensure consistency of the sampling strategies across all countries, all survey firms designed their sampling strategies in close cooperation with the STEP survey methodologist, who approved all sampling plans and drew the sample files used in each country.

The STEP survey has three unique modules: (1) a direct assessment of literacy proficiency and related competencies scored on the same scale as the OECD's PIAAC assessment; (2) a battery of self-reported information on personality, behavior, and preferences; and (3) a series of questions on the task-specific skills that the respondent possesses or uses in his or her job. As mentioned in the Introduction, compared to other data from low- and middle-income countries the STEP data are novel in including information on cognitive and socioemotional skills and retrospective information on respondents' early childhood educational experiences and household socioeconomic characteristics. Pierre et al. (2014) contains further details on the STEP design of the survey instruments, constructs measured, technical standards, and implementation protocols adopted to ensure data quality and comparability across countries.

Covariates

Our key covariate of interest is ECE participation. The basic structure of ECE in the STEP countries is comparable to that in other low- and middle-income countries: primary schooling starts at age 6, and anything prior to grade 1 is considered ECE. Appendix Table A2 shows for each country the current age of entry to primary school and policies for ECE. However, note that these are the current policies; for the STEP data, we are surveying adults who would have been in ECE 20 or more years ago (when few of these countries had any ECE formally established within the system). As we see, only Bolivia, Colombia, Ghana, and Vietnam currently have ECE as part of the compulsory education system, and this would not have been the case when the majority of the adults surveyed were in school several decades ago.

We construct the ECE participation covariate using the following STEP question: *Before age 7, did you attend a kindergarten, crèche, daycare, nursery school or Montessori?* Respondents had "Yes," "No," and "Do not know/Did not respond" response options. We construct ECE participation as a binary variable (1 = "yes" and 0 = "no") and drop individuals who responded, "Do not know/Did not respond." We acknowledge that this is a basic measure of ECE participation, lacking information on the quantity and quality of ECE, and thus has strong limitations. We also recognize that this question does not capture the fact that the nature of ECE has likely changed over time. Furthermore, the retrospective nature of the questions may be contaminated by recall error; this limitation was acknowledged by Garces, Thomas, & Currie (2002) in their study of the long-term benefits of ECE participation in the US.

Figure 1, which presents the relationship between age and ECE participation in the 12 countries, offers insight into both the demand and supply of ECE over time. In general, the figure illustrates that younger adults have participated in ECE at a higher rate than older adults. We observe a steady (linear) expansion in participation in Ghana, Macedonia, Sri Lanka, and Vietnam.

The graphs for Bolivia, Colombia, Laos, and especially Yunnan indicate rapid expansion of ECE participation (increasing at an increasing rate) in recent years; arguably, these latter countries are approaching universal ECE. In contrast, in Armenia, Georgia, and Ukraine we see a *decrease* in participation in the last two decades; this is consistent with a decline in participation in ECE in many post-Soviet economies once state support eroded in the 1990s.

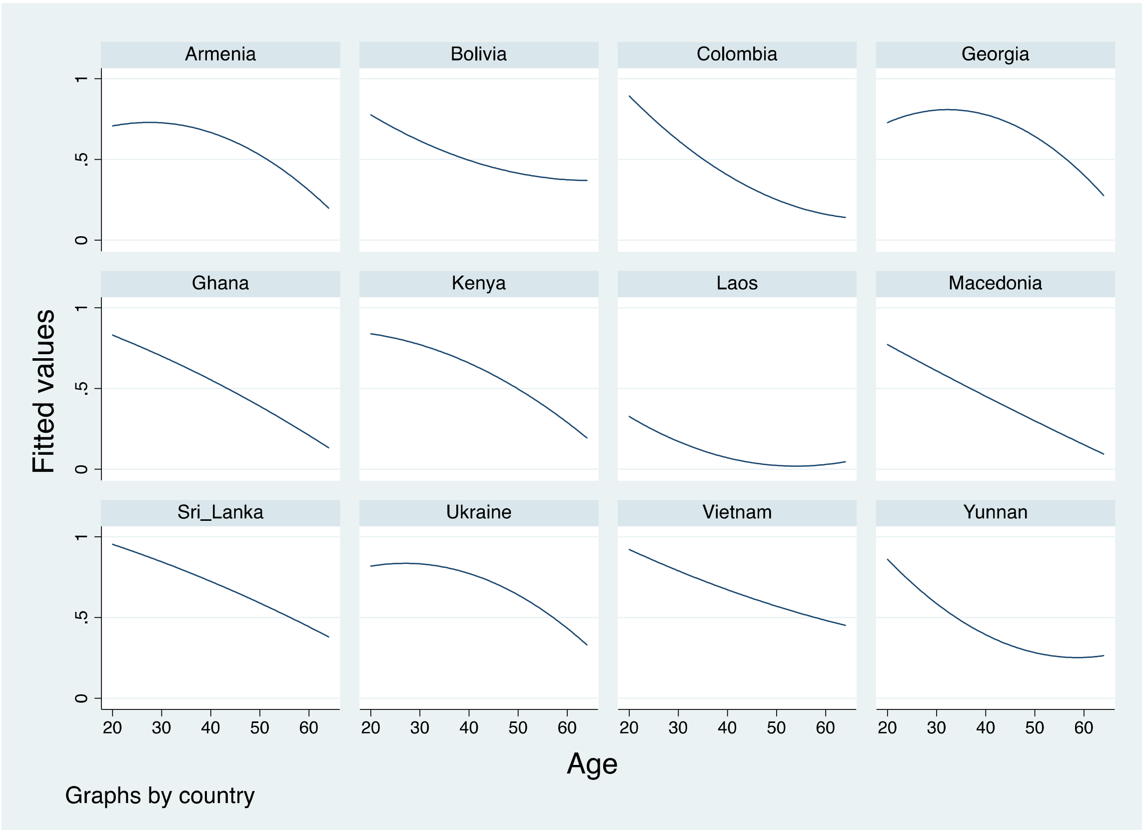

Figure 1. ECE participation rates (quadratic fitted lines) by respondent age and country

The STEP surveys allow us to consider four categories of social origins: (1) parental financial capital, (2) parental human capital, (3) parental social capital, and (4) birth order. The dummy variables on parental financial capital indicate low-income, middle-income, and high-income origins; the STEP survey methodologists constructed this variable based on responses concerning income, expenditure, economic shocks, and parental assets of the individuals at age 15.[6] Parental human capital is measured using an index that is based on the education of the most educated parent: *1* if

[6] The income variables are adjusted using 2010 PPP rates collected from the World Development Indicators database maintained by the World Bank. By converting income variables to 2010 PPP, we effectively adjust for inflation over time and purchasing power across country contexts. To address the possibility of reference bias arising because of retrospective reporting of social origin, we have compared the distribution of socioeconomic status at age 15 to the distribution of current assets as part of our preliminary analysis. We used information on dwelling characteristics, types of assets, and factor analysis to create an asset index for each of the countries in the sample. Measures of assets and dwellings with extremely skewed distributions and agricultural assets, as well as those showing low factor loadings, were excluded from the asset index. We find no evidence that the retrospective data are upwardly biased.

the most educated parent has a primary education, *2* if the most educated parent has a secondary education, and *3* if the most educated parent has higher education.

Drawing on the social capital theory of Coleman (1988), we construct a parental social capital variable that measures the quality of time spent using the STEP question: *When you were attending primary school, did either of your parents/guardians actively keep themselves informed of your exam/test results or grades?* Response choices include: "Yes, always or almost always," "Yes, sometimes," and "No, never or almost never."[7] Consistent with theoretical arguments on the economics of the family (Becker, 1991), we consider birth order as part of social origins, because of the prediction that financially constrained parents invest more in elder children because they provide greater benefits over the parental life cycle. We also consider age and gender to control for age-cohort and gender differences. Further information on these and other variables is available in Appendix Table A3. STEP does not include information on other social origins variables, such as cultural capital and school quality.

In the rest of this study, we acknowledge equity issues by separately presenting results for individuals from low social origins and those from middle and high social origins. Since there are several social origins variables, we can construct a social origin index in multiple ways. But consideration of all these measures also raises complications, such as assigning weights to each social origin variable; for example, should parental human capital be assigned more weight than parental social capital? For simplicity, we use only the STEP-constructed parental financial capital variable to group individuals as of low social origin versus middle or high social origins.[8]

Table 1 presents ECE participation rates for each country by social origin for all individuals and labor force participants only. As described earlier, ECE participation rate is the share (percentage) of adults who said that they attended a kindergarten, crèche, daycare, nursery school, or Montessori before age 7. In 11 countries, more than half of all adult respondents had participated in ECE. Contrary to what one might expect, a higher per-capita income does not imply a higher ECE participation rate. ECE participation rates are highest in Kenya (74.6%) and Sri Lanka (71.8%). ECE participation rates are generally high and comparable in Armenia, Georgia, and Ukraine; this is consistent with the social policies of the former Soviet Union, which emphasized providing childcare for all working families. Among the two countries with the lowest ECE participation rates, there is an enormous gap between Laos (13.1%) and Yunnan (41.5%).

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[7] According to Coleman (1988, p. S111), "Social capital within the family that gives the child access to the adult's human capital depends both on the physical presence of adults in the family and on the attention given by the adults to the child."

[8] Within each country, the STEP team used information on a variety of childhood financial capital variables to construct low social origin, middle social origin, and high social origin categories. These are not broken down by thirds; rather, the shares in each category varied by country. Furthermore, to account for the fact that contexts vary by country, the breakdown is specific to each country; therefore, we allow for the possibility that low social origin in Colombia may be comparable to middle social origin in Laos.

Table 1
ECE Participation Rates, by Country and Social Origin (%)

	All individuals			Labor force participants only		
		By social origin			By social origin	
	All	Low	Middle & high	All	Low	Middle & high
Armenia	58.4	51.6	58.9	61.0	63.2	60.7
Bolivia	58.2	55.8	80.3	57.0	55.2	76.8
Colombia	49.4	33.8	57.4	50.1	35.3	57.7
Georgia	68.2	59.5	69.0	70.5	66.7	70.9
Ghana	62.9	49.5	66.8	60.6	48.7	64.4
Kenya	74.6	68.9	76.8	73.8	67.9	76.0
Laos	13.1	5.3	18.1	12.2	5.2	16.7
Macedonia	43.3	25.6	45.6	49.8	34.4	51.6
Sri Lanka	71.8	64.3	75.0	71.4	63.7	75.2
Ukraine	67.3	60.7	68.9	73.4	74.7	73.0
Vietnam	68.5	61.8	71.6	69.6	65.1	71.7
Yunnan (China)	41.5	30.8	46.4	46.2	34.6	50.7
Pooled	57.2	45.0	60.9	57.7	46.1	61.5

Source: Authors' analysis, based on STEP data for ages 20–64.
Note: Samples and subsamples include ECE participants and nonparticipants; Figure 1 illustrates participation rates (%) by age.

Table 1 also shows ECE participation rates by social origins. As expected, we see lower ECE participation rates for low-origin individuals than middle- and high-origin individuals; the gaps are relatively small in Armenia, Ukraine, and Vietnam. Similar patterns are observed in the subsamples of labor force participants. Appendix Table A3 presents the ECE participation rates for men and women in each country. It shows that male ECE participation rates are slightly higher than female rates in all countries except Laos and Yunnan, which may reflect family preferences for investing in the human capital of sons.

Outcome Variables

Table 2 shows the descriptions of the key outcomes of interest. From the STEP surveys, we categorize long-term outcomes into four categories: (1) post-ECE educational attainment, (2) cognitive skills, (3) socioemotional skills, and (4) labor market outcomes. We initially consider post-ECE educational attainment (measured as years of post-ECE schooling) as an outcome variable. In later analyses, we include post-ECE educational attainment as a control variable to assess the sensitivity of ECE on the outcome variables.

Table 2
Descriptions of Long-Term Outcomes

Outcomes	Description
Post-ECE educational attainment	Constructed from the highest level of educational attainment, excluding year(s) spent in ECE
Cognitive skills:	
Literacy proficiency	The literacy assessment, designed by the Educational Testing Services (ETS), has three parts. The first part evaluates foundational reading skills, including word meaning, sentence processing, and passage comprehension. The second part consists of a core literacy assessment and is intended as a filter to sort the least literate adults from those with higher reading skill levels. The core has a total of eight items. Respondents with three or more correct responses are regarded as having met a minimum reading literacy threshold. The third part is only administered to respondents who have passed the core assessment. Overall reading proficiency scores are reported on a scale ranging from 0 to 500.
Socioemotional skills: (Note that for this section, respondents had the following response options: (1) "Almost never"; (2) "Some of the time"; (3) "Most of the time"; and (4) "All of the time.")	
Openness	Constructed using responses to three questions: *Do you come you come up with ideas other people haven't thought of before?* *Are you very interested in learning new things?* *Do you enjoy beautiful things, like nature, art and music?* We compute a mean score for each respondent, which ranges between 1 ("low openness") and 4 ("high openness").
Conscientious-ness	Constructed using responses to three questions: *When doing a task, are you very careful?* *Do you prefer relaxation more than hard work?* *Do you work very well and quickly?* We compute a mean score for each respondent that ranges between 1 ("low conscientiousness") and 4 ("high conscientiousness").
Extraversion	Constructed using responses to three questions: *Are you talkative?* *Do you like to keep opinions to yourself? Do you prefer to keep quiet when you have an opinion?* *Are you outgoing and sociable, for example, do you make friends easily?* We compute a mean score for each respondent that ranges between 1 ("low extraversion") and 4 ("high extraversion").
Agreeableness	Constructed using responses to three questions: *Do you forgive other people easily?* *Are you very polite to other people* *Are you generous to other people with your time and money?* We compute a mean score for each respondent that ranges between 1 ("low agreeableness") and 4 ("high agreeableness").
Emotional stability	Constructed using responses to three questions: *Are you relaxed during stressful situations?* *Do you tend to worry?* *Do you get nervous easily?* We compute a mean score for each respondent that ranges between 1 ("low emotional stability") and 4 ("high emotional stability").

Table 2 cont.
Descriptions of Long-Term Outcomes

Grit	Constructed using responses to three questions: *Do you finish whatever you begin?* *Do you work very hard? For example, do you keep working when others stop to take a break?* *Do you enjoy working on things that take a very long time (at least several months) to complete?* We compute the mean score for each respondent that ranges between 1 (“low grit”) and 4 (“high grit”).
Patience	To measure patience, we use STEP questions that asked respondents: *Do you prefer X today, or X(1+discount rate) for sure one year from now?* In each country, the amounts were provided in the local currency. We code the patience variable as follows: (1) “Discount rate ≥ 1.0,” (2) “0.5 ≥ Discount rate < 1.0,” (3) “0.2 ≥ Discount rate < 0.5,” and (4) “Discount rate ≤ 0.2.” In other words, an individual’s patience points take on the following discrete and ordinal values: 1 (very impatient), 2 (impatient), 3 (patient), and 4 (very patient).
Labor market outcomes:	
Labor force participation	Labor force participation = 1 if “yes” and = 0 if “no.”
Skill use at work	The subsamples of employed STEP respondents were asked separate questions about whether they use reading, writing, numeracy, and computer skills at the workplace. We construct a skill-use index by combing the “yes” and “no” responses to each of the four items. Thus, our skill use index ranges from 1 (“Does not use any of the four skills at the workplace”) to 4 (“Uses reading, writing, numeracy, and computer skills at the workplace”).
Earnings	We use data on weekly earnings of labor force participants, including unemployed workers (for computational purposes, replacing non-zero earnings of $0 with $1), part-time workers, and full-time workers. We then convert monetary values to natural logs, which facilitates the interpretation of coefficients.

To measure cognitive skills, we use STEP’s Literacy Assessments, particularly a literacy proficiency score that is constructed using a psychometrically proven assessment designed by ETS and scored on the same scale as the test in the OECD’s Programme for the International Assessment of Adult Competencies (PIACC). According to the PIAAC Literacy Expert Group (2009) and the STEP team (Pierre et al., 2014), the ETS assessment approach goes beyond the “literate versus illiterate” dichotomy in the following ways: the material is placed in adult contexts and is not school-based; the questions are task-oriented, requiring the individual to access and identify information, as well as to interpret it; and the material has varying levels of difficulty. Compared to self-reported approaches, the ETS and STEP assessment approach reduces measurement error, because individuals cannot exaggerate their own proficiency. The assessment contained 44 literacy items and was conducted in the language(s) requested by the respective governments. For logistical reasons, the literacy assessment was not carried out in Laos, Macedonia, Sri Lanka, or Yunnan.

A guide produced by the team responsible for the STEP survey provides details on the Literacy Assessment, including the measure of cognitive skills and evidence on score reliability and validity (ETS, 2014). ETS provided the World Bank with an item analysis report, including the statistics for the computation of the alpha reliability coefficient and standard error of measurement for the test (ETS, 2014, pp. 22–25,). In addition, the scorer reliability file provided to the World Bank includes within- and across-country (anchor scoring) Cohen’s Kappa coefficients and percent of scorer agreement per item (ETS, 2014, p. 26). Overall, results in STEP showed high scoring reliability.

We select the socioemotional skills outcome variables based on traditional measures such as the Big 5 Personality Traits: openness, conscientiousness, extraversion, agreeableness, and emotional stability (sometimes referred to as "neuroticism"). We also consider two other socioemotional skills that have recently received attention: grit (a combination of character, passion, and persistence) and patience (sometimes referred to as self-control, cognitive control, and self-discipline); both are thought to be important to children's success in life, but we are still learning how interventions in early childhood may or may not yield improved socioemotional outcomes (Cadena & Keys, 2015; Cappelan, List, Samek, & Tungodden, 2016; Duckworth, 2016; Mischel, 2015).

Although the use of such self-reported socioemotional skills is common among researchers, the data likely suffer from response bias (Paulhus, 1991).[9] For labor force participants only, we consider labor force participation and earnings. We also consider self-reported skill use at the workplace, which is considered a predictor of productivity (Quintini, 2014).

Conceptual Framework and Methodologies

Conceptual Framework

For any given person, participation in ECE can affect long-term outcomes in direct and indirect ways. The direct effect of ECE on long-term outcomes refers to the effect on outcomes regardless of the individual's post-ECE educational attainment. For instance, the direct effect of ECE is the same for an adult with six years of schooling as it is for someone with 14 years of schooling. The indirect effect of ECE refers to a central point raised in Heckman, Pinto, & Savelyev (2013), namely, that "skill begets skill." In other words, the indirect effect of ECE refers to the dynamic aspect of ECE, such that skills acquired during ECE facilitate skill acquisition in later grades. In more technical terms, human capital stocks in each period raise the efficiency of human capital production (Kilburn & Karoly, 2008). In turn, if parents are encouraged by their child's efficiency or disposition, they may make further investments in the child's educational attainment. Another way of thinking about the indirect relationship is to consider post-ECE schooling as the mediator variable, such that ECE affects long-term outcomes through schooling. Although we conceptually acknowledge the direct and indirect effects of ECE, the use of empirical techniques that would permit comparisons of direct and indirect effects is beyond the scope of this study.

Ordinary Least Squares (OLS)

In an ideal experimental setting, ECE treatment would be assigned randomly to some individuals but not to others. In this case, the simplest analytical approach would be to compute the difference between the means of the outcome (*y*) between the treated and the untreated. As numerous methodologists have noted (e.g., Khandker, Samad, & Koolwal, 2009), a better analytical approach would be an OLS regression that controls for observable characteristics of the individuals. The OLS regression equation with control variables for outcomes and ECE is this:

$$y = \alpha_0 + \alpha_1 ECE + \boldsymbol{\alpha_2}\mathbf{X} + \varepsilon$$

[9] We follow the literature and use the term "skills" but acknowledge Steinberg (2015, pp. 118–119) who argues that such traits are "capacities that are nourished, rather than skills that are acquired."

This regression function decomposes the outcome *y* into the sum of four additive parts: the constant terms α_0; the treatment effect of ECE α_1; a linear combination of covariates ***X***; and the residual ε unexplained by the model. This equation is appropriate for an outcome *y* that is either continuous or discrete. The parameter α_2 represents regression coefficients measuring the changes in outcome associated with changes in the determinants.

The comparison of the outcomes of two groups (ECE versus non-ECE) should produce a biased estimate of the causal effect of ECE participation because of endogeneity. Notably, the choice made by the household (when the individual was a young child) to enroll an individual in ECE may be endogenous; for example, parents may be more likely to enroll higher-ability children. If these ability differences affect long-term outcomes in ways other than ECE, a comparison of the outcomes for the two groups will produce a biased estimate of the causal effect of ECE. Thus, the traditional OLS regression approach is considered to produce naïve estimates of the ECE treatment effect.

Propensity Score Matching (PSM)

To address the above-mentioned problem of endogenous choice of ECE participation and reduce the bias, we turn to a propensity score matching (PSM) approach. Essentially, the propensity score is the probability of attending ECE conditional on the covariates. The idea is to compare individuals who, based on observable characteristics, have a very similar probability of attending ECE (having similar propensity scores), choosing them such that one received the treatment and the other did not. The difference in the outcome variable is then attributed to the treatment. Several studies have used PSM techniques to examine ECE and short-term outcomes, including Hill, Waldfogel, & Brooks-Gunn (2002) and Warren & Haisken-DeNew (2013).

Our theory of selection into ECE treatment draws from prior empirical research on ECE that uses secondary data and social science theories of household investment in education (Becker, 1991; Coleman, 1988; Garces et al., 2002). The STEP data contain several covariates that influence selection into ECE, such as parental human capital, parental financial capital, parental social capital, gender, sibling composition, and age-cohort. However, the STEP data do not contain measures of other constructs that affect selection into ECE, such as IQ prior to ECE enrollment or proximity to ECE facilities. As Wong, Valentine, and Miller-Bains (2017) note, it is rare for secondary datasets to have rich covariate information representing multiple domains of interest.

We follow the Abadie & Imbens (2011) approach to propensity score estimation and proceed in three stages. In the first stage, we find the propensity score. We conduct a simple logit regression that places the probability of attending ECE on the left-hand side and the covariates that determine selection into the treatment on the right-hand side:

$$ECE = \theta_0 + \theta_1 \mathbf{X} + \varepsilon_p$$

Next, we use the logistic regressions to predict the probability of ECE treatment, and through prediction derive propensity scores where individuals with ECE are matched with individuals without ECE based on similarities in their estimated probabilities of being treated. We can then obtain the balancing assumption,

$$\mathrm{E}(\mathbf{X}|ECE = 1) = \mathrm{E}(\mathbf{X}|ECE = 0),$$

where conditional on the propensity of the treatment, the treatment assignment (*ECE*) is independent of the characteristics (***X***), which results in treated and nontreated participants having similar post-matching observed characteristics. We opt for the simple nearest neighbor matching with one neighbor and no caliper. If the balancing assumption holds, then we can compare the average outcome for the treated and untreated groups to determine the average treatment effect of ECE.[10] The covariates (***X***) are listed in Appendix Table A4.

As mentioned earlier, to check the sensitivity of ECE coefficients, we exclude years of schooling as an explanatory variable in one set of regressions, and include the variable in a separate set of regressions. To make generalizations, we run regressions for the pooled sample that include individuals from all 12 countries; analytically, we include dummy variables for each country. We also run the analysis on subgroups by social origin (low origin versus middle and high origin) to determine whether ECE benefits vary by social origins (Alderman, 2011; Bassok et al., 2016a).

From a demand-side perspective, if the quality of ECE experienced were the same for all individuals regardless of social origin, then we might expect larger benefits for lower-origin individuals, because the ECE would have helped them overcome their disadvantaged circumstances. A supply-side perspective is that low-origin individuals experience inferior ECE quality that (therefore) does not produce long-term benefits. The policy implications will vary depending on the findings by social origin: relatively large benefits for low-social-origin individuals would provide evidence of the equity-enhancing aspects of ECE. In contrast, relatively larger benefits for privileged-social-origin individuals would draw more policy attention to efforts to improve ECE quality for the disadvantaged. (Because of space considerations, we present ECE coefficients for each country in the Appendix. In the main text, we draw attention to both typical and outlier cases, such as negative and statistically significant ECE coefficients).

Results

As is common practice with PSM studies, we conduct covariance balance checks to compare initial group mean differences between ECE participants (i.e., the treatment group) and nonparticipants (i.e., the control group) in regard to covariates. The results from the balance checks are presented in Appendix Tables A4 and A5 for the pooled sample of individuals and labor force participants, respectively. The results show that the groups' differences were generally reduced after matching, and that the groups are well balanced. The tables in the main text present the ECE coefficients and standard errors obtained from OLS and PSM regressions for the pooled sample of individuals from all 12 STEP countries. We present the ECE coefficients obtained from regressions without controls for schooling along with the ECE coefficients obtained from regressions with controls for schooling, to allow us to consider the sensitivity of ECE coefficients. Finally, we present the results for individuals from low, middle, and high social origins using the STEP-constructed financial capital variable (based on responses on household income, expenditure, assets, and economic shocks at age 15). In the remainder of this section, we describe ECE coefficients for each long-term outcome.

[10] As Austin (2009) notes, there is no clear consensus on the issue of the residual imbalance between treated and untreated subjects in the matched sample: "some researchers have proposed that standardized difference of 0.1 (10%) denotes meaningful imbalance in the baseline covariate." We follow this guideline in interpreting balance checks in terms of acceptable standardized differences between groups.

ECE and Post-ECE Educational Attainment and Cognitive Skills

Post-ECE Educational Attainment. According to the OLS and PSM models in Table 3, there is strong statistical evidence that ECE is associated with higher educational attainment: individuals who received ECE have approximately 0.9 years of additional schooling. The ECE coefficient sizes are slightly larger for children from low social origins, which is consistent with the literature documenting larger ECE benefits for the most disadvantaged children. The results for each country shown in Appendix Table A6 show ECE associations ranging from 0.2 to 1.8 additional years of schooling. The associations are particularly strong in lower-middle-income countries such as Ghana, Vietnam, and Yunnan Province. Sri Lanka is the only case where the ECE coefficient is statistically insignificant. In Bolivia and Kenya, individuals from privileged origins gain more years of schooling from ECE than individuals from low origins, holding other factors constant; this might suggest that the low-origin individuals in Bolivia and Kenya attended ECE programs of inferior quality, although our data do not allow us to explore this hypothesis.

Table 3
ECE coefficients from OLS and PSM regressions of post-ECE schooling using pooled sample

Outcome	All (n = 27,655)		Low social origin (n = 6,140)		Middle & high social origin (n = 21,515)	
	OLS	PSM	OLS	PSM	OLS	PSM
Post-ECE Schooling	.88**	.90**	1.03**	1.15**	.83**	.87**
	(.05)	(.07)	(.11)	(.15)	(.05)	(.09)
R-squared	.367		.301		.333	

Source: Authors' analysis based on STEP data for ages 20-64 in all 12 STEP countries.
Note: Standard errors in parentheses; statistical margin of error at * p < 0.10; ** p < 0.05.

Literacy proficiency. Table 4 shows mixed associations between ECE and literacy proficiency. Without controlling for post-ECE schooling, we see statistically significant but small positive associations between participation in ECE and literacy proficiency. Once we control for years of schooling, the results are no longer statistically significant for the pooled sample of countries. In the analysis by social origin subsamples, we observe statistically significant associations for individuals from middle and high social origins only. The results in Appendix Table A7 show positive and statistically significant associations in Bolivia and Vietnam, after controlling for schooling and other covariates. The negative and statistically significant coefficients for low-origin individuals in Kenya might point to the weak quality of ECE content, but again our data do not allow us to explore this hypothesis.

Table 4
ECE Coefficients from OLS and PSM Regressions of Cognitive Skills, Using Pooled Sample

Outcome	No control for schooling						With control for schooling					
	All (n = 27,655)		Low social origin (n = 6,140)		Middle & high social origin (n = 21,515)		All (n = 27,655)		Low social origin (n = 6,140)		Middle & high social origin (n = 21,515)	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Literacy	5.1**	5.4**	1.0	4.5	6.4**	7.0**	-1.1	-1.4	-8.2**	-6.7**	1.0	1.2
	(1.0)	(1.3)	(2.5)	(3.1)	(1.1)	(1.5)	(.9)	(1.2)	(2.2)	(3.0)	(1.0)	(1.4)
R-squared	.322		.305		.309		.434		.461		.407	

Source: Authors' analysis based on STEP data for ages 20-64 in all STEP countries except Laos, Macedonia, Sri Lanka, and Yunnan.
Note: Standard errors in parentheses; statistical margin of error at * p < 0.10; ** p < 0.05.

ECE and Long-Term Socioemotional Outcomes

Table 5 presents the associations between ECE participation and seven socioemotional skills: openness, conscientiousness, extraversion, agreeableness, emotional stability, grit, and patience.

Table 5
ECE Coefficients from OLS and PSM Regressions of Socioemotional Skills using Pooled Sample

Outcome	No control for schooling						With control for schooling					
	All (*n* = 27,655)		Low social origin (*n* = 6,140)		Middle & high social origin (*n* = 21,515)		All (*n* = 27,655)		Low social origin (*n* = 6,140)		Middle & high social origin (*n* = 21,515)	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Openness	.040**	.039**	.049**	.042**	.038**	.054**	.013	.021	.013	.019	.014*	.028**
	(.008)	(.010)	(.018)	(.021)	(.008)	(.012)	(.008)	(.010)	(.017)	(.021)	(.008)	(.011)
R-squared	.145		.141		.130		.176		.187		.157	
Conscientiousness	.012*	.017	-.017	-.032	.021**	.026**	.001	.013	-.028*	-.028	.010	.013
	(.007)	(.009)	(.015)	(.024)	(.008)	(.011)	(.007)	(.010)	(.015)	(.024)	(.008)	(.011)
R-squared	.108		.146		.097		.114		.152		.103	
Extraversion	.066**	.065**	.043**	.051**	.074**	.070**	.054**	.063**	.023	.033	.063**	.066**
	(.008)	(.011)	(.018)	(.026)	(.009)	(.012)	(.008)	(.012)	(.018)	(.026)	(.009)	(.013)
R-squared	.088		.050		.101		.095		.063		.106	
Agreeableness	.031**	.035**	.029*	.019	.032**	.044**	.022**	.035**	.015	.001	.025**	.046**
	(.008)	(.010)	(.017)	(.022)	(.009)	(.011)	(.008)	(.010)	(.017)	(.022)	(.009)	(.011)
R-squared	.077		.073		.076		.081		.081		.079	
Emotional stability	.001	-.013	-.005	-.032	.001	.004	-.010	-.014	-.016	-.030	-.010	-.016
	(.008)	(.011)	(.018)	(.023)	(.010)	(.013)	(.009)	(.012)	(.018)	(.024)	(.010)	(.013)
R-squared	.155		.164		.154		.158		.168		.158	
Grit	.017**	.024**	.006	.010	.021**	.015	.008	.016	.002	-.006	.011	.015
	(.009)	(.012)	(.019)	(.025)	(.010)	(.013)	(.009)	(.011)	(.019)	(.024)	(.010)	(.013)
R-squared	.084		.075		.086		.087		.077		.089	
Patience	-012	.005	.113**	.130**	-.038**	.004	-.009	.008	.084*	.134**	-.035**	-.039*
	(.016)	(.020)	(.034)	(.047)	(.018)	(.022)	(.016)	(.021)	(.033)	(.049)	(.017)	(.022)
R-squared	.054		.060		.057		.055		.060		.057	

Source: Authors' analysis based on STEP data for ages 20-64 in all 12 STEP countries.
Note: Standard errors in parentheses; statistical margin of error at * $p < 0.10$; ** $p < 0.05$.

Openness. In Table 5, we find consistent evidence of positive and statistically significant associations between ECE and openness scores in models without controls for schooling. After controlling for schooling, we find positive associations only for individuals from middle and high social origins. These results suggest that individuals from all social origins may benefit from ECE indirectly through schooling. In the results arranged by country in Appendix Table A8, we find evidence of ECE benefits among middle and high origin individuals in Bolivia and Kenya only.

Conscientiousness. Table 5 shows several instances of statistically significant associations without controlling for schooling among individuals from middle and high social origins. After including controls for schooling, we find no cases of statistically significant coefficients. The results by country in Appendix Table A9 reveal positive associations in Armenia and Georgia, but negative and statistically significant associations in Ukraine and Vietnam. There is evidence of ECE benefits in Georgia for middle- and high-origin individuals.

Extraversion. We find evidence of positive and statistically significant associations between ECE and extraversion in models without controls for schooling. After controlling for schooling, we observe positive associations only for individuals from middle and high social origins. This suggests that there are benefits for individuals from these origins, but only indirect benefits for those from lower social origins. In the country-level results shown in Appendix Table A10, we find negative associations in Sri Lanka for individuals from low social origins, but relatively large, positive, and statistically significant coefficients in Bolivia, Kenya, and Ukraine.

Agreeableness. Table 5 shows numerous cases of statistically significant associations between ECE and agreeableness in the models both without and with controls for schooling. The only case where coefficients are insignificant concerns individuals from low social origins. The country-level results in Appendix Table A11 show relatively large positive associations for low-social-origin individuals in Macedonia. In Kenya, the associations are positive only for individuals from middle and high origins.

Emotional stability. The pooled results in Table 5 show no cases of statistically significant associations between ECE and emotional stability. Thus, there is no evidence of benefits from ECE concerning this socioemotional skill. The country-level results in Appendix Table A12 show some instances of negative associations in Vietnam, particularly for individuals from low social origins.

Grit. The results in Table 5 suggest that participation in ECE is associated with grit. Without controls for schooling, we see that ECE participation has a positive and statistically significant association with grit scores. After controlling for schooling, however, the ECE coefficients are no longer statistically significant. The results in Appendix Table A13 show that in Colombia, participation in ECE is statistically associated with higher grit scores, particularly for those from low social origins. The results for Kenya suggest benefits for individuals from middle and high social origins only. In contrast, the negative and statistically significant coefficients from Vietnam suggest that ECE participation may have perverse effects on grit, particularly for individuals from middle and high social origins.

Patience. Table 5 shows that the association between ECE and patience is statistically significant for both social origin categories, but in different ways. The coefficients are positive and statistically significant for individuals from low social origins. In contrast, the ECE coefficients are negative and statistically significant for individuals from middle and high origins. The results in Appendix Table A14 provide evidence of positive effects in Armenia and Laos. In Yunnan, there are positive and statistically significant associations for low origin individuals and negative and statistically significant associations for middle and high origin individuals.

ECE and Labor Market Outcomes

Table 6 presents OLS and PSM results concerning labor force participation.[11] Table 7 shows the results for skill use at work and the natural log of earnings obtained using the subsamples of labor force participants.

[11] Labor market participation is a binary outcome. We use OLS methods (sometimes referred to as "linear probability models" when dealing with binary outcomes) because the proportions are not too close to 0 or 1. Thus, the interpretations are straightforward. For example, a 0.204 coefficient indicates that a person with

Labor force participation. Table 6 shows positive and statistically significant ECE coefficients before controlling for schooling. Analysis by social origins indicates that ECE is only statistically associated with higher labor force participation among individuals from low social origins; the ECE coefficients are only statistically significant for these individuals after controlling for schooling. Appendix Table A15 shows that ECE increases labor force participation among middle- and high-origin individuals in Macedonia and Yunnan, and among low-origin individuals in Ukraine. There is evidence of ECE benefits in Macedonia and Ukraine.

Table 6
ECE Coefficients from OLS and PSM Regressions of Labor Market Participation using Pooled Sample

Outcome	No control for schooling						With control for schooling					
	All (*n* = 27,655)		Low social origin (*n* = 6,140)		Middle & high social origin (*n* = 21,515)		All (*n* = 27,655)		Low social origin (*n* = 6,140)		Middle & high social origin (*n* = 21,515)	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Labor market participation	.015**	.016**	.022**	.033**	.012*	-.001	.005	-.003	.019	.035**	.001	-.004
	(.006)	(.008)	(.011)	(.015)	(.007)	(.009)	(.006)	(.008)	(.012)	(.014)	(.007)	(.009)
R-squared	.182		.229		.171		.189		.231		.181	

Source: Authors' analysis based on STEP data for ages 20–64 in all 12 STEP countries.
Note: Standard errors in parentheses; statistical margin of error at * $p < 0.10$; ** $p < 0.05$.

Skill use at work. To examine the relationship between ECE participation and labor productivity, we examine skill use at work using subsamples of employed individuals. In Table 7, the numerous cases of positive and statistically significant ECE coefficients in models with and without controls for schooling suggest that ECE has direct and indirect benefits on productivity. The analyses by social origins show that people from low origins are likely to benefit from ECE. The country-level results in Appendix Table A17 show evidence of ECE benefits in Bolivia, Ghana, and Macedonia for individuals from higher origins only. The evidence from Kenya is generally positive across social origins. Results from Yunnan suggest that low-origin individuals enjoy higher benefits than middle- and high-origin individuals.

Table 7
ECE Coefficients from OLS and PSM Regressions of Labor Market Skill Use using Pooled Sample

Outcome	No control for schooling						With control for schooling					
	All (*n* = 15,709)		Low social origin (*n* = 3,656)		Middle & high social origin (*n* = 12,123)		All (*n* = 15,709)		Low social origin (*n* = 3,656)		Middle & high social origin (*n* = 12,123)	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Skill use at work	.204**	.196**	.214**	.211**	.202**	.231**	.066**	.074**	.056	.033	.070**	.062**
	(.022)	(.030)	(.046)	(.061)	(.025)	(.032)	(.020)	(.026)	(.041)	(.056)	(.022)	(.029)
R-squared	.163		.152		.145		.329		.339		.308	
Earnings	.086*	.102	.042	-.137	.103**	.119	.006	.031	-.077	-.123	.035	-.013
	(.047)	(.075)	(.107)	(.193)	(.052)	(.077)	(.047)	(.085)	(.106)	(.264)	(.052)	(.094)
R-squared	.519		.455		.539		.530		.473		.547	

Source: Authors' analysis based on STEP data for ages 20-64 in all 12 STEP countries.
Note: Standard errors in parentheses; statistical margin of error at * $p < 0.10$; ** $p < 0.05$.

ECE is 20.4 percentage points more likely to participate in the labor force than a person who did not attend ECE, holding other observable characteristics constant.

Extensions

We also ran additional analyses that we summarize here (and will make available upon request). To address the possibility of gender gaps in educational outcomes (OECD, 2012), we ran OLS and PSM regressions for subsamples of males versus females, and we found some patterns in ECE coefficients by gender. For example, in the case of literacy proficiency, ECE coefficients for females are smaller than those for males. In contrast, in the cases of grit and extraversion, ECE coefficients for females are larger than those for males. In the case of emotional stability, we find negative associations in Sri Lanka, Ukraine, and Vietnam for females but not for males.

We also ran separate OLS and PSM regressions for subsamples of individuals in the 20–30 and 31–64 age cohorts. To our surprise, pooled results from subsamples of individuals in the two age groups generally show comparable associations for the two age groups.

Summary, Discussion, and Policy Implications

Summary

The association between ECE participation and post-ECE educational attainment is striking. Across 11 of 12 countries, adults who participated in an ECE program tend to stay in school 0.2 to 1.8 years longer than peers who did not. The pooled figure across countries is 0.9 years. These results control for differences in social origin, gender, and age. Once we look more closely at differences by social origins, we see that the association between ECE participation and post-ECE educational attainment tends to be stronger for individuals from low origins than for those from middle and high origins.

Moving beyond post-ECE educational attainment, we examine associations between participation in ECE and long-term cognitive skills, socioemotional skills, and labor market outcomes. For cognitive skills outcomes, there is a strong positive association between ECE participation and literacy proficiency. However, once we control for post-ECE years of schooling, the results are no longer statistically significant. This suggests that the effect on literacy outcomes is delivered through the channel of post-ECE years of schooling.

When we move on to examine statistical associations between ECE participation and socioemotional skills and labor market outcomes, the picture is less clear. Across countries, we find some evidence of ECE's effect on higher workplace skill use, but we do not find anything conclusive for any of the socioemotional and labor market outcomes. Within countries, we see some differences in statistical associations by social origins, but no clear patterns. In addition, within countries, we find evidence of ECE benefits on openness, conscientiousness, extraversion, agreeableness, grit, patience, and skill use.

There is a range of possible interpretations of our finding of minimal cases of statistically significant associations between ECE and long-term socioemotional skills and labor market earnings. Again, part of the explanation may lie with measurement issues related to the explanatory variable (the duration, quality, or content of the ECE programs attended) or to the outcome variables (the self-reported measures used to assess adults' socioemotional skills).

Discussion

Our findings both converge on and diverge from the prior research reviewed earlier in this paper. As was found in previous studies of the Abecedarian, Perry, Nurse Family Partnership, Argentina, Jamaica, and Montevideo programs (Aguilar & Tansini, 2012; Berlinski, Galiani & Gertler, 2009; Berlinski, Galiani & Manacorda, 2008; Gertler et al., 2014; Heckman, 2011; Olds et al., 1998; Stevens & English, 2016), we find statistically significant and positive associations between

ECE participation and long-term outcomes. This is unusual, because those previous studies focused on higher quality programs that targeted (disadvantaged) individuals who were most likely to benefit from such programs. In contrast, we find positive associations between a variety of ECE programs for individuals from low, medium, *and* high socioeconomic backgrounds.

Some of our findings are also consistent with previous findings from Norway's high-quality universal childcare program (Cascio, 2015), with associations between ECE participation and long-term outcomes being larger for individuals from lower social origins. Furthermore, our finding of no statistically significant associations between ECE participation and short-term outcomes echoes the previous research on ECE participation and short-term outcomes in South Africa's Grade R and Brazil's PAIC programs (Costa & Carnoy, 2015; Goldman, 2014).

Unlike the previous studies, we also find some instances of negative associations between ECE participation and long-term outcomes. Again, this is to be expected, because previous studies have focused on high-quality ECE programs. By considering the variety of ECE programs that have been in place, we have likely captured lower-quality programs that may not lead to long-term benefits.

Our results point to several areas deserving further study. Methodologically, we acknowledge that PSM is not a perfect strategy for establishing causality. It relies on the assumption that all factors relevant for selection into treatment are observed and taken into account by the matching algorithm. Since matching unobservables is not possible, to the extent that there exist individual characteristics that influence both selection into treatment and the outcome that we cannot control for, our estimates may still be biased. The richness of the STEP data, however, allows us to consider some traditionally unobserved characteristics. As a result, the effects of these unobservables on our estimates will be relatively small, so the PSM model represents an improvement over the OLS regression model.

Other issues arise from evaluating ECE effects without a randomized experiment. For example, Smith and Todd (2005) found that PSM results are highly sensitive to both the set of explanatory variables included and the particular analysis sample used in the estimation. We recognize and address this point by the inclusion and omission of the post-ECE schooling variable and by running separate analyses by subsample of advantaged and disadvantaged groups; nevertheless, issues with the PSM results are likely to persist.

We would have preferred to use additional techniques that have been recently used to study the long-term benefits of ECE. Unfortunately, the cross-sectional and relatively small size of the STEP data do not permit the kind of methods permitted by large panel data, such as those used in the Panel Study of Income Dynamics (Bauer & Schanzenbach, 2016) and the National Longitudinal Study of Youth (Garces, Thomas, & Currie, 2002). Data limitations also prevent us from considering supply-side variables such as the concentration of ECE facilities in neighborhoods (Loeb, Bridges, Bassok, Fuller, & Rumberger, 2007). In short, methodological extensions for stronger claims of causality could involve the use of large randomized-control trials or longitudinal data from low- and middle-income countries. To date, few randomized-control trial studies of ECE follow participants into adulthood, and few longitudinal datasets include items on early childhood and long-term outcomes.

Other future studies with cross-sectional or panel data should consider causal mediation analytical techniques (see Bein et al., 2018; Pearl, 2012). As indicated in our conceptual framework, ECE affects long-term outcomes both directly and indirectly (via schooling). While we considered using causal mediation techniques for this study, we realized that the results for all countries, outcomes, and sub-samples could not be adequately captured in a single article. Future causal studies should also consider the cost-effectiveness of early childhood programs (Reynolds & Temple, 2008).

The challenge is to identify ECE programs that balance cost and effectiveness in a way that permits nationwide expansion, with an emphasis on reaching those most in need.

Other strands for research extension are case studies that explicitly consider the quality and equity aspects of ECE within countries (Bassok et al., 2016b; Fuller, 2007). For example, there may be useful lessons from studying ECE in Colombia, where we find a relatively high number of positive findings. In contrast, there may be cautionary lessons from studying Sri Lanka, where positive findings are rare. A careful examination of ECE programs is also recommended for countries where we observe both positive and negative findings, including Kenya, Vietnam, Ukraine, and Yunnan; it is possible that ECE programs in these countries have both beneficial and harmful features.[12] Since we find that certain ECE benefits are larger among low-origin individuals in Ghana and Macedonia, it may be useful to explore the equity features of ECE programs in those countries.

As an added bonus, case studies that document the timing and location of ECE expansion can help guide alternative empirical methods, such as difference-in-difference and regression discontinuity, for future quantitative studies of ECE benefits. Finally, case study approaches can help document changes in the quality and equity aspects of ECE programs over time.

Policy Implications

The potential policy implications of this study are several. The study provides an indication of the potential benefits of ECE, particularly in regard to post-ECE educational attainment, indicating that current policies being considered to expand public ECE do merit consideration and could yield benefits, including long-term ones. As more and more countries, states, and cities expand ECE, experimentation should be prioritized to examine quality, including careful studies of the benefits from differing levels of program quality. With more and more pressure on assessment, it will be important, especially in ECE, to consider pedagogically and age- appropriate program content, structure, and assessment.

Finally, while this study did not allow us to examine these questions, there is a vast literature suggesting that as ECE programs are scaled, it is critical that they be designed to support children's holistic learning rather than have an excessive focus on cognitive performance alone (Bodrova & Leong, 2010; Duncan et al., 2007; Nicolopoulou, 2010; Weisberg, Hirsh-Pasek, & Golinkoff, 2013).

Conclusions

In this study, we examined the long-term benefits of ECE participation in low- and middle-income countries. Using the STEP Skills Measurement surveys of urban adults and statistical

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[12] Exposure to inadequate ECE is potentially harmful (Currie, 2001). While inadequacy can entail unqualified staff, it could also entail an overemphasis on testing. For example, in the United Kingdom, 127 senior figures signed a letter in the *Telegraph* newspaper that warned of the harmful effects of excessive testing: "The role of play is being down-valued in England's nurseries. For many children today, nursery education provides their only opportunity for the active, creative and outdoor play which is recognised by psychologists as vital for physical, social, emotional and cognitive development…. Research does not support an early start to testing and quasi-formal teaching, but provides considerable evidence to challenge it. … Instead of pursuing an enlightened approach informed by global best practice, successive ministers have prescribed an ever-earlier start to formal learning. This can only cause profound damage to the self-image and learning dispositions of a generation of children." "The government should stop intervening in early education," *The Telegraph,* September 11, 2013. Retrieved from http://www.telegraph.co.uk/comment/letters/10302844/The-Government-should-stop-intervening-in-early-education.html.]

techniques, we compared the outcomes of ECE participants and nonparticipants in Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Laos, Macedonia, Sri Lanka, Ukraine, Vietnam, and the Yunnan Province of China. Our OLS and PSM analyses suggest that there may be some long-term benefits from ECE in most of the countries. We find strong, positive associations between ECE participation and post-ECE educational attainment. Yet we also find inconclusive evidence on ECE participation and long-term socioemotional and labor market outcomes. Our comparative approach also reveals that there are no consistent patterns by social origins or regions.

Previous studies from low- and middle-income countries have examined the short-term benefits from participating in small-scale ECD programs in a single country. In contrast, our study addressed the long-term outcomes from the multitude of early childhood programs experienced by the urban residents of the STEP countries. Future research should consider collecting large panel data that include more detailed information on the quality and quantity of ECE. Such data would permit causal analyses of the effects of participating in various ECE and ECD programs. Regardless, our results point to the need for policymakers to focus on quality in ECE expansion efforts.

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Appendix

Appendix Table A1
Sample and Sub-Sample Sizes, by Country

	All individuals			Labor force participants only		
	All	By social origin		All	By social origin	
		Low	Middle & High		Low	Middle & High
Armenia	2,433	196	2,237	908	74	834
Bolivia	1,781	553	1,228	1,443	467	976
Colombia	2,097	709	1,388	1,523	514	1,009
Georgia	2,679	212	2,467	881	59	822
Ghana	1,317	214	1,103	1,002	173	829
Kenya	3,083	757	2,326	2,075	514	1,561
Laos	1,272	417	855	1,107	362	745
Macedonia	3,482	369	3,113	1,777	162	1,615
Sri Lanka	933	219	714	544	130	414
Ukraine	2,115	405	1,710	1,212	208	1,004
Vietnam	2,738	845	1,893	2,007	654	1,423
Yunnan (China)	1,846	577	1,269	1,230	339	891
Pooled	27,615	6,132	21,483	17,066	4,141	12,925

Source: Authors' analysis based on STEP data for ages 20-64.
Note: Samples and subsamples include ECE participants and non-participants; Figure 1 illustrates participation rates (%) by age.

Appendix Table A2
Current age of entry to primary school and policies for ECE in STEP countries

	Official entrance age for ECE (years)	Official entrance age for primary education (years)	Official entrance age for compulsory education (years)	Theoretical duration for ECE (years)	ECE as part of compulsory education?
Armenia	3	6	6	3	No
Bolivia	4	6	4	2	Yes
Colombia	3	6	5	3	Yes
Georgia	3	6	6	3	No
Ghana	4	6	4	2	Yes, in last 5 years
Kenya	3	6	6	3	No
Laos	3	6	6	3	No
Macedonia	3	6	6	3	No
Sri Lanka	4	5	5	1	No
Ukraine	3	6	6	3	No
Vietnam	3	6	5	3	Yes, in last 5 years
China	3	6	6	3	No

Source: Unesco Institute for Statistics page on Official entrance age to pre-primary education (http://data.uis.unesco.org)

Appendix Table A3
ECE Participation Rates by Country and gender (%)

	Male	Female
Armenia	57.3	60.9
Bolivia	60.8	57.3
Colombia	51.4	47.3
Georgia	70.0	67.2
Ghana	77.6	79.6
Kenya	75.1	79.9
Laos	17.2	18.6
Macedonia	46.1	41.9
Sri Lanka	78.6	76.8
Ukraine	69.4	65.5
Vietnam	68.5	70.8
Yunnan (China)	38.9	44.1

Source: Authors' analysis based on STEP data for ages 20-64.

Appendix Table A4
Covariate Variable Names and Descriptions

Covariate	Description
Social origins:	
parentses1	Dummy = 1 if family status during childhood is 'poorest'
parentses2	Dummy = 1 if family status during childhood is 'middle class'
parentses3	Dummy = 1 if family status during childhood is 'upper middle class' or 'rich'
econshocks	Dummy=1 if family suffered economic shocks during childhood
parenteducation	Index =1 if most educated parent has primary, =2 if most educated parent has secondary, =3 if most educated parent has higher education
parentengage	Dummy = 1 if parents are 'highly engaged' in *i*'s education during childhood
elderbrothers	Number of elder brothers
eldersisters	Number of elder sisters
youngbrothers	Number of younger brothers
youngsisters	Number of younger sisters
Controls:	
schooling	Years of schooling
female	Dummy=1 if female
age	Age
age2	Age-squared
married	Dummy = 1 if married

Note: Schooling is only included as a covariate in regressions under the heading "with controls for schooling." *Married* is only included as a covariates in analyses of labor market outcomes.

Appendix Table A5

Results of Covariate Balance Checks: Standardized Mean Differences Before and After Matching between Treatment Group (ECE Participation) and Control Group (Non-ECE Participation), Pooled Sample of Individuals from 12 countries

Covariate	All		Low social origin		Middle & high social origin	
	Before matching	After matching	Before matching	After matching	Before matching	After matching
schooling	.4461	.0069	.4050	.0118	.4053	-.0078
parentses2	.0958	-.0162	-	-	-	-
parentses3	.1106	.0151	-	-	.0628	.0071
parenteducation	.6809	-.0064	.6448	.0401	.6440	-.0149
parentengage	.0858	.0112	.0538	.0192	.0785	.0076
elderbrothers	-.1334	.0029	-.0688	.0579	-.1343	.0244
eldersisters	-.1811	-.0034	-.1578	.0338	-.1714	.0075
youngbrothers	-.1879	.0131	-.1755	.0264	-.1671	.0110
youngsisters	-.1876	.0070	-.1690	.0206	-.1698	.0017
female	.0121	-.0071	-.0121	-.0272	.0072	.0039
age	-.6765	.0029	-.6742	.0121	-.6694	-.0015
age2	-.6649	.0034	-.658	.0131	-.6601	.0007

Source: Authors' analysis based on STEP data for ages 20-64.

Appendix Table A6

Results of Covariate Balance Checks: Mean Differences Before and After Matching between Treatment Group (ECE Participation) and Control Group (Non-ECE Participation), Pooled Sample of Labor Force Participants from 12 Countries

Covariate	All		Low social origin		Middle & high social origin	
	Before matching	After matching	Before matching	After matching	Before matching	After matching
schooling	-	-	-	-	-	-
parentses2	.0942	.0168	-	-	-	-
parentses3	.142	-.015	-	-	.1004	.0006
parenteducation	.724	.0057	.6938	.0121	.6835	-.0094
parentengage	.0685	.0280	.0364	.0559	.0607	.0348
elderbrothers	-.1428	.0207	-.1043	.0038	-.1376	-.0144
eldersisters	-.1727	-.0110	-.1820	.0072	-.1510	.0023
youngbrothers	-.2078	.0262	-.1933	.0126	-.1861	.0308
youngsisters	-.2188	.0188	-.2165	.0189	-.1954	-.0147
female	.0236	.0014	-.0252	-.0232	.0270	.0088
age	-.5719	.0089	-.5794	.0038	-.5657	-.0092
age2	-.5617	.0119	-.5632	-.0067	-.5589	-.0060
married	-.2527	-.0046	-.2401	.02792	-.2534	.0039

Source: Authors' analysis based on STEP data for labor force participants ages 20-64.

Appendix Table A7

ECE Coefficients obtained from OLS and PSM Regressions by Country: Literacy Proficiency

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.5	.4	-8.0	-11.2*	1.3	1.5	.1	-1.1	-8.4	-5.4	1.0	1.2
	(1.5)	(1.8)	(5.1)	(6.4)	(1.6)	(1.9)	(1.5)	(1.7)	(5.2)	(4.9)	(1.5)	(1.9)
Bolivia	17.2**	17.4**	10.9	7.6	20.2**	22.1**	6.7**	6.5*	.0	.8	10.4**	12.3**
	(3.5)	(4.3)	(7.1)	(7.8)	(3.9)	(5.8)	(3.2)	(3.7)	(6.3)	(7.1)	(3.6)	(4.6)
Colombia	2.5	3.1	-.3.4	.6	4.9	-3.1	-3.3	-.5	-8.5*	-8.7	-1.3	1.6
	(2.8)	(3.3)	(5.4)	(6.4)	(3.3)	(3.5)	(2.5)	(3.1)	(4.7)	(6.3)	(2.9)	(4.4)
Georgia	3.9**	5.2**	-3.6	-2.9	4.6**	6.8**	2.5	3.6	-4.1	2.7	3.1	3.4
	(1.9)	(2.5)	(6.9)	(6.7)	(2.0)	(3.0)	(1.9)	(2.4)	(6.8)	(4.6)	(2.0)	(2.5)
Ghana	18.4**	35.0**	.9	21.2	21.5**	31.6**	1.6	3.1	-16.3	-8.1	6.6	5.6
	(.64)	(8.2)	(15.2)	(.14.5)	(7.2)	(.10.3)	(5.6)	(8.7)	(14.2)	(15.6)	(6.2)	(7.0)
Kenya	-8.0	-5.8	-14.6**	-16.9**	-5.6	-6.5	-17.4**	-17.3**	-24.3**	-21.6**	-14.9**	-10.9**
	(3.5)	(3.8)	(7.3)	(8.4)	(4.0)	(4.3)	(3.2)	(.4.0)	(6.4)	(8.8)	(3.7)	(4.8)
Laos	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Macedonia	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Sri Lanka	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Ukraine	2.7	3.1	9.6*	9.6	1.1	1.0	1.9	2.4	6.5	5.8	.7	1.9
	(2.0)	(2.2)	(5.3)	(6.5)	(2.2)	(3.2)	(2.0)	(2.4)	(5.2)	(5.0)	(2.2)	(2.7)
Vietnam	15.0**	14.5**	6.9	7.1**	18.5**	17.8**	6.1**	5.5**	-4.9	-2.8	11.4**	14.3**
	(2.4)	(2.9)	(4.9)	(6.1)	(2.7)	(3.8)	(2.2)	(2.6)	(4.4)	(5.0)	(2.5)	(3.1)
Yunnan (China)	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Source: Authors' analysis based on STEP data for ages 20-64.

Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A8
ECE Coefficients obtained from OLS and PSM Regressions by Country: Openness

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.013	.018	.009	.030	.013	.004	.007	.020	-.008	-.019	.009	.003
	(.021)	(.028)	(.076)	(.080)	(.021)	(.024)	(.021)	(.026)	(.076)	(.073(	(.021)	(.025)
Bolivia	.075**	.082**	.079	.125**	.069**	.108**	.043	.055	.039	.074	.046	.044
	(.029)	(.039)	(.053)	(.061)	(.035)	(.042)	(.029)	(.034)	(.051)	(.057)	(.035)	(.047)
Colombia	.037	.066**	.085*	.059	.020	-.015	.019	.051	.073	.018	-.002	-.054
	(.027)	(.033)	(.051)	(.075)	(.032)	(.041)	(.027)	(.037)	(.050)	(.074)	(.032)	(.043)
Georgia	.025	.011	.017	-.041	.029	-.003	.009	-.019	.013	.074	.011	.021
	(.023)	(.027)	(.091)	(.109)	(.023)	(.028)	(.022)	(.027)	(.091)	(.106)	(.023)	(.028)
Ghana	.054	.052	.043	-.094	.050	-.009	.019	.005	-.004	.008	.020	.066
	(.053)	(.070)	(.152)	(.210)	(.057)	(.074)	(.052)	(.057)	(.147)	(.200)	(.056)	(.057)
Kenya	.064**	.081**	-.046	-.018	.103**	.071**	.041*	.027	-.054	-.092	.075**	.016
	(.024)	(.032)	(.049)	(.059)	(.028)	(.031)	(.024)	(.034)	(.050)	(.057)	(.028)	(.035)
Laos	.112**	.124*	.131	.170	.107**	.094	.060	.035	.097	.089	.059	.055
	(.046)	(.072)	(.108)	(.178)	(.050)	(.056)	(.044)	(.053)	(.101)	(.167)	(.049)	(.101)
Macedonia	.011	-.007	.002	-.089	.014	.034	.001	.002	-.036	-.014	.005	.006
	(.021)	(.029)	(.081)	(.061)	(.021)	(.029)	(.021)	(.027)	(.081)	(.066)	(.021)	(.028)
Sri Lanka	-.013	-.018	-.085	-.108	.016	.037	-.009	.047	-.093	-.079	.017	.013
	(.047)	(.051)	(.083)	(.071)	(.057)	(.079)	(.045)	(.060)	(.081)	(.078)	(.054)	(.074)
Ukraine	-.023	-.021	.007	.019	-.026	-.014	-.035	-.019	-.029	-.079	-.034	-.021
	(.027)	(.034)	(.067)	(.089)	(.029)	(.035)	(.026)	(.036)	(.066)	(.063)	(.028)	(.033)
Vietnam	.062**	.086**	.093**	.142**	.046	.038	.009	.017	.027	.033	.001	.028
	(.025)	(.036)	(.047)	(.059)	(.030)	(.045)	(.025)	(.033)	(.046)	(.063)	(.029)	(.038)
Yunnan (China)	.075**	.037	.086	.053	.072**	.084*	.001	-.002	.005	.060	.001	-.020
	(.028)	(.034)	(.055)	(.067)	(.033)	(.043)	(.028)	(.038)	(.054)	(.064)	(.033)	(.038)

Source: Authors' analysis based on STEP data for ages 20-64.
Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A9

ECE Coefficients obtained from OLS and PSM Regressions by Country: Conscientiousness

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.053**	.052*	-.027	-.080	.061**	.064**	.052**	.045*	-.019	-.009	.059**	.034
	(.021)	(.027)	(.086)	(.097)	(.022)	(.027)	(.021)	(.026)	(.088)	(.096)	(.022)	(.027)
Bolivia	.049*	.024	.041	.028	.047	.056	.032	.016	.026	.030	.032	.042
	(.026)	(.032)	(.046)	(.053)	(.032)	(.038)	(.026)	(.031)	(.046)	(.052)	(.032)	(.041)
Colombia	.024	.002	.015	-.016	.023	.093	.015	.026	.009	.024	.012	.084*
	(.025)	(.032)	(.043)	(.050)	(.031)	(.066)	(.025)	(.034)	(.044)	(.053)	(.031)	(.046)
Georgia	.092**	.086**	.146	.244**	.091**	.107**	.082**	.083**	.145	.156*	.080**	.090**
	(.024)	(.030)	(.090)	(.094)	(.025)	(.032)	(.024)	(.030)	(.090)	(.084)	(.025)	(.031)
Ghana	-.006	-.055	-.201	-.224	.048	.098	-.031	-.019	-.252*	-.230*	.028	-.082
	(.049)	(.074)	(.148)	(.266)	(.053)	(.073)	(.049)	(.064)	(.141)	(.122)	(.053)	(.081)
Kenya	-.014	-.005	-.004	.004	-.017	-.019	-.020	-.001	-.001	.036	-.027	-.017
	(.023)	(.026)	(.043)	(.065)	(.027)	(.031)	(.023)	(.030)	(.044)	(.050)	(.027)	(.031)
Laos	-.033	-.016	-.017	-.018	-.035	-.019	-.047	.033	-.025	-.082	-.048	.105
	(.037)	(.060)	(.081)	(.122)	(.042)	(.056)	(.037)	(.066)	(.081)	(.109)	(.043)	(.075)
Macedonia	-.008	.010	.026	-.005	-.009	-.011	-.017	-.004	.017	-.011	-.018	-.020
	(.019)	(.024)	(.069)	(.055)	(.020)	(.025)	(.019)	(.023)	(.070)	(.086)	(.020)	(.023)
Sri Lanka	.001	-.027	-.058	-.014	.018	-.002	-.005	-.062	-.059	-.029	.011	-.002
	(.040)	(.049)	(.078)	(.069)	(.048)	(.056)	(.040)	(.064)	(.079)	(.070)	(.048)	(.047)
Ukraine	-.057**	-.052*	-.034	-.039	-.060**	-.035	-.067**	-.055*	-.061	-.128*	-.066**	-.066*
	(.024)	(.028)	(.058)	(.066)	(.027)	(.032)	(.024)	(.033)	(.057)	(.074)	(.027)	(.035)
Vietnam	-.025	.005	-.089**	-.110**	.007	.041	-.043**	-.043	-.108**	-.112	-.007	.010
	(.022)	(.028)	(.038)	(.039)	(.026)	(.037)	(.022)	(.031)	(.038)	(.041)	(.027)	(.033)
Yunnan (China)	.056**	.008	.010	-.003	.073**	.038	.023	-.007	-.014	-.093**	.035	.026
	(.025)	(.031)	(.045)	(.050)	(.030)	(.032)	(.025)	(.028)	(.046)	(.044)	(.030)	(.038)

Source: Authors' analysis based on STEP data for ages 20-64.

Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A10

ECE Coefficients obtained from OLS and PSM Regressions by Country: Extraversion

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.022	.015	-.022	.013	.026	.010	.026	.020	-.032	-.084	.031	.018
	(.026)	(.034)	(.012)	(.117)	(.027)	(.034)	(.026)	(.032)	(.103)	(.091)	(.027)	(.034)
Bolivia	.162	.151**	.097	.126*	.199**	.236**	.125**	.131**	.063	.085	.157**	.210**
	(.036)	(.047)	(.065)	(.072)	(.044)	(.054)	(.036)	(.048)	(.065)	(.077)	(.044)	(.060)
Colombia	.038	.052	.021	-.005	.052	.046	.019	.015	.001	-.085	.035	.047
	(.035)	(.050)	(.066)	(.087)	(.041)	(.044)	(.035)	(.050)	(.065)	(.093)	(.041)	(.047)
Georgia	.050**	.054**	.101	.130*	.045*	.038	.040*	.040	.096	.061	.035	.037
	(.024)	(.026)	(.089)	(.074)	(.024)	(.30)	(.023)	(.029)	(.089)	(.067)	(.024)	(.031)
Ghana	.073	.185**	.164	.357*	.030	.156*	.042	.228**	.169	.348**	-.003	.143
	(.054)	(.079)	(.158)	(.196)	(.058)	(.086)	(.054)	(.094)	(.159)	(.125)	(.058)	(.115)
Kenya	.167**	.196**	.068	.113**	.201**	.171**	.156**	.200**	.053	.098	.190**	.178**
	(.026)	(.029)	(.051)	(.055)	(.031)	(.039)	(.026)	(.033)	(.052)	(.060)	(.031)	(.038)
Laos	.054	.030	.034	.075	.050	-.029	.024	.029	.018	.016	.017	.086
	(.042)	(.062)	(.094)	(.157)	(.048)	(.068)	(.042)	(.066)	(.092)	(105)	(.048)	(.074)
Macedonia	.069**	.064**	.179**	.233**	.059**	.088**	.066**	.080**	.179**	.239*	.057**	.061
	(.024)	(.030)	(.083)	(.109)	(.025)	(.028)	(.024)	(.030)	(.084)	(.123)	(.025)	(.032)
Sri Lanka	-.028	-.115**	-.182**	-.246**	.032	-.056	-.032	-.109	-.182**	-.293**	.028	-.115
	(.045)	(.057)	(.078)	(.066)	(.055)	(.068)	(.045)	(.074)	(.078)	(.063)	(.055)	(.079)
Ukraine	.085**	.086**	.038	.052	.097**	.138**	.081**	.085**	.021	-.005	.095**	.081*
	(.030)	(.036)	(.074)	(.074)	(.033)	(.040)	(.030)	(.038)	(.074)	(.090)	(.033)	(.041)
Vietnam	.038*	.058**	.036	.045	.041	.019	.028	.015	.014	.010	.037	.026
	(.023)	(.028)	(.043)	(.047)	(.027)	(.042)	(.023)	(.027)	(.043)	(.045)	(.027)	(.031)
Yunnan (China)	.020	-.030	.057	.045	.003	-.007	.009	.006	.046	.005	-.009	-.011
	(.027)	(.029)	(.051)	(.071)	(.031)	(.035)	(.027)	(.032)	(.053)	(.084)	(.032)	(.035)

Source: Authors' analysis based on STEP data for ages 20-64.

Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A11

ECE Coefficients obtained from OLS and PSM Regressions by Country: Agreeableness

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.016	.021	-.140	-.131	.029	.036	.018	.011	-.121	-.107	.029	.003
	(.023)	(.028)	(.090)	(.084)	(.024)	(.027)	(.023)	(.027)	(.091)	(.079)	(.024)	(.029)
Bolivia	-.001	-.007	.085	.056	-.046	-.008	-.007	-.013	.076	.047	-.051	-.001
	(.033)	(.050)	(.059)	(.067)	(.040)	(.047)	(.034)	(.043)	(.059)	(.062)	(.041)	(.060)
Colombia	.032	.078**	.004	.001	.045	.042	.023	.014	-.007	-.032	.037	-.010
	(.029)	(.037)	(.052)	(.059)	(.035)	(.046)	(.029)	(.037)	(.052)	(.084)	(.035)	(.063)
Georgia	.033	.059**	.050	.074	.033	.068**	.028	.079**	.051	.131	.028	.020
	(.024)	(.028)	(.104)	(.114)	(.024)	(.029)	(.024)	(.028)	(.104)	(.110)	(.024)	(.027)
Ghana	.081	.071	-.014	.027	.108*	.081	.051	.094	-.053	.051	.079	.056
	(.057)	(.058)	(.175)	(.330)	(.062)	(.098)	(.057)	(.068)	(.174)	(.170)	(.061)	(.104)
Kenya	.051**	.053*	-.025	.038	.086**	.080**	.047*	.053	-.034	-.042	.084**	.110**
	(.025)	(.027)	(.049)	(.053)	(.029)	(.037)	(.025)	(.033)	(.050)	(.059)	(.030)	(.036)
Laos	.104**	.064	-.035	-.010	.146**	.107*	.076	.083	-.048	-.032	.115**	.131**
	(.047)	(.056)	(.103)	(.064)	(.053)	(.057)	(.046)	(.052)	(.102)	(.071)	(.052)	(.059)
Macedonia	.025	.043	.197**	.270**	.009	.040	.027	.049*	.202**	.264**	.011	.009
	(.023)	(.028)	(.077)	(.055)	(.024)	(.028)	(.023)	(.028)	(.078)	(.060)	(.024)	(.028)
Sri Lanka	.051	.119**	.096	.132*	.014	.103	.045	.072	.097	.140	.007	.055
	(.044)	(.052)	(.076)	(.132)	(.053)	(.095)	(.044)	(.069)	(.076)	(.083)	(.053)	(.113)
Ukraine	-.018	-.018	-.057	-.042	-.005	.016	-.020	-.020	-.058	-.054	-.007	-.019
	(.028)	(.033)	(.068)	(.076)	(.031)	(.042)	(.028)	(.035)	(.069)	(.072)	(.031)	(.037)
Vietnam	.041*	.053*	.040	.014	.041	.010	.026	.018	.020	.021	.030	.017
	(.022)	(.028)	(.042)	(.053)	(.027)	(.030)	(.023)	(.028)	(.042)	(.061)	(.027)	(.038)
Yunnan (China)	.050**	.017	.025	-.026	.062**	.062	.010	.050*	-.018	.015	.023	.031
	(.026)	(.032)	(.048)	(.054)	(.030)	(.040)	(.026)	(.029)	(.049)	(.058)	(.031)	(.037)

Source: Authors' analysis based on STEP data for ages 20-64.

Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A12

ECE Coefficients obtained from OLS and PSM Regressions by Country: Emotional Stability

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.010	.009	-.131	-.181	.021	.015	-.003	.021	-.138	-.145	.008	.027
	(.028)	(.035)	(.102)	(.128)	(.029)	(.034)	(.028)	(.035)	(.104)	(.109)	(.029)	(.034)
Bolivia	.003	.055	.022	-.045	-.004	-.016	-.018	-.030	.009	-.040	-.030	-.054
	(.036)	(.056)	(.057)	(.063)	(.046)	(.068)	(.036)	(.045)	(.057)	(.068)	(.046)	(.074)
Colombia	.028	-.024	.003	-.036	.042	.010	.007	-.028	-.009	-.004	.014	-.002
	(.036)	(.045)	(.067)	(.070)	(.044)	(.051)	(.036)	(.045)	(.067)	(.109)	(.043)	(.091)
Georgia	.020	.025	.134	-.019	.007	.032	.010	.027	.128	.127	-.004	.048
	(.031)	(.041)	(.117)	(.116)	(.032)	(.041)	(.031)	(.038)	(.117)	(.141)	(.032)	(.039)
Ghana	-.049	-.030	.037	.231	-.047	-.033	-.063	-.050	.023	-.028	-.061	-.131
	(.049)	(.055)	(.132)	(.238)	(.054)	(.054)	(.049)	(.059)	(.133)	(.079)	(.054)	(.079)
Kenya	-.013	-.018	.020	.024	-.027	-.027	-.017	-.013	.020	-.018	-.031	-.044
	(.022)	(.028)	(.044)	(.064)	(.026)	(.030)	(.023)	(.027)	(.044)	(.059)	(.026)	(.035)
Laos	.061	.079	.026	.027	.071	.101	.043	.081	.016	-.021	.051	-.004
	(.041)	(.055)	(.089)	(.117)	(.046)	(.066)	(.041)	(.053)	(.089)	(105)	(.047)	(.063)
Macedonia	.040	.029	-.001	-.038	.044	.050	.030	.038	-.022	-.020	.035	.025
	(.026)	(.032)	(.085)	(.082)	(.027)	(.037)	(.026)	(.031)	(.086)	(.065)	(.027)	(.037)
Sri Lanka	-.008	-.007	-.069	-.132	.002	.001	-.012	-.014	-.070	-.148*	-.002	.055
	(.044)	(.082)	(.080)	(.098)	(.054)	(.060)	(.044)	(.087)	(.080)	(.084)	(.054)	(.069)
Ukraine	-.034	-.011	.069	.107	-.052	-.047	-.039	.021	.054	.083	-.055	-.058
	(.031)	(.040)	(.079)	(.091)	(.034)	(.042)	(.031)	(.042)	(.079)	(.096)	(.034)	(.040)
Vietnam	-.060**	-.076**	-.080*	-.070	-.050*	-.038	-.080**	-.079**	-.098**	-.127**	-.067**	-.053
	(.024)	(.028)	(.041)	(.048)	(.029)	(.042)	(.024)	(.033)	(.042)	(.046)	(.029)	(.035)
Yunnan (China)	.010	-.006	-.004	-.001	.017	.021	.007	-.008	-.003	-.030	.010	-.014
	(.023)	(.031)	(.045)	(.051)	(.026)	(.033)	(.023)	(.027)	(.046)	(.059)	(.027)	(.038)

Source: Authors' analysis based on STEP data for ages 20-64.

Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A13

ECE Coefficients obtained from OLS and PSM Regressions by country: Grit

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.043	.045	.006	-.023	.043*	.077**	.042*	.047	.019	.061	.047*	.077**
	(.025)	(.034)	(.093)	(.102)	(.026)	(.033)	(.025)	(.030)	(.094)	(.085)	(.026)	(.033)
Bolivia	.040	.048	.065	.082	.030	-.021	.028	.018	.063	.057	.010	-.021
	(.032)	(.038)	(.058)	(.065)	(.040)	(.045)	(.033)	(.038)	(.058)	(.066)	(.041)	(.045)
Colombia	.130**	.117**	.120**	.020	.131**	.069	.128**	.140**	.121**	.194**	.126**	.069
	(.030)	(.035)	(.055)	(.081)	(.036)	(.061)	(.030)	(.037)	(.056)	(.067)	(.036)	(.061)
Georgia	.030	.054	.090	.228*	.028	.040	.015	.023	.079	.100	.013	.040
	(.027)	(.034)	(.105)	(.121)	(.028)	(.036)	(.027)	(.032)	(.103)	(.095)	(.028)	(.036)
Ghana	.030	-.012	-.015	-.212	.039	-.063	.021	-.002	-.044	-.007	.033	-.063
	(.052)	(.055)	(.159)	(.449)	(.057)	(.082)	(.053)	(.062)	(.159)	(.088)	(.057)	(.082)
Kenya	.047*	.056*	-.018	-.063	.070**	.012	.044*	.036	-.017	-.065	.066**	.012
	(.027)	(.032)	(.052)	(.070)	(.031)	(.043)	(.027)	(.032)	(.053)	(.066)	(.031)	(.043)
Laos	-.034	.034	-.001	.109	-.038	-.070	-.040	.041	-.003	.076	-.045	-.070
	(.046)	(.066)	(.105)	(.092)	(.050)	(.077)	(.045)	(.064)	(.105)	(.129)	(.051)	(.077)
Macedonia	.007	.025	.060	.066	.003	-.023	-.005	-.006	.043	.087	-.009	-.023
	(.024)	(.030)	(.084)	(.217)	(.025)	(.033)	(.024)	(.032)	(.084)	(.253)	(.025)	(.033)
Sri Lanka	.027	-.009	-.055	-.032	.028	-.031	.0195	-.071	-.056	-.032	.020	-.031
	(.049)	(.054)	(.082)	(.082)	(.060)	(.058)	(.048)	(.060)	(.082)	(.087)	(.059)	(.058)
Ukraine	-.024	-.069*	-.045	-.023	-.014	-.039	-.026	-.046	-.075	-.040	-.022	-.039
	(.031)	(.037)	(.073)	(.089)	(.034)	(.040)	(.031)	(.038)	(.073)	(.071)	(.034)	(.040)
Vietnam	-.073**	-.026	-.072*	-.091*	-.066**	-.022	-.073**	-.066**	-.065	-.044	-.070**	-.022
	(.023)	(.032)	(.041)	(.050)	(.028)	(.035)	(.023)	(.031)	(.042)	(.052)	(.028)	(.035)
Yunnan (China)	.016	-.024	.023	-.030	.015	-.016	-.014	-.013	.006	.006	-.022	.016
	(.027)	(.046)	(.050)	(.060)	(.032)	(.053)	(.028)	(.044)	(.052)	(.052)	(.033)	(.053)

Source: Authors' analysis based on STEP data for ages 20-64.

Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A14
ECE Coefficients obtained from OLS and PSM Regressions by Country: Patience

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high origin		All		Low social origin		Middle & high origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.011	.045	.390**	.352**	-.018	-.030	.011	.021	.390**	.332*	-.018	-.009
	(.037)	(.047)	(.140)	(.166)	(.038)	(.044)	(.037)	(.042)	(.140)	(.177)	(.038)	(.047)
Bolivia	.026	-.026	.038	.101	.002	-.048	.015	-.019	.038	.087	.002	-.079
	(.065)	(.075)	(.114)	(.137)	(.081)	(.100)	(.066)	(.082)	(.114)	(.145)	(.081)	(.010)
Colombia	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Georgia	.039	-.005	.224	.180	.025	.010	.039	.027	.224	.083	.025	.060
	(.046)	(.058)	(.166)	(.140)	(.049)	(.064)	(.047)	(.055)	(.166)	(.194)	(.049)	(.054)
Ghana	-.049	.040	.007	-.023	-.027	-.006	-.028	-.037	.007	.009	-.027	-.010
	(.073)	(.084)	(.176)	(.164)	(.083)	(.098)	(.074)	(.097)	(.176)	(.174)	(.083)	(.092)
Kenya	.005	.045	.070	.112	-.016	.021	.008	-.037	.070	.038	-.016	.034
	(.041)	(.052)	(.075)	(.082)	(.049)	(.060)	(.041)	(.053)	(.075)	(.101)	(.049)	(.057)
Laos	.078	.143	.310*	.506**	.048	.042	.089	.293**	.310*	.424**	.048	-.024
	(.079)	(.109)	(.167)	(.152)	(.091)	(.120)	(.079)	(.121)	(.167)	(.123)	(.091)	(.104)
Macedonia	-.050	-.031	.238	.241	-.088*	.005	-.057	-.017	.238	.233	-.088*	-.066
	(.047)	(.060)	(.152)	(.233)	(.050)	(.068)	(.047)	(.057)	(.152)	(.234)	(.050)	(.058)
Sri Lanka	.234**	.188*	.423**	.137	.178	.204	.242**	.186	.423**	.219	.178	.084
	(.092)	(.108)	(.158)	(.170)	(.114)	(.158)	(.092)	(.114)	(.158)	(.149)	(.114)	(.160)
Ukraine	-.040	.005	.105	.077	-.081	-.040	-.046	-.016	.105	.141	-.081	-.037
	(.047)	(.053)	(.101)	(.100)	(.053)	(.068)	(.047)	(.059)	(.101)	(.114)	(.053)	(.060)
Vietnam	.015	.013	.031	.031	-.001	.023	.011	-.044	.031	-.069	-.001	-038
	(.042)	(.050)	(.076)	(.094)	(.051)	(.062)	(.040)	(.054)	(.076)	(.108)	(.051)	(.054)
Yunnan (China)	-.106*	-.105	.084	.133	-.189**	-.194**	-.118**	-.047	.084	.221**	-.189**	-.170
	(.057)	(.083)	(.104)	(.127)	(.071)	(.079)	(.058)	(.081)	(.104)	(.107)	(.071)	(.108)

Source: Authors' analysis based on STEP data for ages 20-64.
Notes: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A15

ECE Coefficients obtained from OLS and PSM Regressions by Country: Labor Force Participation

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.003	-.027	.059	-.010	-.003	-.008	-.007	-.031	.032	.082	-.012	-.037
	(.021)	(.026)	(.073)	(.089)	(.022)	(.025)	(.021)	(.025)	(.073)	(.080)	(.022)	(.026)
Bolivia	-.003	.014	-.004	.024	-.005	-.023	-.012	.001	-.004	-.013	-.020	-.022
	(.018)	(.020)	(.027)	(.029)	(.023)	(.028)	(.018)	(.027)	(.027)	(.031)	(.023)	(.035)
Colombia	-.021	-.014	.018	.024	-.034	-.032	-.023	-.024	.015	.028	-.037	-.032
	(.018)	(.021)	(.033)	(.038)	(.022)	(.023)	(.018)	(.022)	(.033)	(.037)	(.023)	(.021)
Georgia	-.015	-.001	-.002	-.047	-.003	.011	-.011	-.003	-.008	-.052	-.007	-.001
	(.021)	(.025)	(.075)	(.087)	(.030)	(.027)	(.021)	(.025)	(.075)	(.095)	(.022)	(.026)
Ghana	-.005	-.008	-.038	.075	.001	.014	-.003	.014	-.044	-.009	-.003	.103
	(.026)	(.042)	(.051)	(.111)	(.030)	(.055)	(.026)	(.075)	(.052)	(.057)	(.030)	(.078)
Kenya	-.015	-.027	-.021	-.026	-.006	-.028	-.020	.002	-.009	-.022	-.031	-.014
	(.016)	(.019)	(.039)	(.036)	(.021)	(.023)	(.016)	(.020)	(.030)	(.036)	(.019)	(.027)
Laos	.014	.043	-.019	-.120*	.024	.031	.006	-.012	-.014	-.012	.011	-.018
	(.025)	(.031)	(.056)	(.069)	(.029)	(.046)	(.025)	(.038)	(.055)	(.038)	(.029)	(.146)
Macedonia	.063**	.063**	.072	-.016	.065**	.045**	.043**	.046**	.052	-.016	.043**	.045**
	(.016)	(.021)	(.054)	(.069)	(.023)	(.022)	(.016)	(.023)	(.054)	(.058)	(.016)	(.022)
Sri Lanka	-.032	-.058	-.013	-.027	.002	-.066	-.033	-.051	-.102	-.046	.042	-.041
	(.035)	(.040)	(.064)	(.064)	(.042)	(.057)	(.035)	(.037)	(.064)	(.067)	(.048)	(.049)
Ukraine	.022	.010	.143**	.156**	-.008	-.036	.016	.012	.130**	.109*	-.015	-.025
	(.021)	(.028)	(.050)	(.056)	(.023)	(.029)	(.021)	(.025)	(.049)	(.065)	(.023)	(.025)
Vietnam	.030*	.010	.053*	.054	.019	.013	.020	-.012	.045	.041	.009	-.013
	(.017)	(.020)	(.028)	(.036)	(.021)	(.027)	(.017)	(.019)	(.029)	(.037)	(.021)	(.028)
Yunnan (China)	.061**	.034	.020	-.005	.075**	.059**	.023	-.040	-.007	-.094*	.026	.027
	(.022)	(.027)	(.041)	(.053)	(.025)	(.030)	(.022)	(.029)	(.042)	(.051)	(.026)	(.041)

Source: Authors' analysis based on STEP data for ages 20-64.

Notes: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A16
ECE Coefficients obtained from OLS and PSM Regressions by Country: Post-ECE Years of Schooling

	All individuals			Low social origins			Middle & high social origins		
	n	OLS	PSM	*n*	OLS	PSM	*n*	OLS	PSM
Armenia	2433	.39**	.36**	196	.41	.38	2237	.36**	.23
		(.12)	(.15)		(.48)	(.51)		(.12)	(.15)
Bolivia	1781	1.29**	1.24**	553	1.15**	.98**	1228	1.32**	1.25**
		(.19)	(.23)		(.37)	(.43)		(.21)	(.24)
Colombia	2097	.71**	.82**	709	.61*	.61	1388	.78**	.51*
		(.17)	(.19)		(.32)	(.41)		(.19)	(.31)
Georgia	2679	.50**	.43**	212	.20	-.21	2467	.52**	.63**
		(.11)	(.14)		(.44)	(.47)		(.11)	(.15)
Ghana	1317	1.49**	1.83**	214	1.80**	2.94**	1103	1.28**	2.17**
		(.29)	(.63)		(.65)	(.77)		(.33)	(.65)
Kenya	3083	1.01**	.90**	757	.95**	.89**	2326	1.05**	1.16**
		(.17)	(.21)		(.35)	(.40)		(.19)	(.23)
Laos	1272	1.37**	1.39**	417	.69	1.63**	855	1.57**	1.34**
		(.35)	(.47)		(.79)	(.144)		(. 38)	(.49)
Macedonia	3482	.59**	.38**	369	1.02**	.70*	3113	.55**	.62**
		(.12)	(.16)		(.40)	(.36)		(.12)	(.15)
Sri Lanka	933	.33	.28	219	.19	.57	714	.34	.49
		(.24)	(.32)		(.43)	(.44)		(.28)	(.39)
Ukraine	2115	.24**	.31**	405	.50**	.52**	1710	.16	.22
		(.10)	(.14)		(.21)	(.25)		(.11)	(.14)
Vietnam	2738	1.25**	1.04**	845	1.37**	1.64**	1893	1.14**	.92**
		(.15)	(.18)		(.28)	(.35)		(.18)	(.25)
Yunnan (China)	1846	1.60**	1.50**	577	1.71**	1.77**	1269	1.54**	1.56**
		(.15)	(.20)		(.32)	(.35)		(.17)	(.23)

Source: Authors' analysis based on STEP data for ages 20-64.
Note: Standard errors in parentheses; statistical margin of error at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A17

ECE Coefficients obtained from OLS and PSM Regressions by Country: Skill Use at the Workplace

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high social origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	.132	.000	.476	.055	.111	-.027	.091	-.033	.320	.222	.083	.019
	(.090)	(.110)	(.465)	(.930)	(.092)	(.106)	(.081)	(.097)	(.381)	(.906)	(.084)	(.095)
Bolivia	.357**	.412**	.202*	.261*	.439**	.434**	.189**	.196**	.069	.069	.256**	.274**
	(.064)	(.084)	(.113)	(.154)	(.077)	(.115)	(.057)	(.071)	(.099)	(.115)	(.071)	(.115)
Colombia	.119*	.158*	.138	-.189	.096	.203**	.013	.073	.052	-.156	-.017	.020
	(.071)	(.083)	(.129)	(.142)	(.085)	(.101)	(.064)	(.075)	(.116)	(.111)	(.078)	(.098)
Georgia	.162	.207	.210	-.237	.174	.186	.055	-.025	.042	-.373	.073	.135
	(.103)	(.130)	(.526)	(.916)	(.106)	(.124)	(.097)	(.111)	(.466)	(.858)	(.100)	(.115)
Ghana	.121	.266**	-.056	-.081	.125	.493**	-.082	-.206	-.269	-.156	-.047	.273
	(.084)	(.103)	(.180)	(.221)	(.096)	(.155)	(.072)	(.176)	(.173)	(.192)	(.081)	(.172)
Kenya	.291**	.308**	.193*	.179	.343**	.419**	.141**	.116*	.068	.348**	.187**	.243**
	(.059)	(.075)	(.114)	(.130)	(.069)	(.087)	(.055)	(.068)	(.106)	(.110)	(.064)	(.090)
Laos	.128	-.058	.040	.191	.167	-.074	-.028	-.009	-.048	-.072	-.010	-.206
	(.093)	(.125)	(.206)	(.441)	(.105)	(.156)	(.081)	(.104)	(.176)	(.440)	(.092)	(.178)
Macedonia	.025**	.184**	.813**	.222*	.204**	.214**	.186**	.099	.600**	.463**	.154**	.107
	(.065)	(.075)	(.242)	(.305)	(.068)	(.077)	(.061)	(.070)	(.217)	(.174)	(.064)	(.075)
Sri Lanka	.077	.282	.088	.092	.064	.278	.088	.222	.085	.231	.099	.273*
	(.131)	(.227)	(.251)	(.227)	(.159)	(.174)	(.117)	(.199)	(.209)	(.216)	(.143)	(.152)
Ukraine	-.149*	-.066	.012	-.176	-.188**	-.160*	-.182**	-.103	-.175	-.295*	-.188**	-.166*
	(.081)	(.099)	(.209)	(.192)	(.089)	(.090)	(.073)	(.085)	(.196)	(.172)	(.079)	(.087)
Vietnam	.127**	.130	.070	.185	.147**	.106	-.089*	-.110	-.109	.049	-.089	-.101
	(.059)	(.080)	(.105)	(.121)	(.072)	(.096)	(.051)	(.070)	(.092)	(.108)	(.062)	(.078)
Yunnan (China)	.459**	.469**	.579**	.597**	.415**	.432**	.228**	.277**	.304**	.319**	.202**	.197*
	(.073)	(.095)	(.153)	(.210)	(.083)	(.123)	(.067)	(.098)	(.132)	(.176)	(.078)	(.105)

Source: Authors' analysis based on STEP data for ages 20-64.

Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

Appendix Table A18

ECE Coefficients obtained from OLS and PSM Regressions by Country, Earnings (Natural Logs)

	No controls for schooling						With controls for schooling					
	All		Low social origin		Middle & high social origin		All		Low social origin		Middle & high origin	
	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM	OLS	PSM
Armenia	-.044	-.017	.029	.155	-.009	.019	.004	-.017	-.042	.155	-.000	.019
	(.073)	(.081)	(.289)	(.262)	(.075)	(.083)	(.072)	(.081)	(.270)	(.262)	(.076)	(.082)
Bolivia	.128	.068	.090	.006	.112	.229	.198	.068	.055	.006	.101	.229
	(.112)	(.123)	(.161)	(.155)	(.147)	(.180)	(.032)	(.123)	(.161)	(.155)	(.149)	(.180)
Colombia	.098	.253	.257	-.054	-.007	-.267	.050	.253	.228	-.054	-.047	-.267
	(.15)	(.344)	(.248)	(.374)	(.185)	(.741)	(.147)	(.344)	(.248)	(.374)	(.185)	(.741)
Georgia	.066	.009	.668	-.132	.051	-.029	.036	.009	.510	-.132	.032	-.029
	(.107)	(.101)	(.555)	(.338)	(.108)	(.108)	(.105)	(.101)	(.528)	(.338)	(.108)	(.108)
Ghana	.145	-.055	-.003	-.225	.189	.154	.067	-.055	-.136	-.225	.112	.154
	(.125)	(.134)	(.242)	(.188)	(.143)	(.140)	(.122)	(.134)	(.246)	(.188)	(.142)	(.140)
Kenya	.214*	.039	-.200	-.085	.363**	.144	.118	.039	-.273	-.085	.255*	.144
	(.114)	(.157)	(.218)	(.307)	(.134)	(.220)	(.114)	(.157)	(.217)	(.307)	(.134)	(.220)
Laos	.480	.587	1.026	.247	.437	.393	.112	.587	.808	.247	.072	.393
	(.415)	(.434)	(.953)	(1.565)	(.453)	(.538)	(.399)	(.434)	(.899)	(1.565)	(.443)	(.538)
Macedonia	-.191	-.255	-.438	-.242	-.177	-.147	-.197	.256	-.415	-.242	-.184	-.147
	(.148)	(.158)	(.472)	(.300)	(.156)	(.179)	(.149)	(.157)	(.477)	(.300)	(.157)	(.179)
Sri Lanka	-.100	-.521**	-1.031	-1.187**	.310	.115	-.127	-.521**	-1.031**	-1.119**	.336	.115
	(.291)	(.223)	(.496)	(.429)	(.353)	(.349)	(.285)	(.223)	(.496)	(.429)	(.349)	(.348)
Ukraine	-.049	-.088	.157	.404	-.087	-.194*	-.054	-.106	.156	.454	-.087	-.292**
	(.081)	(.100)	(.207)	(.269)	(.087)	(.101)	(.080)	(.095)	(.210)	(.335)	(.087)	(.097)
Vietnam	-.187*	.003	-.393**	-.015	-.055	-.066	-.293**	-.138	-.478**	-.525**	-.209*	-.178
	(.104)	(.124)	(.180)	(.206)	(.127)	(.129)	(.103)	(.119)	(.180)	(.161)	(.126)	(.120)
Yunnan (China)	.300**	.294**	.173	.174	.381**	.321**	.205**	.158	.032	.067	.280**	.253**
	(.089)	(.110)	(.180)	(.145)	(.103)	(.105)	(.089)	(.117)	(.178)	(.154)	(.104)	(.117)

Source: Authors' analysis based on STEP data for ages 20-64.
Note: Standard errors in parentheses; statistical significance at * $p < 0.10$; ** $p < 0.05$.

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