Understanding the Mechanisms and Outcomes of Skill Formation: The Effects of Preschool on the Quality of Early Careers in Peru

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Abstract

Preschool education represents a critical investment in skill development, contributing to long-term quality of life and human development outcomes, including labor market results. Most of the existing evidence has primarily focused on assessing the effects of preschool on labor outcomes, particularly income levels, but much less is known about whether it exerts similar effects on non-monetary aspects of job quality. We thus study the impact of preschool attendance in Peru on early-career quality of employment, proxied by access to job benefits aligned with ILO's notion of Decent Work. We build on a suitable theoretical framework linking preschool and other educational investments with job quality outcomes in early career stages, positing the dynamic development of multifaceted skill stocks as the key mediating factor in this connection. This framework is estimated using a Structural Equation Model (SEM) with longitudinal data from the Young Lives study in Peru spanning 2002 to 2016. Our results show that preschool significantly increases the likelihood of obtaining jobs with health insurance, pension contributions, and paid sick leave. These effects are primarily transmitted through the development of cognitive skills in early childhood, which are indeed key determinants in the formation of both cognitive and non-cognitive skills later in life.

JEL Codes: I21, J24, J31

Keywords: Preschool education; Job quality; Skills formation; Peru; Structural equation modelling

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1. Introduction

Countries in Latin America and the Caribbean face significant challenges regarding employment quality, with 51% of the region's workers earning labor incomes insufficient to pass the moderate poverty threshold and 55% of workers being employed in the informal sector, lacking social security coverage (IDB, 2024a). The outlook for youth employment is even more complex, as young people in the region are disproportionately employed in lower-quality jobs, even though the youth population has, on average, completed more years of education than the general population (CABEI & OEI, 2022). In the region, Peru shows one of the most vulnerable employment situations for youth employment. In 2022, it had the second lowest percentage of workers contributing to social security, and the third highest rate of self-employed workers (IDB, 2024b).

The connection between education and job quality for young people is well understood theoretically; skill development is a key mechanism for accessing better-quality jobs throughout life. In restricted, highly informal labor markets like Peru's, skills serve as a key mechanism for the sorting of employees into the limited formal and higher-quality jobs (Berniell, 2021). This skill-based sorting can be powerful and long-lasting; evidence from informal economies shows that early human capital investments effectively lead to better quality job trajectories and earnings (see e.g. Gertler et al., 2014, for the case of Jamaica and Hovhannisyan et al., 2022 for Latin American countries). It is also known that among the various formative stages, early childhood is crucial for the development of cognitive (e.g., Magnuson et al., 2007; Bietenbeck et al., 2017) and non-cognitive skills (e.g., Heckman & Kautz, 2013). Educational investments during this formative period have a significant long-term impact on various aspects of quality of life and human development. These investments determine early-career employment characteristics, which in turn shape long-term job trajectories measured by wage dynamics (e.g., Eberlein et al., 2024). Educational investments can have positive impacts on wages that persist even up to age 60 (Bingley & Westergaard-Nielsen, 2012).

Much less is known about whether these effects extend to other indicators of job quality that are not necessarily tied to wage levels. Yet, virtually all international development agendas call for a multidimensional view of job quality that goes beyond wages, including frameworks such as ILO's Decent Works agenda, OECD's Measurement of Job Quality, and SDG8. While research in developed countries—such as the US (e.g. Campbell et al., 2002; Reynolds et al., 2011)—has demonstrated a clear link between early childhood education and non-monetary labor outcomes during the initial stages of professional careers, this relationship remains understudied in developing countries. The challenge in closing this knowledge gap lies in the scarcity of longitudinal data that follows individuals from early childhood through their entry into the labor market. Only this type of data enables a comprehensive understanding of how early life experiences—such as preschool education—shape later life outcomes, including access to labor market opportunities and the quality of employment attained. In this regard, Peru is uniquely positioned for such a longitudinal analysis by virtue of the Young Lives (YL) study, coordinated by the Department of International Development at the University of Oxford, which tracks cohorts from early childhood into adulthood. This is a rare dataset in the region, which often lacks long-term labor market data. This longitudinal data offers a unique opportunity to explore the effects of preschool education and entry-level job quality outcomes, a relationship that is particularly relevant given Peru's highly informal labor market.

Using Peru's YL dataset, we analyze the effect of preschool attendance on the quality of jobs obtained at the start of a professional career, proxied by access to job benefits beyond income levels. We apply a framework drawing upon Cunha & Heckman (2007, 2008) and Krishnakumar & Nogales (2020), linking educational investments and the development of cognitive and non-cognitive skills to job quality outcomes in the early career years. This framework is estimated using a Structural Equation Model (SEM), which allows us to identify the indirect effects of preschool attendance on job quality outcomes. We follow a multidimensional conception of job quality in line with the ILO's decent work agenda, considering job quality as a concept composed of several related but distinct dimensions (income and productivity, security and social protection, and prospects for personal development) rather than a single monetary metric. This framework is closely aligned with the Capability Approach, one the most prominent modern human development paradigms, which emphasizes multiple functionings and freedoms that jobs may enable rather than reduce well-being to wages alone (Sen, 1999). In our empirical specification, therefore, a contract, health insurance, pension contributions and paid sick leave should be understood as related facets of formal employment and social protection, each with potentially different determinants and welfare implications, rather than interchangeable direct substitutes for higher wages.

Our study contributes to the literature in three ways. First, unlike most existing work that focuses primarily on wage or educational outcomes, we examine non-monetary dimensions of early-career job quality. We explicitly study the effect of preschool on health/social insurance, pension contributions and paid sick leave, which are outcomes that are central to the ILO's Decent Work agenda and to SDG 8. Although fundamental from a human development perspective, these outcomes are not often studied as endpoints of early-childhood investments in middle-income countries. Second, methodologically the paper uses a Structural Equation Model (SEM) that combines measurement equations for latent cognitive and non-cognitive skills with instrumental variable identification of investment decisions. This allows us to estimate mediated (i.e. indirect) pathways from preschool to job quality through skill stocks across different formative periods, rather than relying on single reduced-form estimates. Third, our empirical setting based on the Young Lives Peru older cohort data provides long-run, individual-level longitudinal evidence connecting preschool attendance to job-quality outcomes observed at labor market entry in a developing-country context. Taken together, we argue that these three elements deliver novel policy-relevant insights on how preschool shapes decent-work prospects in the context of a developing country.

Among some salient results, we find that, while preschool education does not show significant effects on income at the start of a career, it has positive and significant effects on the likelihood of accessing health or social insurance, contributing to the pension system, and enjoying paid sick leave. These effects are transmitted through the development of early cognitive skills, which subsequently support the formation of both cognitive and non-cognitive skills later in life. We also show that non-cognitive skills in the second formative period have a direct effect on the probabilities of having health/social insurance and contributing to the pension system, while cognitive skills directly influence the likelihood of receiving paid sick leave. These results are consistent with evaluations of early childhood interventions such as the Abecedario program (Campbell et al., 2014) and the HighScope Perry Preschool program in the United States (Heckman et al., 2010).

The document is organized as follows: The second section presents the context of preschool education and youth employment in Peru. The third section outlines the theoretical and conceptual foundations linking preschool education to job quality outcomes in early career employment. The fourth section describes the dataset and variables used in the study. The fifth section details the methodological strategy employed in the research. The sixth section presents the study results, including the main model and additional techniques used to examine the mechanisms through which preschool education impacts early career job quality outcomes. Finally, the seventh section provides the study's conclusions and potential extensions for further research in this area.

2. Preschool education and youth employment in Peru

Officially, basic education in Peru is the stage of learning that fosters the holistic development of students and enhances their competencies to act effectively in various societal domains (Ministry of Education of Peru, 2020[1]). This is the first stage of the formal educational system and comprises three modalities: Regular Basic Education, Special Basic Education, and Alternative Basic Education. Early childhood education is the first level of Regular Basic Education and targets children aged 0 to 5 through two educational cycles: Cycle I (ages 0–2), provided via daycare services or Non-School-Based Early Childhood Education Programs (PRONOEI), and Cycle II (ages 3–5), delivered through preschool services or PRONOEI in areas lacking formal education options (Arapa et al., 2021).

Cycle II curriculum emphasizes language and vocabulary learning. It teaches comparison and grouping exercises, and establishes relationships of quantity, space, time, and causality as the foundation for developing mathematical thinking (Ministry of Education of Peru, 2016[2]). The curriculum also specifies that preschool teachers must base their planning on learning objectives and assess relevant information about students' competency development levels.

According to data from the Ministry of Education of Peru (2024[3]), the net enrollment rate in initial education (3 to 5 years old) increased from 53.5% in 2001 (59.8% in urban areas and 42.9% in rural areas) to 89.5% in 2023 (88.4% in urban areas and 92.5% in rural areas). Despite becoming mandatory in 2003, universal access was not achieved, although enrollment gaps in rural areas have been steadily closing over recent years.

However, progress in expanding access to education in Peru may have not fully translated into equitable work opportunities if the skill acquisition process is deficient. Precisely, preschool attendance has been shown to be a crucial investment for a better, more efficient process of skill

[1] See document entitled What is Basic Education? Curriculum by the Ministry of Education of Peru in https://sites.minedu.gob.pe/curriculonacional/2020/11/10/que-es-la-educacion-basica-2

[2] See document entitled Regular Basic Education: Initial Education Curriculum Program. Curriculum by the Ministry of Education of Peru.in www.minedu.gob.pe/curriculo/pdf/programa-curricular-educacion-inicial.pdf

[3] See document entitled Net Enrollment Rate, Early Childhood Education (% of population aged 3-5) by the Ministry of Education of Peru in https://escale.minedu.gob.pe/ueetendencias2016?p_auth=ya3orTbR&p_p_id=TendenciasActualPortlet2016_WAR_tendencias2016portlet_INSTANCE_t6xG&p_p_lifecycle=1&p_p_state=normal&p_p_mode=view&p_p_col_id=column-1&p_p_col_pos=1&p_p_col_count=3&_TendenciasActualPortlet2016_WAR_tendencias2016portlet_INSTANCE_t6xG_idCuadro=251

acquisition (Agostinelli and Wiswall, 2025; Arteaga et al., 2014; Attanasio et al., 2020a; Havnes and Mogstad, 2015). This is important because, following Haanwinckel and Soares (2021), when students advance through the system without acquiring the competencies demanded by a modern economy, their chances of securing stable and productive employment diminish. Focusing on Brasil, they show that improvements in workforce skill composition have been the most important factor behind reductions in informality; without such increases, informality and unemployment would have risen rather than declined. In addition, Novella et al. (2019) show that there is a skill-level mismatch between potential employees and formal employers in Peru. This underscores how weak linkages between education and skill formation help explain why large segments of young Peruvians remain concentrated in informal or low-quality jobs despite higher levels of schooling.

Turning to the labor market, these dynamics are clearly reflected in the employment outcomes of young Peruvians. The 2022 Peru Annual Youth Employment Report (Ministry of Labor and Employment Promotion of Peru, 2024[4]) shows that the employment rate among individuals aged 15 to 29 was 58.3%, with 24.1% belonging to households classified as poor based on per capita expenditure. Typically, young Peruvians hold jobs in low-paying occupations and sectors. Furthermore, many of them are employed under poor-quality labor conditions besides low payments: 34.7% of employed youth worked independently or as unpaid family workers. The economic sector with the highest concentration of employed youth was services (39.1%), followed by extractive industries (22.4%), commerce (20.8%), manufacturing (9.8%), and construction (7.9%). The most common jobs among young people were agricultural, fishing, and forestry laborers (15.5%), salespersons (13.6%), laborers in mining, construction, manufacturing, and transportation (8.5%), office clerks (8.1%), and technical professionals (7.9%). Overall good job quality is still uncommon for Peruvian youths: only 36.4% of them had a signed contract, 29.0% contributed to the pension system, and 80.2% had access to health insurance. Only 10.0% of the employed youth simultaneously earned incomes above the minimum wage, had a signed contract, health insurance, pension system contributions, and worked a maximum of 48 hours per week.[5]

3. Theoretical Framework

Vast evidence suggests that early-life skills are strong predictors of later educational outcomes and academic achievements (e.g., Schmitt et al., 2025; Robson et al., 2020). Skills acquired in early childhood enhance the complementarity between cognitive and non-cognitive skills (e.g., Cunha et al., 2006) and contribute to self-productivity in later formative stages (e.g., Cunha & Heckman, 2010). Consequently, programs designed to mitigate the adverse effects of unfavorable environments on skill development tend to be more effective when implemented earlier in life (Cunha & Heckman, 2010). This can be explained primarily by the fact that exposure to malnutrition, conflict-ridden family environments, lack of early stimulation, or other adverse conditions during early childhood can have significant consequences on brain development, which are difficult to reverse in later stages (Nelson et al., 2025).

[4] See document entitled Annual Report on Youth Employment in Peru 2022 by the Ministry of Labor and Employment Promotion of Peru in https://www.gob.pe/institucion/mtpe/informes-publicaciones/4992368-informe-anual-del-empleo-juvenil-en-el-peru-2022.

[5] Established as a threshold for weekly working hours under Law 27671 in 2002.

In this context, preschool education emerges as one of the most critical early investments. The literature shows that preschool attendance is associated with long-term improvements in cognitive skills, measured by higher reading and math proficiency (e.g., Bietenbeck et al., 2017), and better academic performance during both primary and secondary education (e.g., Loeb et al., 2007; Havnes & Mogstad, 2015). Additionally, preschool attendance has been directly linked to higher educational attainment, an increased likelihood of pursuing higher education (e.g., Dietrichson et al., 2020).

The impact of preschool education on cognitive skills appears to be generally consistent across studies in both developed (e.g., Magnuson et al., 2007) and developing countries (e.g., Woldehanna, 2016). However, its effect on non-cognitive skills remains unclear. For instance, Carneiro & Heckman (2003) report positive effects on school behavior, while Magnuson et al. (2007) find that preschool attendance is associated with higher levels of misbehavior. These discrepancies may be explained by differences in preschool pedagogical orientation, as previous studies found that negative behavioral outcomes are more frequent among children who attended teacher-directed preschools focused on basic cognitive skills, compared to child-centered programs emphasizing stimulation (e.g., Durkin et al., 2022). Beyond behavioral measures, research has identified broader non-cognitive benefits associated with preschool education. These include higher scores on the "Grit" scale—measuring perseverance toward long-term educational and career goals—during adolescence (World Bank, 2014; Bozgün & Akin-Kösterelioglu, 2020), improved self-regulation skills in school, such as attention, effort, and class participation (Berlinski et al., 2008; Tarullo et al., 2009), and greater development of socio-emotional skills, including self-esteem and self-efficacy (e.g., Heckman & Kautz, 2013; Arapa et al., 2021).

Also, preschool education has been found to have positive effects on individuals' earnings, with impacts persisting even up to the age of 60 (e.g., Bingley & Westergaard-Nielsen, 2012; Haimovich Paz, 2015; Herbst, 2017; Havnes & Mogstad, 2011). However, the literature has not extensively explored its effects on non-monetary labor market outcomes related to the concept of "decent jobs". A decent job is one that provides dignity and fosters individuals' capabilities while adhering to fundamental labor rights and ensuring social protection (Levaggi, 2004). Typically, access to such jobs is measured through employer-provided benefits and working conditions that contribute to workers' well-being, such as working hours, health benefits (Johnson & Corcoran, 2003), contractual stability (Sehnbruch, 2004), and workplace safety (Floro & Messier, 2011). Studies linking skill development to these dimensions of job quality are relatively scarce. One exception is Krishnakumar & Nogales (2020) who focus on Bolivia and find that cognitive and non-cognitive skills are directly related to access to jobs with legally regulated working hours and safe work environments. However, two key issues remain unsolved. First, there is limited evidence on the role of early educational investments in securing decent employment. Second, considering the crucial role of first jobs in shaping future career trajectories (e.g., Eberlein et al., 2024), it is essential to establish a clearer connection between skill formation and the quality of individuals' initial jobs.

The literature discussed above is compelling and it can be translated to a formal economic model in order to understand the mechanisms through which investments and skills acquired during different stages of education and training translate into dimensions of job quality in adulthood, we propose a theoretical framework for the process of skill formation drawing upon the works of Cunha & Heckman (2007, 2008) and Krishnakumar & Nogales (2020). In our framework,

this process predicts that early cognitive and non-cognitive skills increase the likelihood of obtaining formal contracts and social protection, even in constrained labor markets. Thus, in several empirical versions of our main model, tenure of formal contract is a crucial mediating employment characteristic.

Formally, this model considers T formative stages, followed by a post-formative stage $T+1$, when individuals begin their participation in the labor market. In each formative period t, investments I_t are made, which subsequently develop skills θ_t^k that can be either cognitive $(k = C)$ or non-cognitive $(k = N)$.

The skills acquired in period $t+1$ depend on the previous investments made, the set of cognitive and non-cognitive skills developed up to period t, and a set of exogenous variables $\tilde{x}_{1,t}^k$ representing the individual's environment at time t. Thus, the process of type $k = \{C, N\}$ skill formation can be represented as shown in Equation 1.

$$\theta_{t+1}^k = f_1(\theta_t^C, \theta_t^N, I_t, \tilde{x}_{1,t}^k, v_{1,t+1}). \quad (1)$$

Where $v_{1,t+1}$ is a random error term. Educational investments are endogenous in this setting, either due to unobserved factors or shocks that influence both the investments and outcomes, or because existing skills affect the level of investment they receive, leading to potential reverse causality (Krishnakumar and Nogales, 2020). To address this problem, investments in period $t+1$ are explicitly modelled through Equation 2.

$$I_{t+1} = h(\theta_t^C, \theta_t^N, y_{t+1}, \eta_{t+1}). \quad (2)$$

Where η_{t+1} is random error term and y_{t+1} represents instrumental variables that are related with educational investments decisions but are not directly linked to the skill formation process.

On the other hand, labor quality outcomes (Q_t) are observed in period $T+1$. They are explained by the stock of cognitive and non-cognitive skills acquired up to T, and by a set of exogenous variables $\tilde{x}_{2,T+1}$, as depicted in Equation 3, where v_2 represents a random error term.

$$Q_{T+1} = f_2(\theta_T^C, \theta_T^N, \tilde{x}_{2,T+1}, v_2) \quad (3)$$

It is important to note that skills θ_t^k are latent variables that manifest themselves through various observable measures Z_t^k. Therefore, the cognitive and non-cognitive skills are transformed into observable measures as per Equation 4, where ϵ_t^k represent random error terms.

$$.Z_t^k = m_1(\theta_t^C, \theta_t^N, \epsilon_t^k) \quad (4)$$

In summary, Equations 1, 2, and 3 constitute the structural equations of the model, illustrating the mechanisms linking investments, skills, and labor quality outcomes. Meanwhile, Equation 4 is a measurement equation that explains how latent variables are transformed into observable indicators. This system establishes a theoretical intertemporal relationship between the acquired skills and the educational investments made during different formative periods t and the labor outcomes achieved in T. The framework holds for any number of periods; however, the model must be adapted to the availability of data. Therefore, an estimable version of the theoretical

model is proposed here consisting of two formative periods ($T = 2$), in which $t = 1$ includes all education received up to the completion of primary school, and $t = 2$ encompasses secondary education. The complete estimable System of Equations is presented below:

$$\begin{gathered}
\theta_1^k = f_{1,1}\left(I_1, \tilde{x}_{1,1}^k, v_{1,1}\right) \; para \; k = \{C, N\} \\
\theta_2^k = f_{1,2}\left(\theta_1^C, \theta_1^N, I_2, \tilde{x}_{1,2}^k, v_{1,2}\right) \; para \; k = \{C, N\} \\
I_1 = h_1(y_1, \eta_1) \\
I_2 = h_2\left(\theta_1^C, \theta_1^N, y_2, \eta_2\right) \\
Q_3 = f_2\left(\theta_2^C, \theta_2^N, \tilde{x}_{2,3}, v_2\right) \\
Z_1^k = m_1\left(\theta_1^C, \theta_1^N, \epsilon_1^k\right) \; para \; k = \{C, N\} \\
Z_2^k = m_2\left(\theta_2^C, \theta_2^N, \epsilon_2^k\right) \; para \; k = \{C, N\}
\end{gathered} \tag{5}$$

In this study, System 5 will be used to estimate the effects of preschool education (included in I_1) on four different labor outcomes. The first one is a traditional measure of labor quality: monthly labor income. The other three outcomes are job benefits aligned with the decent work concept (Levaggi, 2004): social and health insurance, pension contributions, and paid sick leave. Due to data availability, all these outcomes are observed before the age of 25, representing an initial period in individuals' working careers.

It is important to highlight that each structural equation includes exogenous variables $\tilde{x}_{1,t}^k$, $\tilde{x}_{2,T}$ and y_t, which, by satisfying the exclusion restriction with the other equations of the model, serve as instrumental variables. These variables will enable the identification of causal effects resulting from this system as accurately as possible.

4. Data

In this study, we use data from the Young Lives (YL) longitudinal study. Since 2002, the YL study has collected data in Ethiopia, India, Peru, and Vietnam from children in two distinct age cohorts, with the goal of examining the causes and consequences of child poverty and inequality (Briones, 2018). The younger cohort consists of children born between 2001 and 2002, whereas the older cohort includes those born between 1994 and 1995. Although these data are not meant to be nationally representative[6], they provide detailed insights into how early-life circumstances affect later outcomes (Sánchez et al., 2015). YL data collection was carried out in five rounds between 2002 and 2016. In response to the COVID-19 pandemic, an additional telephone round—comprising five separate calls—was conducted between 2020 and 2021.

We used data from rounds 1 through 5 of the older cohort in Peru, as these rounds include educational and employment information for individuals who have completed secondary education. Calls made during round 6 were excluded to avoid distortions arising from the COVID-19 pandemic when assessing outcomes related to quality of life and labor wellbeing. The variables used in this study are grouped into 1) investment variables; 2) skill measurement variables; 3) job quality variables; and 4) control/instrumental variables.

[6] The YL sample was drawn from sentinel sites using a multi-stage random sampling procedure. Sites were purposively selected to represent different types of communities, with an intentional oversampling of poorer districts to ensure representation of the low-income population. Within each site, children were randomly selected from households with eligible ages (Sánchez et al., 2015).

Investment variables are constructed using the child's school enrollment information in every round of the study. The question regarding preschool attendance was asked retrospectively in round 1, as the children were already 8 years old at the time of the interview[7]. In period $t = 1$, the investment variables are represented by dummy variables indicating preschool attendance ($I_{1,1}$), and school enrollment status at the time of the interviews in rounds 1 and 2 ($I_{1,2}$ y $I_{1,3}$, respectively). In $t = 2$, enrollment during rounds 3 ($I_{2,1}$) and 4 ($I_{2,2}$) is captured. To preserve statistical power in our estimations, we include only educational investments up to the completion of secondary education, as no individuals in YL Round 5 had completed higher education programs. For the same reason, we do not distinguish between enrollment in public and private education systems.

Skills are modelled as latent variables estimated from observable measures of cognitive and non-cognitive abilities collected as part of the YL study. The cognitive skill measures in $t = 1$ include: the percentage of correct responses on the Raven Progressive Matrices test in round 1; the math achievement test score from round 2; and the score on the Peabody Picture Vocabulary Test-Revised (PPVT-R) in round 2. In $t = 2$, the cognitive measures comprise the math achievement test scores from rounds 3 and 4; the PPVT-R score from round 3; and the reading comprehension test score from round 4. All the measurements listed above are standardized.

For non-cognitive skills, we use measures of socio-emotional competencies approximated using the Agency and Pride scales (Dercon & Krishnan, 2009). These competencies were evaluated based on a series of statements, with each participant responding on a five-point scale: 1) Strongly disagree; 2) Disagree; 3) Neutral; 4) Agree; and 5) Strongly agree. In round 2, responses were categorized into three groups: 1) Yes; 2) No; and 3) Neutral. To convert this categorization to match the scale used in the other rounds, "Yes" was assumed to be equivalent to "Strongly agree" and "No" to "Strongly disagree". The statements, their data availability, and the inverted scales for negatively worded items (indicated by the term *(Inverted)*) are presented in Table 1[8].

Table 1: Agency and Pride Scales by round, Peru

	Round				
	1	**2**	**3**	**4**	**5**
Agency Scales					
A1: "If I try hard, I can improve my situation in life"	-	*A*	*A*	*A*	*A*
A2: "Other people in my family make all the decisions about how I spend my time" (Inverted)	-	*A*	*A*	*A*	*A*
A3: "I like to make plans for my future studies and work"	-	*A*	*A*	*A*	*A*
A4: "If I study hard at school I will be rewarded by a better job in future"	-	*A*	*A*	*A*	*A*
A5: "I have no choice about the work I do" (Inverted)	-	*A*	*A*	*A*	*A*
Pride Scales					

[7] As with any retrospective measure, this raises the possibility of recall bias. However, preschool attendance is a salient event that can be safely assumed to have been recalled with reasonable accuracy, as this variable has been widely used in the Young Lives literature in Peru, official reports from Peruvian authorities and other academic studies (e.g., Díaz, 2006; Streuli, 2012; Cueto et al., 2016; Crookston et al., 2014). While this limitation should be kept in mind, the soundness of these studies suggests that recall bias does not hinder our conclusions.

[8] We have corroborated that the measurement scale of non-cognitive skills does not alter our results. Also, please note that Agency and pride scales were adapted from existing validated instruments so they can be used with children (Yorke & Ogando, 2018) and have been extensively tested across diverse cultural contexts (Dercon & Krishnan, 2009). They have previously been employed to measure socioemotional skills with the Young Lives Study in Peru (Arapa et al., 2021). Additional information on their statistical validity can be found in Dercon & Krishnan (2009).

O1: "I am proud to show my friend here I live"	-	*A*	-	-	-
O2: "I am proud of my clothes"	-	*A*	*A*	*A*	*A*
O3: "I am proud of the work done by the head of household"	-	*A*	-	-	-
O4: "I am often embarrassed because I do not have the right supplies for school" (Inverted)	-	*A*	*A*	-	-
O5: "I am proud of my achievements in school"	-	*A*	-	-	-
O6: "I am proud by the work I have to do"	-	*A*	*A*	*A*	*A*
O7: "I am proud of my shoes or of having shoes"	-	*A*	*A*	*A*	*A*
O8: "I am proud to have the correct uniform"	-	*A*	*A*	-	-

Note: '*A*' denotes data availability for the Scale in each survey round

Source: Own elaboration based on YL study, rounds 1 to 5

In addition, hourly labor income, access to social/health insurance, AFP (pension funds administrators) membership and paid sick leave were used to study the effects of pre-school education on job quality outcomes. Labor income ($Q_{1,3}$) is measured as hourly monetary earnings; access to social and health insurance ($Q_{2,3}$), AFP ($Q_{3,3}$) and paid sick leave ($Q_{4,3}$) are binary variables taking the value of 1 if the person has access to each one of these benefits from work.

4.1. Sample characteristics

In YL Round 1, data were collected from 714 children with an average age of 8 years. By Round 5, the sample size had declined to 608 participants, reflecting an attrition rate of approximately 15%. This rate is relatively low compared to similar longitudinal studies, some of which report attrition rates exceeding 50% over 15 years (e.g., Gustavson et al., 2012). However, the final analytical sample—restricted to observations with complete data across all variables—consisted of 322 participants, all of them occupied[9].

Table 2 shows some general occupational characteristics of the sample in Round 5 that allow us to better understand the working conditions of people in our sample. The majority (79.5%) of individuals are salaried employees, while 14.9% are self-employed and 5.6% work without pay or as apprentices. Despite the predominance of salaried work, only 24.5% of individuals had a signed contract, highlighting the prevalence of informal employment arrangements in Peru (Ministry of Labor and Employment Promotion of Peru, 2024). About 41.9% of the sample combined work and study, and the average daily workload is 8.16 hours, suggesting a high labor burden even among students. Monthly earnings average S/ 856.58 (PPP $463.02), and hourly wages stand at S/ 5.10 (PPP $2.76), slightly above the 2016 national minimum wage (S/ 850 per month) but below the national average wage in the same year (S/ 1370.7 per month) (INEI,

[9] Although the YL panel shows an overall attrition of 15% between Round 1 (n=714) and Round 5 (n=608), which is intrinsic to the original dataset, our final analytical sample (n=322) reflects additional sample drop due to missing data in the variables included in our models. Indeed, the final analytical sample can only include individuals with complete information for all variables used in system (5). Any individual with at least one missing value in these variables is excluded. To assess whether this additional sample drop is random, a probit regression to predict sample drop was conducted using sex of the household head, area of residence, household wealth quintiles (from the Young Lives Wealth Index), and sentinel site/cluster identifiers (from 1 to 20). Results show that only individuals living in sentinel clusters 9 and 14 have a marginally significantly lower likelihood of being dropped (at 10% significance). Therefore, while the smaller sample size reduces estimation efficiency, one can be less concerned about lack of consistency.

2023[10]). These values indicate a degree of labor vulnerability for young workers at the start of their careers[11].

Table 2: Occupational Profile and Labor Income in the Sample

	N	Percentage/Average
Total Observations	**322**	**100%**
Self-employed workers	48	14.91%
Salaried workers	256	79.50%
Unpaid family workers or trainees	18	5.59%
Signed contract at work	79	24.46%
Study and work simultaneously	135	41.9%
Hours worked per week	-	8.16
Monthly Wage (Soles)	-	S/ 856.58
Monthly Wage (PPP $)	-	$463.02
Hourly Wage (Soles)	-	S/ 5.10
Hourly Wage (PPP $)	-	$2.76

Source: Own elaboration based on YL study, rounds 1 to 5

Table 3 presents statistics of educational investments, specifically the share of individuals who reported attending preschool and those enrolled in the education system at the time of each survey round. 83.2% of the sample (268 observations) attended preschool. Also, enrollment rates were above 95% in rounds 1, 2, and 3, which correspond to the primary and secondary school years. By round 4, however, enrollment declined to 60%, reflecting the fact that some individuals had completed secondary education but did not pursue higher studies.

Table 3: School Enrollment by round

	Round				
	Preschool	**1**	**2**	**3**	**4**
Enrollment	268	314	320	306	194
(%)	83.2%	97.5%	99.4%	95.0%	60.3%

Source: Own elaboration based on YL study, rounds 1 to 4

Examining the labor quality outcomes most closely aligned with the concept of decent work, Table 4 shows a slightly higher share of individuals with pension contributions among those without preschool education, although the difference amounts to only 0.2 percentage points. By contrast, access to social/health insurance and paid sick leave is higher among those with preschool education, by 0.5 and 3.8 percentage points, respectively. Since these differences are not statistically significant, they do not provide clear evidence of a relationship between preschool attendance and labor quality outcomes, underscoring the need to further investigate the potential transmission mechanisms at play.

Table 4: Job quality outcomes descriptive statistics

	No preschool		**Preschool**		Mean Diff.
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	
Hourly labor income	-0.099	0.361	0.014	0.686	-0.113

[10] See the official series of monthly minimum wage in https://www.inei.gob.pe/estadisticas/indice-tematico/ocupacion-y-vivienda/

[11] Please note that the small sample size by type of workers (salaried, self-employed, and family workers) prevents us from performing a heterogeneity analysis at this level. Given their characteristics, self-employed workers and unpaid family workers are usually deprived in our outcome variables.

Social/health insurance	0.204	0.407	0.209	0.407	-0.005
Pension contributions	0.148	0.359	0.146	0.353	0.002
Paid sick leave	0.093	0.293	0.131	0.338	-0.038

* p<0.10, ** p<0.05, *** p<0.01

Source: Own elaboration based on YL study, rounds 1 to 5

5. Empirical Strategy

One particular aspect of our study is that the estimation of all parameters in System 5 is conducted simultaneously. For this, we estimate a Structural Equation Model (SEM) that relates variables using the path analysis concepts developed by Wright (1921), which determine the direction of potential causal relationships. Latent variables are modelled through measurement equations, while the main relationships in the theoretical model are represented in the structural equations. Our measurement equations are based on the hypothesis that the results from the learning tests in the YL study are appropriate measures of the latent constructs related to cognitive skills in each developmental period, and that the socio-emotional scales serve as indicators of the latent non-cognitive skills.

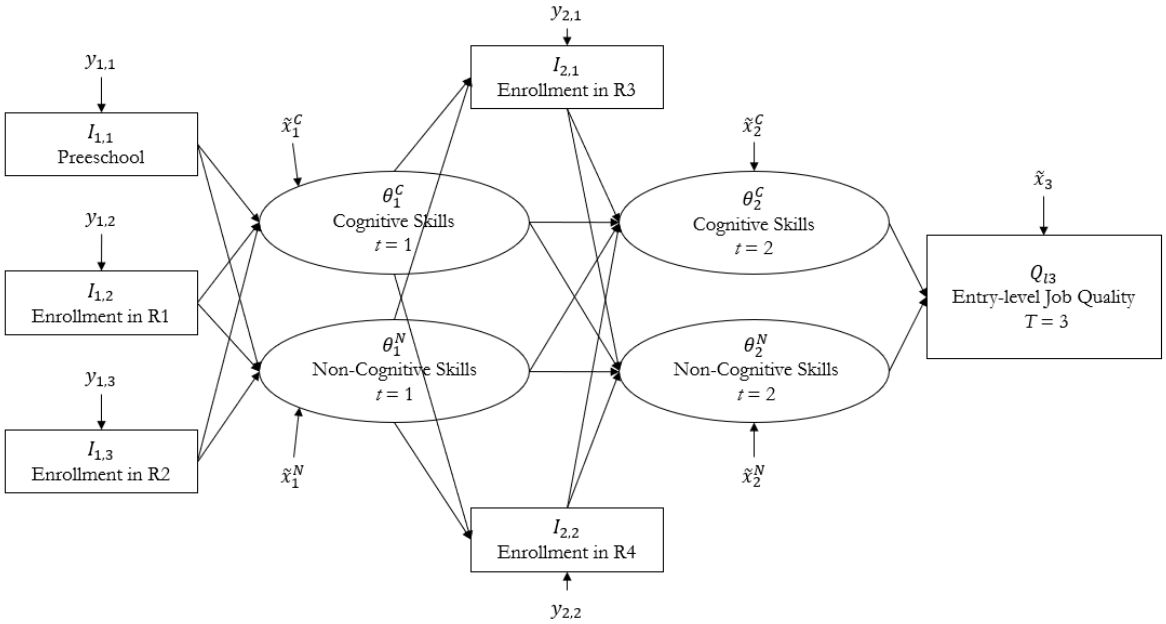
The proposed SEM structure is presented in Figure 1. Note that preschool education does not have a structural coefficient that directly affects job quality outcomes, so it is necessary to identify the indirect, mediating effects that occur along the pathway connecting the two variables. Simultaneous estimation via SEM ensures greater efficiency in mediation estimators compared to approaches using separate sequential regressions (Iacobucci, 2008). Also note that a separate version of System 5 was estimated for each job quality outcome in turn: labor income, access to social/health insurance at work, pension contributions, and access to paid sick leave[12].

The structural coefficients provide information about the correlations among the analyzed variables, although they do not directly imply causality. As Iacobucci (2009) points out, establishing causality in SEMs can be more effective when it is based on a solid theoretical foundation, a condition met in this study by adopting the skill formation framework proposed by Cunha & Heckman (2007). Nevertheless, to improve the identification of causal relationships in the model, instrumental variables are used to correct potential endogeneity issues in the structural equations[13]. Following the approach outlined in System 5, the variables $\boldsymbol{y_{t,i}}$ serve as instruments for the educational investment equations; the variables $\tilde{\boldsymbol{x}}_{\boldsymbol{t}}^{\boldsymbol{k}}$ are employed as instruments in the equations reflecting the skill formation processes; and $\tilde{\boldsymbol{x}}_{\boldsymbol{3}}$ provides a source of exogenous variation for the structural equation that contains the early job quality outcomes.

Figure 1: SEM Path Analysis

[12] Note that we estimate all these SEM variants as systems of linear structural equations, with ML used as the numerical optimizer. This strategy follows authoritative studies in the related literature (Deming, 2009; Heckman et al., 2010), where binary outcomes are specified as linear probability models (LPM) estimated by ML with heteroskedasticity-robust standard errors, so reporting R-squared coefficients is appropriate. Moreover, the LPM framework because coefficients are directly interpretable as average partial effects and allow straightforward decomposition of direct and indirect (mediated) effects, (see MacKinnon et al., 2007).

[13] The relation between the instruments and the exogenous variables over time is a key element for the validity of the exclusion restrictions. To see a summary of each instrument direction and exclusion restriction justification, see Annex A1.



Source: Own elaboration

Following Helmers & Patman (2011) and Woldehanna (2016), the instruments for investments include household composition variables, the Wealth Index constructed within the YL study framework (Briones, 2018), and variables related to events or shocks that have negatively impacted the household's economic situation, as these can influence investment decisions across different periods.

The household shock variables take the value of 1 when the household head reports a deterioration of the family's economy. The instrumental variable $y_{1,1}$ corresponds to the Wealth Index calculated in round 1; $y_{1,2}$ represents the number of individuals aged 0 to 5 in the household during round 1; and $y_{1,3}$ is a dummy variable that indicates the occurrence of a family-related shock between rounds 1 and 2. For the second developmental period, reports of natural disaster shocks experienced between rounds 2 and 3 is used as an instrument for enrollment in round 3 ($y_{2,1}$); and the number of children aged 0 to 5 in the household during round 4 serves as an instrument for enrollment in round 4 ($y_{2,2}$). The relevance and strength of all these instruments is proven and presented in Table A2 in the appendix.

The exclusion restriction for this first group of instrumental variables is based on the premise that household composition and economic conditions can affect skill formation during childhood and adolescence only through educational investment decisions made by the parents. In our model, parental background variables affect the choice of investment but are explicitly excluded from directly determining the child's skill production. This pathway is empirically consistent. For instance, Wolf & McCoy (2019) show that educational investments serve as the main mechanism that connect family wealth or socioeconomic status to skill development measures. Near (2022) explicitly finds that the relationship between early family income and adolescent outcomes is mediated almost entirely by parental support, while Brown (2006) demonstrates that parental education primarily affects child skill development by increasing parental goods and time investments in their education. Moreover, by using variables measured in rounds specific to each developmental period, we mitigate concerns that these instruments could be correlated with investment decisions or outcomes in other periods, thereby reinforcing

the plausibility of the exclusion restriction. Indeed, our dataset includes variables representing temporally bounded shocks (e.g., family-related or natural disaster events) based on questions phrased in such a way that their influence on skill formation is mediated only by current-period investment, rather than persisting as direct inputs.

The instruments in the cognitive skill formation equations are the incidence of chronic malnutrition (stunting) in round 2, as a proxy for the children's health status ($\tilde{x}_1^C$) (Attanasio et al., 2020b), and the number of hours per day the child spends studying outside of school hours in round 3 ($\tilde{x}_2^C$) (Mitchell et al., 2023).

The exclusion restriction for these instruments is based on the idea that neither chronic malnutrition nor time spent studying outside of school directly affect parental educational investment decisions or subsequent labor market outcomes. Evidence suggests that the pathway linking poor nutrition to socioemotional traits operates through neurocognitive development (Lui & Raine, 2017), which is in turn strongly associated with cognitive skill measures (Suárez-Pellicioni et al., 2021). Indeed, Helmers & Patnam (2011) demonstrate that child health, in general, positively and statistically significantly affects cognitive skills by age five, an effect which is often established early due to the critical developmental window for intellectual, cerebral capacity (Carneiro et al., 2003). This literature simultaneously shows that the direct effect of early health on non-cognitive skills is statistically insignificant. While early health strongly determines cognitive skill development, its effect on non-cognitive skills is mediated through the "cross-productivity" effect of the initial cognitive foundation. This mediation pathway is corroborated by Sánchez (2017) using data from Ethiopia, Vietnam, India, and Peru.

Finally, for the non-cognitive skill equations, socio-emotional competencies of the caregiver is used as instrument for the first developmental period ($\tilde{x}_1^N$), and family shocks experienced during rounds 2 and 3 ($\tilde{x}_2^N$) are posited as instruments for the second developmental period (Arapa et al., 2021). We argue that while parents' socio-emotional competencies have direct effects on children's non-cognitive skills, they are not directly related with the formation of cognitive skills. Empirical evidence indicates that caregivers' non-cognitive traits—such as those reflected in parenting style—have a direct influence on children's non-cognitive development, but not on their cognitive skill formation. Cognitive skills, in contrast, are more strongly shaped by factors such as time allocated to educational activities (Fiorini & Keane, 2014). Complementary findings from Xia (2023) further suggest that the influence of caregivers' non-cognitive skills on child cognitive outcomes operate indirectly, through their impact on children's own non-cognitive traits, rather than directly affecting cognitive skills. Similarly, there is robust evidence that past family material losses affect mainly the development of non-cognitive skills (García-Miralles & Gensowski, 2025).

We recognize that job quality outcomes are influenced by sources of variation exogenous to the skill formation technology. Traditionally, years of experience have been identified as determinants of job outcomes (e.g., Hall & Farkas, 2011; Díaz et al., 2013). However, it is difficult to include this variable here since job quality outcomes are observed at the beginning of one's career. Therefore, other employment characteristics are used as instruments in the structural equation for job outcomes, including the economic sector (for the labor income model) and the size of the firm (Dueñas et al., 2010) for models of non-monetary job benefits.

6. Results

As mentioned earlier, we run separate estimations of System 5 for each labor quality outcome variable. As a robustness check, we compare coefficients across different model specifications. For all outcome variables, the first specification assumes that educational investments, skill formation, and labor quality outcomes are fully explained by the variables in the model's structural equations, using instrumental variables for educational investments and skill formation. The second specification includes a control variable related to a key employment characteristic that influences labor quality: the economic activity classification, for the labor income model (Herrendorf & Schoellman, 2018) and firm size for job benefit access models Auerbach et al., 2011). The third specification controls for having a signed employment contract (Arranz et al., 2017). The estimated models identify direct effects (DE), which capture direct structural dependence; indirect effects (IE), which reflect the influence of one variable on another through mediating variables; and total effects (TE), which are the sum of DE and IE[14].

Effect on hourly labor income

Our results show that, when not controlled by any employment characteristic, preschool education ($I_{1,1}$) increases hourly labor income (Q_3) by 2.9 standard deviations, mainly through the development of cognitive skills in early childhood (see Table 5). Preschool education has a positive and statistically significant direct effect on the cognitive skill stock in $t = 1$ (θ_1^C) but does not have any significant effect on non-cognitive skills (θ_1^N). This can be due to the fact that preschool education in Peru focuses mainly on cognitive content (see section 2 above and Durkin et al., 2022). Furthermore, the cognitive skill-stock in $t = 1$ has a positive and highly significant direct effect on both cognitive (θ_2^C) and non-cognitive (θ_2^N) skill stocks in the next period.

We find that the indirect effects of preschool on early-career labor income become non-significant once we control for the economic sector of employment, and only the cognitive skill stock in $t = 2$ (θ_2^C) remains significant after controlling for whether individuals have a signed contract. This result aligns with the findings in Heckman et al. (2010), who argue that the effects of preschool education on labor income are not particularly noticeable before age 27, but they become more evident as individuals gain experience in the labor market. Also, as Palmer (2017) notes, low- and middle-income countries' labor markets with high levels of informality (such as Peru) often operate in a low-skill equilibrium, where individuals are matched to low-skill, low-paying jobs regardless of their accumulated skills stock. Young workers are particularly likely to experience this type of mismatching. While this pattern could also be explained by a lack of work experience among observations, it is crucial to examine whether a similar trend holds for other labor quality outcomes related to access to decent employment.

Table 5: SEM Results, Model with Q_3: Total Labor Income

Structural Equation	Path	(1)			(2)			(3)		
		DE	IE	TE	DE	IE	TE	DE	IE	TE
Cognitive (t=1) (θ_1^C)	$\theta_1^C \leftarrow I_{1,1}$	0.150**	-	0.150**	0.150**	-	0.150**	0.150**	-	0.150**
Non-Cognitive (t=1)	$\theta_1^N \leftarrow I_{1,1}$	0.030	-	0.030	0.030	-	0.030	0.030	-	0.030

[14] To see the complete results tables for every model, see Tables OA-OE in the online appendix.

(θ_1^N)										
Cognitive (t=2) (θ_2^C)	$\theta_2^C \leftarrow I_{1,1}$	-	0.216**	0.216**	-	0.216**	0.216**	-	0.216**	0.216**
	$\theta_2^C \leftarrow \theta_1^C$	1.351***	0.045**	1.396***	1.351***	0.045**	1.396***	1.351***	0.044**	1.395***
	$\theta_2^C \leftarrow \theta_1^N$	0.230	-0.008	0.222	0.230	-0.008	0.222	0.230	-0.008	0.222
Non-Cognitive (t=2) (θ_2^N)	$\theta_2^N \leftarrow I_{1,1}$	-	0.055**	0.055**	-	0.055**	0.055**	-	0.055**	0.055**
	$\theta_2^N \leftarrow \theta_1^C$	0.284***	0.041*	0.325***	0.285***	0.041*	0.326***	0.285***	0.041*	0.326***
	$\theta_2^N \leftarrow \theta_1^N$	0.220	-0.005	0.215	0.220	-0.005	0.215	0.220	-0.005	0.215
Income (T=3) (Q_3)	$Q_3 \leftarrow I_{1,1}$	-	0.029*	0.029*	-	0.023	0.023	-	0.021	0.021
	$Q_3 \leftarrow \theta_1^C$	-	0.191**	0.191**	-	0.152*	0.152*	-	0.141	0.141
	$Q_3 \leftarrow \theta_1^N$	-	0.007	0.007	-	-0.001	-0.001	-	-0.005	-0.005
	$Q_3 \leftarrow \theta_2^C$	0.170**	-	0.170**	0.146**	-	0.146**	0.140**	-	0.140**
	$Q_3 \leftarrow \theta_2^N$	-0.141	-	-0.141	-0.157	-	-0.157	-0.168	-	-0.168
R^2			0.781			0.782			0.780	
N			321			321			321	

* p<0.10, ** p<0.05, *** p<0.01

(1) Base SEM model with IV in Investments and Skills structural equations.
(2) Model (1) + IV in Employment Quality structural equation (Economic Activity Classification).
(3) Model (2) + Signed Employment Contract control.
Note that Total Effect (TE) = Direct Effect (DE) + Indirect Effect (IE) always, and that DE and IE are reported only when they exist in system (5)

Source: Own elaboration based on YL study, rounds 1 to 5

Effects on access to social/health insurance

Table 6 presents the results of the models analyzing access to health or social insurance. Preschool education has significant indirect and total effects on the likelihood of having health or social insurance at work, even after controlling for firm size. More precisely, preschool increases access to jobs with social or health insurance by 2.2%. These effects are transmitted through early development of cognitive skills, which, in turn, contribute to the formation of cognitive and non-cognitive skills in $t = 2$. We then find that it is rather non-cognitive skills that contribute significantly to the likelihood of having health or social insurance at work, even when controlling for firm size (specification 2) and having a signed contract (specification 3). This highlights the crucial role of non-cognitive skill development in shaping various future outcomes, as previously documented by Kautz et al. (2014) and Robson et al. (2020). However, preschool attendance does not significantly affect the likelihood of having health or social insurance when controlling for signed contract status. This suggests that the contract variable captures the full effect, potentially indicating an overlap with this job quality measure.

Table 6: SEM Results, Model with Q_3: Social/Health insurance

Structural Equation	Path	(1)			(2)			(3)		
		DE	IE	TE	DE	IE	TE	DE	IE	TE
Cognitive (t=1) (θ_1^C)	$\theta_1^C \leftarrow I_{1,1}$	0.147**	-	0.147**	0.147**	-	0.147**	0.147**	-	0.147**
Non-Cognitive (t=1) (θ_1^N)	$\theta_1^N \leftarrow I_{1,1}$	0.031	-	0.031	0.032	-	0.032	0.031	-	0.031
Cognitive (t=2) (θ_2^C)	$\theta_2^C \leftarrow I_{1,1}$	-	0.213**	0.213**	-	0.214**	0.214**	-	0.213**	0.213**
	$\theta_2^C \leftarrow \theta_1^C$	1.354***	0.048**	1.402***	1.356***	0.048**	1.404***	1.357***	0.048**	1.405***
	$\theta_2^C \leftarrow \theta_1^N$	0.223	-0.012	0.211	0.222	-0.012	0.210	0.222	-0.012	0.210
Non-Cognitive (t=2)	$\theta_2^N \leftarrow I_{1,1}$	-	0.060**	0.060**	-	0.060**	0.060**	-	0.059**	0.059**

(θ_2^N)	$\theta_2^N \leftarrow \theta_1^C$	0.314***	0.058**	0.372***	0.316***	0.056**	0.372***	0.309***	0.054**	0.363***
	$\theta_2^N \leftarrow \theta_1^N$	0.184	-0.013	0.171	0.183	-0.013	0.171	0.199	-0.012	0.187
Social/health insurance (T=3) (Q_3)	$Q_3 \leftarrow I_{1,1}$	-	0.019*	0.019*	-	0.022*	0.022*	-	0.006	0.006
	$Q_3 \leftarrow \theta_1^C$	-	0.120**	0.120**	-	0.141***	0.141***	-	0.040	0.040
	$Q_3 \leftarrow \theta_1^N$	-	0.044	0.044	-	0.044	0.044	-	0.019	0.019
	$Q_3 \leftarrow \theta_2^C$	0.025	-	0.025	0.049	-	0.049	0.003	-	0.003
	$Q_3 \leftarrow \theta_2^N$	0.227**	-	0.227**	0.196**	-	0.196**	0.099*	-	0.099*
R^2			0.775			0.804			0.917	
N			322			322			322	

* p<0.10, ** p<0.05, *** p<0.01

(1) Base SEM model with IV in Investments and Skills structural equations.
(2) Model (1) + IV in Employment Quality structural equation (Firm size).
(3) Model (2) + Signed Employment Contract control.
Note that Total Effect (TE) = Direct Effect (DE) + Indirect Effect (IE) always, and that DE and IE are reported only when they exist in system (5)

Source: Own elaboration based on YL study, rounds 1 to 5

Effects on pension contributions

Next, we focus on pension contributions as the labor outcome variable. Table 7 reveals a pattern consistent with the social/health insurance access results, suggesting similar underlying mechanisms. Non-cognitive skills on $t = 2$ have a positive and significant direct effect, even when controlling for firm size and the presence of a signed employment contract. Again, the effects of preschool education are first transmitted through cognitive skills in $t = 1$, which subsequently has positive and significant direct effects on both cognitive and non-cognitive skills in the next period.

Additionally, Table 7 shows that attending preschool increases the probability to contribute to pensions by 1.8%, even after controlling for firm size. However, like the previous model, these effects lose significance when accounting for the presence of a signed contract. This finding suggests that, in entry-level jobs, job characteristics exert a more direct influence on the likelihood of achieving quality labor outcomes than preschool itself. Nonetheless, the robustness of the significance of non-cognitive skills across all four specifications, along with the positive effects of preschool education on this variable, highlights a mediating effect that links early educational investments to labor quality outcomes in the early stages of a career. This reinforces the idea that non-cognitive skills, rather than purely cognitive abilities, play a crucial role in securing formal employment benefits such as pension contributions in the Peruvian labor market.

Table 7: SEM Results, Model with Q_3: Contributions to AFP

Structural Equation	Path	(1)			(2)			(3)		
		DE	IE	TE	DE	IE	TE	DE	IE	TE
Cognitive (t=1) (θ_1^C)	$\theta_1^C \leftarrow I_{1,1}$	0.018*	-	0.018*	0.147**	-	0.147**	0.147**	-	0.147**
Non-Cognitive (t=1) (θ_1^N)	$\theta_1^N \leftarrow I_{1,1}$	0.031	-	0.031	0.032	-	0.032	0.031	-	0.031
Cognitive (t=2) (θ_2^C)	$\theta_2^C \leftarrow I_{1,1}$	-	0.213**	0.213**	-	0.213**	0.213**	-	0.213**	0.213**
	$\theta_2^C \leftarrow \theta_1^C$	1.355***	0.048**	1.403***	1.357***	0.047**	1.404***	1.358***	0.047**	1.405***
	$\theta_2^C \leftarrow \theta_1^N$	0.222	-0.012	0.210	0.220	-0.012	0.208	0.221	-0.012	0.209
Non-Cognitive (t=2) (θ_2^N)	$\theta_2^N \leftarrow I_{1,1}$	-	0.060**	0.060**	-	0.060**	0.060**	-	0.059**	0.059**

	$\theta_2^N \leftarrow \theta_1^C$	0.315***	0.054**	0.369***	0.316***	0.052**	0.368***	0.309***	0.050**	0.360***
	$\theta_2^N \leftarrow \theta_1^N$	0.189	-0.012	0.177	0.189	-0.012	0.177	0.200	-0.011	0.189
AFP contributions (T=3) (Q_3)	$Q_3 \leftarrow I_{1,1}$	-	0.016*	0.016*	-	0.018*	0.018*	-	0.007	0.007
	$Q_3 \leftarrow \theta_1^C$	-	0.100**	0.100**	-	0.116**	0.116**	-	0.042	0.042
	$Q_3 \leftarrow \theta_1^N$	-	0.037	0.037	-	0.037	0.037	-	0.019	0.019
	$Q_3 \leftarrow \theta_2^C$	0.024	-	0.024	0.040	-	0.040	0.006	-	0.006
	$Q_3 \leftarrow \theta_2^N$	0.179**	-	0.179**	0.160**	-	0.160**	0.094*	-	0.094*
R^2			0.776			0.796			0.874	
N			322			322			322	

* p<0.10, ** p<0.05, *** p<0.01

(1) Base SEM model with IV in Investments and Skills structural equations.
(2) Model (1) + IV in Employment Quality structural equation (Firm size).
(3) Model (2) + Signed Employment Contract control.
Note that Total Effect (TE) = Direct Effect (DE) + Indirect Effect (IE) always, and that DE and IE are reported only when they exist in system (5)

Source: Own elaboration based on YL study, rounds 1 to 5

Effects on access to paid sick leave

Table 8 shows that cognitive skills at $t = 2$ have positive and significant direct effects, even when controlling for firm size and signed employment contract. In contrast to the previous models, this is the only case where non-cognitive skills do not exhibit a significant effect. This suggests that, for this specific outcome, cognitive skills play a particularly important role in obtaining jobs that offer paid sick leave. This finding aligns with existing evidence that suggests access to paid sick leave and other discretionary job benefits may be closely associated with educational attainment, which is a primary channel for the development of cognitive skills (e.g. Berdahl, 2017).

Additionally, preschool attendance has positive and significant effects across all model specifications. Preschool increases the probability of paid sick leave access by 2.4% when controlling for firm size, and this effect decreases to 1.6%, but remains significant at the 90% of confidence, after controlling for signed contract status. Cognitive skill stocks in all periods have positive and significant total effects on access to paid sick leave, although skills acquired earlier show stronger effects. The stability in both the significance and magnitude of the effects of preschool education underscores the importance of cognitive skills acquired in early childhood in obtaining this labor benefit. This finding suggests that preschool education plays a crucial role in the development of cognitive abilities that are highly valued in the labor market and positively influence future working conditions, particularly those related to health-related benefits.

Table 8: SEM Results, Model with Q_3: Paid sick leave

Structural Equation	Path	(1)			(2)			(3)		
		DE	IE	TE	DE	IE	TE	DE	IE	TE
Cognitive (t=1) (θ_1^C)	$\theta_1^C \leftarrow I_{1,1}$	0.148**	-	0.148**	0.148**	-	0.148**	0.148**	-	0.148**
Non-Cognitive (t=1) (θ_1^N)	$\theta_1^N \leftarrow I_{1,1}$	0.031	-	0.031	0.032	-	0.032	0.031	-	0.031
Cognitive (t=2) (θ_2^C)	$\theta_2^C \leftarrow I_{1,1}$	-	0.214**	0.214**	-	0.216**	0.216**	-	0.216**	0.216**
	$\theta_2^C \leftarrow \theta_1^C$	1.358***	0.048**	1.406***	1.361***	0.047**	1.408***	1.362***	0.047**	1.410***
	$\theta_2^C \leftarrow \theta_1^N$	0.231	-0.012	0.219	0.232	-0.012	0.220	0.233	-0.012	0.221
Non-Cognitive (t=2) (θ_2^N)	$\theta_2^N \leftarrow I_{1,1}$	-	0.059**	0.059**	-	0.059**	0.059**	-	0.059**	0.059**
	$\theta_2^N \leftarrow \theta_1^C$	0.307***	0.053**	0.359***	0.307***	0.052**	0.359***	0.307***	0.051**	0.358***

	$\theta_2^N \leftarrow \theta_1^N$	0.201	-0.011	0.190	0.201	-0.011	0.190	0.203	-0.011	0.192
Paid sick leave (T=3) (Q_3)	$Q_3 \leftarrow I_{1,1}$	-	0.022**	0.022**	-	0.024**	0.024**	-	0.016*	0.016*
	$Q_3 \leftarrow \theta_1^C$	-	0.141***	0.141***	-	0.155***	0.155***	-	0.104***	0.104***
	$Q_3 \leftarrow \theta_1^N$	-	0.030	0.030	-	0.030	0.030	-	0.016	0.016
	$Q_3 \leftarrow \theta_2^C$	0.085**	-	0.085**	0.100***	-	0.100***	0.076**	-	0.076**
	$Q_3 \leftarrow \theta_2^N$	0.059	-	0.059	0.041	-	0.041	-0.006	-	-0.006
R^2			0.778			0.796			0.839	
N			322			322			322	

* p<0.10, ** p<0.05, *** p<0.01

(1) Base SEM model with IV in Investments and Skills structural equations.
(2) Model (1) + IV in Employment Quality structural equation (Firm size).
(3) Model (2) + Signed Employment Contract control.
Note that Total Effect (TE) = Direct Effect (DE) + Indirect Effect (IE) always, and that DE and IE are reported only when they exist in system (5)

Source: Own elaboration based on YL study, rounds 1 to 5

Preschool education and signed employment contract

Our results consistently show that preschool education has positive effects on achieving quality labor outcomes. However, certain job characteristics, such as having a signed employment contract, exert a more direct influence. Therefore, to better understand the role of preschool education in accessing these employment conditions, we estimate an additional model in which the presence of a signed contract is considered the dependent variable in the labor outcome equation (Q_3). Unlike in the previous versions of our model, in this one, having a contract is modelled as part of the outcome pathway rather than as a control variable.

Table 9 shows that cognitive skills at $t = 1$ have positive and significant effects on the likelihood of obtaining a job with a signed contract. Additionally, preschool education increases the probability of having a signed employment contract by 1.9%, chiefly mediated by the acquisition of cognitive skills in the first stage of skill development. This finding suggests that, while preschool education does not show significant effects to social security access or pension contributions when controlling for having a signed contract, it does have a significant direct relationship with securing employment conditions that, in turn, lead to quality labor outcomes at the start of an individual's career.

Table 9: SEM Results, Model with Q_3: Signed employment contract

Structural Equation	Path	DE	IE	TE
Cognitive (t=1) (θ_1^C)	$\theta_1^C \leftarrow I_{1,1}$	0.147**	-	0.147**
Non-Cognitive (t=1) (θ_1^N)	$\theta_1^N \leftarrow I_{1,1}$	0.031	-	0.031
Cognitive (t=2) (θ_2^C)	$\theta_2^C \leftarrow I_{1,1}$	-	0.213**	0.213**
	$\theta_2^C \leftarrow \theta_1^C$	1.354***	0.048**	1.402***
	$\theta_2^C \leftarrow \theta_1^N$	0.222	-0.012	0.210
Non-Cognitive (t=2) (θ_2^N)	$\theta_2^N \leftarrow I_{1,1}$	-	0.060**	0.060**
	$\theta_2^N \leftarrow \theta_1^C$	0.314***	0.055**	0.369***
	$\theta_2^N \leftarrow \theta_1^N$	0.189	-0.012	0.177
Contract (T=3) (Q_3)	$Q_3 \leftarrow I_{1,1}$	-	0.019*	0.019*
	$Q_3 \leftarrow \theta_1^C$	-	0.120**	0.120**
	$Q_3 \leftarrow \theta_1^N$	-	0.037	0.037
	$Q_3 \leftarrow \theta_2^C$	0.043	-	0.043
	$Q_3 \leftarrow \theta_2^N$	0.161*	-	0.161*

R^2	0.776
N	322

* p<0.10, ** p<0.05, *** p<0.01

Notes: Base SEM model with IV in Investments and Skills structural equations.
Total Effect (TE) = Direct Effect (DE) + Indirect Effect (IE) always, and that DE and IE are reported only when they exist in system (5)

Source: Own elaboration based on YL study, rounds 1 to 5

The transmission mechanisms: Effects of preschool education on skill formation

Our results so far show that the relationship between preschool education and labor quality outcomes is established through skill development. We found that access to health or social insurance and pension contributions is directly linked to the development of non-cognitive skills, whereas the likelihood of obtaining paid sick leave increases with higher cognitive skills. These findings are robust even after controlling for signed employment contract. Additionally, preschool education has a positive impact on the development of both cognitive and non-cognitive skills during both formative periods. These dynamics suggest the existence of implicit mechanisms that transmit the positive effects of preschool education toward achieving high-quality labor outcomes. We now show that individuals who attended preschool systematically exhibit superior cognitive and non-cognitive skills, validating that this is the mechanism connecting preschool education to quality labor outcomes.

First, regarding cognitive skills, Table 10 shows that individuals who attended preschool have significantly higher cognitive stocks than those who did not, with this difference being particularly notable in period $t = 2$. The average cognitive skill stock of preschool attendees is statistically significantly higher in both formative periods. Additionally, individuals with preschool education exhibit higher cognitive skills at the 25th, 50th, and 75th percentiles, further reinforcing the role of early education in skill formation and its long-term impact on labor market outcomes.

Table 10: Estimated cognitive skills formation by preschool attendance

	Cognitive Skills (t=1)		**Cognitive Skills (t=2)**	
	No Preschool (0)	**Preschool (1)**	**No Preschool (0)**	**Preschool (1)**
Mean	0.688	0.867	1.147	1.422
Diff. (0) – (1)	-0.179***		-0.275***	
Median	0.802	0.950	1.125	1.485
p25	0.535	0.683	0.751	1.119
p75	0.802	0.950	1.521	1.824

* p<0.10, ** p<0.05, *** p<0.01

Source: Own elaboration based on YL study, rounds 1 to 5

To confirm that the skill distributions differ between individuals with and without preschool education, Table 11 presents the Kolmogorov-Smirnov test for equality of cognitive skill distributions in each formative period. The results indicate that across both periods, individuals without preschool education exhibit consistently lower skill distributions compared to their preschool-attending counterparts. This systematic trend suggests that preschool education plays a crucial role in the early development of cognitive skills, leading to a sustained advantage across different formative periods. Preschool education not only enhances cognitive abilities in early childhood, but it also establishes a strong foundation that contributes to future educational and labor market outcomes (e.g., Bingley & Westergaard-Nielsen, 2012; Dietrichson et al., 2020).

These differences in cognitive skills can translate into better educational and employment opportunities, emphasizing the importance of investing in preschool education as a key strategy for improving long-term outcomes, as highlighted by Heckman et al. (2010) and Cunha & Heckman (2010).

Table 11: Kolmogorov-Smirnov test for the equality of distribution functions, Cognitive Skills

Lower group	**Cognitive Skills (t=1)**	**Cognitive Skills (t=2)**
No Preschool	0.739***	0.268***
Preschool	0.000	0.786
Combined K-S	0.739***	0.268***

* p<0.10, ** p<0.05, *** p<0.01

Source: Own elaboration based on YL study, rounds 1 to 5

We find a similar pattern for non-cognitive skills. When performing the mean difference test between both sample groups, Table 12 shows that these differences are significant in both formative periods, favoring individuals who attended preschool. Once again, the values of the latent non-cognitive skills variable are higher at the median, as well as at the 25th and 75th percentiles of the distribution. This consistent pattern further reinforces the role of preschool education in fostering early skill development, not only in cognitive domains but also in essential non-cognitive abilities that contribute to long-term educational and labor market success.

Table 12: Estimated non-cognitive skills formation by preschool attendance

	Non-Cognitive Skills (t=1)		**Non-Cognitive Skills (t=2)**	
	No Preschool (0)	**Preschool (1)**	**No Preschool (0)**	**Preschool (1)**
Mean	-0.143	-0.112	0.477	0.554
Diff. (0) – (1)	-0.032***		-0.076***	
Median	-0.135	-0.096	0.486	0.564
p25	-0.173	-0.146	0.388	0.470
p75	-0.108	-0.072	0.571	0.666

* p<0.10, ** p<0.05, *** p<0.01

Source: Own elaboration based on YL study, rounds 1 to 5

Finally, Table 13 shows that the distribution of non-cognitive skills is consistently lower for individuals without preschool education in both formative periods. These results suggest that preschool education also has a positive influence on the development of non-cognitive skills, thus contributing to a range of positive outcomes in adulthood.

Table 13: Kolmogorov-Smirnov test for the equality of distribution functions, Non-Cognitive Skills

Lower group	**Non- Cognitive Skills (t=1)**	**Non- Cognitive Skills (t=2)**
No Preschool	0.437***	0.281***
Preschool	-0.037	-0.063
Combined K-S	0.437***	0.281***

* p<0.10, ** p<0.05, *** p<0.01

Source: Own elaboration based on YL study, rounds 1 to 5

In sum, we confirm that positive effects of preschool education on quality labor outcomes take place through the development of both cognitive and non-cognitive skills, a finding supported by early childhood intervention studies such as the Abecedario program (Campbell et al., 2014) and the HighScope Perry Preschool program in the United States (Heckman et al., 2010). This is evident in the cumulative distributions of estimated skills, where individuals who attended preschool consistently exhibit higher levels of these skills compared to their peers without preschool education. This early preparation not only strengthens academic competencies for subsequent educational stages but also establishes a fundamental foundation for skills such as problem-solving, teamwork, and adaptability. These non-cognitive skills are essential for productivity and high-quality performance in the workplace throughout one's professional life.

7. Final Remarks

The existing evidence on the effects of preschool education on labor outcomes has primarily focused on income levels (e.g., Bingley & Westergaard-Nielsen, 2012). We sought to understand whether preschool education in Peru has similar effects on quality labor outcomes that are not necessarily linked to salary levels during the early years of one's career. For this, we used the Young Lives study data to perform structural estimations exploiting the longitudinal nature of these data and connect individuals' early childhood experiences with their outcomes in adulthood.

Our findings show that preschool education does not have significant effects on income at the start of a career when controlling for an array of job characteristics, possibly because income is observed at a stage when individuals have limited work experience and earn low wages due to local labor market restrictions. However, we find positive and highly significant effects on the likelihood of having health/social insurance, contributing to pensions, and receiving paid sick leave. We show that non-cognitive skills in the second formative period have a direct effect on the probabilities of having health/social insurance and pension contributions, while cognitive skills directly influence the likelihood of receiving paid sick leave.

These findings hold particular policy relevance given the challenge of high labor market informality in Peru. Our results suggest that preschool attendance acts as a critical sorting mechanism. In highly competitive environments with limited high-quality jobs, the enhanced cognitive and non-cognitive skills developed in early childhood provide individuals with a decisive competitive advantage for securing positions that include social protection benefits like health insurance and pensions, thereby directly contributing to the Decent Work agenda in a resource-constrained setting.

Our results are consistent with evaluations of early childhood interventions such as the Abecedario program (Campbell et al., 2014) and the HighScope Perry Preschool program in the United States (Heckman et al., 2010). Strengthening non-cognitive elements in preschool aligns naturally with SDG 8, which advocates promoting sustained, inclusive and sustainable economic growth, full and productive employment, and decent work for all. Policies seeking to accelerate SDG 8 in Peru should thus explicitly consider early childhood development as part of the decent-work toolkit. We have shown that expanding access to preschool while also rethinking curricula that deliberately target both cognitive and non-cognitive development can be a forward-looking strategy to tackle two pressing sustainable development imperatives. On the one hand, this would expand children's opportunities for skill acquisition during the later stages of their

schooling process, improving their human development and expanding their capabilities. On the other hand, at an aggregate level, it would increase the supply of youth entering the labor market with skills that make them more likely to access formal jobs with social protection. This will positively expand to their families and the Peruvian society overall.

Moreover, we have shown that preschool attendees have higher cognitive and non-cognitive skill stocks (Tables 10–13), which implies that preschool creates advantages across the skill distribution rather than only at the top. These results show that one can expect realistic gains from expanding access to preschool in typically underserved population subgroups, such as people living in rural areas, members of indigenous communities, or low-income households. However, as the Young Lives sample is not nationally representative, we are not able to perform a specific heterogeneity analysis by socioeconomic status, ethnicity, rural/urban or other marginalization indicators, so we cannot definitively show whether preschool attendance is pro-poor in that it disproportionately benefits better-off children in Peru. Thus, from a policy perspective, we lay the grounds for a call for more and better data to verify whether further access to preschool can have inequality-reducing impacts over time. Until such subgroup evidence is reported, we argue that the precautionary policy stance should be to grant access expansion explicitly with equity objectives (targeting and quality monitoring) to avoid reinforcing existing inequalities in the country.

Although our study shows compelling and robust results, we acknowledge some limitations. First, preschool attendance for the Young Lives older cohort is self-reported retrospectively around age 8 (Round 1), which may introduce recall-related measurement error. We have already flagged this caveat, but let us stress that the Younger Cohort data may be a source of better temporally proximate measures, and they could be used in the future to gain further insights. Second, attrition and sample selection in our study may have resulted in reduced statistical power, although we have shown that they do not introduce bias. Third, as in much of the related literature (e.g. Dercon and Krishnan, 2009; Mitchell et al, 2025), the measurement of non-cognitive skills remains especially challenging. Our methodological strategy allows us to partially control for potential measurement errors, but it cannot annul it altogether. Fourth, as we have stated from the outset, the Young Lives data were not designed to be nationally representative, so our findings cannot be generalized to the Peruvian population as a whole. Finally, our focus is on skill formation up to the end of secondary education. Given data constraints up to round 5 of the YL Older Cohort in Peru, we are not yet able to capture transitions into or returns from tertiary education.

Let us now highlight some promising lines for further research. First, we use the older cohort Young Lives data in our study because it is the only source of information allowing us to credibly and consistently link preschool with labour outcomes in Peru. In the future, more data will be available. The Young Lives program will release round 7 in the upcoming years, so it would be valuable to replicate this study with data for the younger cohort, as these individuals will be, on average, 23 years old and have detailed information about various aspects of their development since they were 1 year old. Moreover, the upcoming round 7 data for the older cohort will help assess how and why our findings are updated as individuals accumulate more work experience or attain full higher education degrees. We will do so when these data are available, but so far, we can confidently state that preschool is key in shaping skills that influence the quality of employment at the start of one's career, and that different skill stocks play a crucial mediating role in achieving these outcomes. Improving access to preschool is a promising development

strategy, not only to improve future incomes but also to ensure access to dignified jobs with adequate benefits and increased human development.

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Appendix

Table A1: Instrumental variables direction and exclusion restriction justification

Outcome Variables*	Endogenous Variable	Instrumental Variable	Exclusion restriction justification*
θ_1^C: Latent Cognitive Skills variable, estimated with Round 1 and 2 measurements θ_1^N: Latent Non-Cognitive Skills variable, estimated with Round 1 and 2 measurements	$I_{1,1}$: Preschool attendance (retrospective)	$y_{1,1}$: YL Wealth Index in Round 1	Educational investments serve as the main mediator that connect family wealth or socioeconomic status to skill development (e.g. Wolf & McCoy, 2019; Near, 2022).
θ_1^C: Latent Cognitive Skills variable, estimated with Round 1 and 2 measurements θ_1^N: Latent Non-Cognitive Skills variable, estimated with Round 1 and 2 measurements	$I_{1,2}$: Educational Enrolment in Round 1	$y_{1,2}$: Number of individuals aged 0 to 5 in the household in Round 1	Household composition affects educational investment decisions, prioritizing the investments in younger children, but is not directly linked with skill formation. (e.g. Woldenhanna, 2016).
θ_1^C: Latent Cognitive Skills variable, estimated with Round 1 and 2 measurements θ_1^N: Latent Non-Cognitive Skills variable, estimated with Round 1 and 2 measurements	$I_{1,3}$: Educational Enrolment in Round 2	$y_{1,3}$: Family-related shock between rounds 1 and 2.	As the shocks are reported to have affected economic conditions of the household between Round 1 and 2, the justification is the same as for $y_{1,1}$. (see Briones, 2018 in addition to the references above).
$y_{2,1}$: Educational Enrolment in Round 3 $y_{2,2}$: Educational Enrolment in Round 4 θ_2^C: Latent Cognitive Skills variable, estimated with Round 3 and 4 measurements θ_2^N: Latent Non-Cognitive Skills variable, estimated	θ_1^C: Latent Cognitive Skills variable, estimated with Round 1 and 2 measurements	$\tilde{x}_1^C$ Stunting in Round 2	Early health strongly determines cognitive skill development (Attanasio et al., 2020b), and its effect on socio-emotional (non-cognitive) skills is mediated through the "cross-productivity" effect of the initial cognitive foundation (Sánchez, 2017).

with Round 3 and 4 measurements			
$y_{2,1}$: Educational Enrolment in Round 3 $y_{2,2}$: Educational Enrolment in Round 4 θ_2^C: Latent Cognitive Skills variable, estimated with Round 3 and 4 measurements θ_2^N: Latent Non-Cognitive Skills variable, estimated with Round 3 and 4 measurements	θ_1^N: Latent Non-Cognitive Skills variable, estimated with Round 1 and 2 measurements	$\tilde{x}_1^N$: Caregiver's latent non-cognitive skills variable, estimated with round 2 measurements	Caregivers' non-cognitive skills effects on child cognitive skills operate indirectly, through their impact on children's non-cognitive skill development (Xia, 2023).
θ_2^C: Latent Cognitive Skills variable, estimated with Round 3 and 4 measurements θ_2^N: Latent Non-Cognitive Skills variable, estimated with Round 3 and 4 measurements	$y_{2,1}$: Educational Enrolment in Round 3	$y_{2,1}$: Natural disaster shocks between rounds 2 and 3	As the shocks are reported to have affected economic conditions of the household between Round 2 and 3 (Briones, 2018), the justification is the same as for $y_{1,1}$. See also the corresponding references above.
θ_2^C: Latent Cognitive Skills variable, estimated with Round 3 and 4 measurements θ_2^N: Latent Non-Cognitive Skills variable, estimated with Round 3 and 4 measurements	$y_{2,2}$: Educational Enrolment in Round 4	$y_{2,2}$: Number of individuals aged 0 to 5 in the household in Round 4	Household composition affects educational investment decisions, prioritizing the investments in younger children (e.g. Woldenhanna, 2016); but is not directly linked with skill formation.
Q_3: Early Career Job Quality Outcome	θ_2^C: Latent Cognitive Skills variable, estimated with Round 3 and 4 measurements	$\tilde{x}_2^C$: Hours per day the child spends studying outside school in Round 3	Study time has a direct effect on cognitive skill development (Fiorini & Keane, 2014), which in turn mediates the effect on non-cognitive skills (Hoorani et al., 2022).
Q_3: Early Career Job Quality Outcome	θ_2^N: Latent Non-Cognitive Skills variable, estimated	$\tilde{x}_2^N$: Family-related shock between rounds 2 and 3.	Past family shocks (disease, loss, divorces, etc.) affects the

	with Round 3 and 4 measurements		development of non-cognitive skills but no cognitive skills (García-Miralles & Gensowski, 2025).

Note: The justifications explain the exclusion restrictions from the endogenous variables that are not in the same row as each IV in the table. The temporal relation between the IV and the exogenous variables is a key part of the exclusion restriction.
* Outcome Variables for which the Endogenous Variable presents Direct Effects.

Table A2: Instrumental variables strength test: First-stage F-statistic

Structural Equation	First-stage equations	F stat	p-value
$\theta_1^C = f_{1,1}(I_{1,1}, I_{1,2}, I_{1,3}\, \tilde{x}_1^C, v_{1,1})$	$I_{1,1} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^N, y_{2,1}, y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$ $I_{1,2} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^N, y_{2,1}, y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$ $I_{1,3} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^N, y_{2,1}, y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$	16.41 18.80 17.71	0.0877 0.0429 0.0387
$\theta_1^N = f_{1,1}(I_{1,1}, I_{1,2}, I_{1,3}\, \tilde{x}_1^N, v_{1,1})$	$I_{1,1} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, y_{2,1}, y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$ $I_{1,2} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, y_{2,1}, y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$ $I_{1,3} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, y_{2,1}, y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$	16.44 18.56 17.44	0.0877 0.0462 0.0423
$I_{2,1} = h_2(\theta_1^C, \theta_1^N, y_{2,1}, \eta_1)$	$\theta_1^C = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$ $\theta_1^N = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$	32. 16 6. 33	0.0000 0.0000
$I_{2,2} = h_2(\theta_1^C, \theta_1^N, y_{2,2}, \eta_1)$	$\theta_1^C = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$ $\theta_1^N = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1}, \tilde{x}_2^C, \tilde{x}_2^N, \tilde{x}_3)$	33. 77 6. 46	0.0000 0.0000
$\theta_2^C = f_{1,2,C}(\theta_1^C, \theta_1^N, I_{2,1}, I_{2,2}, \tilde{x}_2^C, v_{1,2})$	$\theta_1^C = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^N, \tilde{x}_3)$ $\theta_1^N = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^N, \tilde{x}_3)$ $I_{2,1} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^N, \tilde{x}_3)$ $I_{2,2} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^N, \tilde{x}_3)$	30.99 6.72 26.52 47.65	0.0000 0.0000 0.0031 0.0000
$\theta_2^N = f_{1,2,N}(\theta_1^C, \theta_1^N, I_{2,1}, I_{2,2}, \tilde{x}_2^N, v_{1,2})$	$\theta_1^C = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^C, \tilde{x}_3)$ $\theta_1^N = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^C, \tilde{x}_3)$ $I_{2,1} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^C, \tilde{x}_3)$ $I_{2,2} = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^C, \tilde{x}_3)$	33.09 6.78 43.74 54.65	0.0000 0.0000 0.0000 0.0000
$Q_3 = f_2(\theta_2^C, \theta_2^N, \tilde{x}_3, v_2)$	$\theta_2^C = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N)$ $\theta_2^N = f(y_{1,1}, y_{1,2}, y_{1,3}, \tilde{x}_1^C, \tilde{x}_1^N, y_{2,1} y_{2,2}, \tilde{x}_2^C, \tilde{x}_2^N)$	23.45 7.36	0.0000 0.0000

Note 1: All equations were estimated separately using all information available for each equation.

Note 2: Instruments for the non-cognitive latent variables yield first-stage F-statistics below the conventional threshold of 10. This is attributed to the known measurement error and response heterogeneity inherent in socio-emotional survey scales (Morris et al., 2021; Mitchell et al., 2025), which attenuates the observed correlation between the instrument and the endogenous variable. Despite the modest F-statistics, all first-stage coefficients are statistically significant ($p < 0.01$), indicating instrument relevance. Furthermore, the full structural estimation is undertaken within a Structural Equation Model (SEM), which simultaneously models the latent variables and structural paths, mitigating the impact of measurement error.