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Bridging the gap: The impact of cognitive and noncognitive abilities on early-career wages in Taiwan

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Abstract

This study investigates how cognitive and noncognitive abilities shape earnings among new entrants to Taiwan's labor market. Drawing on six waves of the Taiwan Education Panel Survey (TEPS) and its follow-up, TEPS-B, spanning 2001–2014, we capture cognitive ability via comprehensive test scores, and noncognitive abilities are conceptualized across three dimensions: interpersonal skills, self-discipline/diligence, and norm compliance. To address selection into employment, we implement a two-stage Heckman model and estimate wage equations that include controls for education, labor market experience, gender, and family socioeconomic status. Our analysis reveals that incorporating direct measures of ability substantially alters traditional wage determinants: the premiums for education and family background decline by about 60% and 23%, respectively. A one-standard-deviation increase in cognitive ability is linked to a 3.24% wage gain, while self-discipline/diligence and interpersonal skills yield 1.41% and roughly 1% increases. Contrary to expectations, we find limited evidence of strong complementarities between cognitive and noncognitive skills among new entrants, though subgroup analyses suggest these complementarities may emerge as job complexity and experience grow. These findings underscore the need for policies and educational reforms that invest in both hard and soft skills to accurately assess returns to human capital and foster more equitable labor market outcomes.

Keywords: Cognitive ability, Labor market, Noncognitive skills, Taiwan, Wage determination.
JEL Classification: J01; J30; J40.

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Contents

1. Introduction **34**
2. Literature Review **34**
3. Data and Methodology **36**
4. Estimation Results **37**
5. Discussion **41**
6. Conclusion and Policy Implications **42**
References **42**
Appendix **43**

Contribution of this paper to the literature

This paper enriches the literature by integrating multidimensional measures of cognitive and noncognitive skills into a longitudinal wage determination model, using longitudinal TEPS data. It shows that direct measures of ability significantly reduce education and family background wage premiums, while self-discipline, interpersonal skills, and cognitive ability independently shape early-career earnings.

1. Introduction

The determination of wages in the labor market has been a central focus of economic research for decades. Classic human-capital theories (Mincer, 1974) posit that education and work experience are the primary drivers of wage differentials. However, in recent years, both academic scholarship and policy debates have increasingly turned to the roles played by innate and acquired skills. In particular, cognitive abilities, traditionally measured by standardized test scores and academic performance, have long been recognized as central ingredients in explaining worker productivity and earnings. Yet an emerging strand of research has highlighted that noncognitive skills, which encompass interpersonal abilities, self-discipline, and compliance with social norms, can be equally significant in shaping labor market outcomes (Deming, 2017).

Taiwan provides a compelling context for studying these issues. Over the past few decades, rapid industrialization, technological change, and the globalization of labor markets have transformed both the nature of work and the skills demanded from workers. In this evolving environment, the role of cognitive skills remains critical, but the ability to interact effectively with others, demonstrate resilience, and adhere to institutional norms has become increasingly important, as these noncognitive dimensions constitute "soft skills" or interpersonal capital. Specifically, among new entrants to the Taiwanese labor market, often characterized by limited work experience and emerging job responsibilities, the relative contributions of cognitive and noncognitive abilities to wage determination remain an open question.

This paper uses data derived from the Taiwan Education Panel Survey (TEPS) and its follow-up TEPS-B to examine the impact of both cognitive and noncognitive abilities on young workers' wages. The TEPS dataset is particularly valuable because it not only provides detailed test scores that serve as proxies for cognitive ability but also includes extensive questions and even tutor assessments that capture multiple dimensions of noncognitive skills. In our conceptual framework, we view wages as a function of human capital inputs, including formal education and work experience, as well as intrinsic personal abilities. A critical innovation in this study is the simultaneous estimation of wage equations that account for both types of abilities alongside traditional controls such as family socioeconomic status (SES), gender, and region of employment.

A methodological challenge that arises in wage determination studies is the potential selection bias associated with nonrandom entry into the labor market. New entrants to the labor force may systematically differ from non-participants with respect to both observed and unobserved characteristics. To address this, we implement a two-stage Heckman selection model (Heckman, 1979) in which we first model the likelihood of becoming a full-time worker and then estimate the wage equation after including an inverse Mills ratio to correct for selection.

Our findings suggest that when cognitive and noncognitive abilities are controlled for explicitly, a large portion of the wage premiums previously attributed to education and family background is absorbed. In particular, a one-standard-deviation increase in the cognitive ability score is associated with a notable 3.24% increase in wages, while self-discipline and diligence contribute an additional 1.41% premium, and interpersonal skills yield a wage gain of about 1%. Moreover, our analysis finds no strong evidence of a significant interactive or complementary effect between cognitive and noncognitive skills in the overall sample; however, subgroup analyses by occupational skill intensity hint that complementarities may emerge in higher-skilled job categories with greater managerial or communicative demands.

The contributions of this paper are threefold. First, by integrating multiple measures of cognitive and noncognitive skills into a comprehensive wage determination model, we provide a more nuanced estimate of individual ability rewards. Second, our use of the TEPS and TEPS-B datasets, which offer detailed measures collected longitudinally, enables us to capture lifetime skill accumulation effects among new labor market entrants. Third, our findings carry salient policy implications. Given that traditional estimates of education and family background effects may be overstated, public policy aimed at improving economic outcomes must also focus on developing both hard (cognitive) and soft (noncognitive) skills. In an era when automation and artificial intelligence increasingly substitute routine cognitive tasks, human interpersonal and self-regulation abilities could become the decisive factors in attaining higher wages.

In the sections that follow, we first review the pertinent literature on wage determination and the effects of skill formation. We then describe our data sources, variable definitions, and empirical strategy in detail, before presenting the estimation results from both the selection and wage equations. We conclude with a discussion of our findings, their policy implications, and directions for future research.

2. Literature Review

2.1. Theoretical Foundations of Wage Determination

Human capital theory has long explained wage differentials through education and work experience, viewing schooling as an investment that raises productivity and earnings over the life cycle (Dearden, McIntosh, Myck, & Vignoles, 2002; Link & Ratledge, 1975; Mincer, 1974). Traditional models emphasize cognitive skills such as problem-solving, literacy, and quantitative reasoning as key channels through which education translates into higher productivity and wages (Hanushek & Woessmann, 2008). However, behavioral approaches to wage determination highlight that preferences, social norms, and personality traits also shape labor market outcomes, suggesting that education may affect earnings not only by raising cognitive ability but also by altering noncognitive traits and behavior (Bowles, Gintis, & Osborne, 2001).

More recent work integrates these perspectives by modeling both cognitive and noncognitive skills as distinct but jointly important determinants of wages and social behavior. It shows that cognitive and noncognitive abilities

both predict schooling, employment, and wages, and that omitting noncognitive skills can bias estimates of the returns to education. This framework implies that wage determination in modern labor markets must consider a broader skill vector that includes personality traits, motivation, perseverance, and social skills alongside traditional measures of cognitive ability.

2.2. Empirical Evidence on Noncognitive Abilities

A growing empirical literature documents that noncognitive abilities such as perseverance, teamwork, and self-control strongly predict educational success and later labor market outcomes. Early work using the GED program showed that individuals with similar measured cognitive ability but weaker noncognitive skills experienced substantially worse labor market outcomes, underscoring the independent role of noncognitive traits (Heckman & Rubinstein, 2001). Subsequent studies demonstrate that personality traits rival cognitive ability in predicting a wide array of life outcomes, including educational attainment, earnings, health, and even criminal behavior (Almlund, Duckworth, Heckman, & Kautz, 2011; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007).

Show that interpersonal traits and personality dimensions derived from the Big Five framework explain substantial wage differences, even after controlling for education and cognitive scores. Deming (2017) provides evidence that the labor market return to social skills has increased over time, particularly in occupations requiring intensive teamwork and customer interaction. Fletcher (2013), using sibling data, finds that personality traits significantly affect adult earnings, suggesting that noncognitive skills capture within-family differences not explained by shared background. Nyhus and Pons (2005) similarly document that personality traits such as conscientiousness and emotional stability are associated with higher earnings in Europe. In organizational settings, personality and self-esteem have been shown to predict job performance and job success, reinforcing the economic relevance of noncognitive traits (Judge, Bono, & Locke, 2000).

Research on skill formation emphasizes that noncognitive traits are malleable and shaped by early environments. Model skill formation as a dynamic process in which early investments raise both cognitive and noncognitive abilities, leading to dynamic complementarity and long-run effects on earnings. Show that early childhood interventions can significantly improve noncognitive skills and that these changes translate into long-term gains in education, employment, and wages. Duckworth and Seligman (2005) find that self-discipline outperforms IQ in predicting academic performance, suggesting that noncognitive skills influence human capital accumulation and, indirectly, wage trajectories. Together, this literature suggests that policies and environments that foster noncognitive abilities can yield substantial returns in the labor market.

Evidence from Asia complements and extends these findings. In Taiwan, Chen (2002) shows that teamwork-related skills, such as adaptability, coordination, communication, and interpersonal skills, significantly influence performance appraisals and, indirectly, salary in a high-performance work organization. In China, recent research demonstrates that noncognitive abilities shape occupational choice and earnings (Chen & Wang, 2025) while socio-cognitive occupations requiring interpersonal and management skills earn substantially higher wages than sensory-physical jobs (Xu et al., 2021). Liu (2026) shows that soft skills such as self-discipline and communication directly enhance graduate employability amid labor market complexity. Yamamoto and Brinton (2010) document that Japanese employers place a high value on soft skills such as cooperation, adaptability, and communication in hiring and promotion decisions. Together, these studies indicate that noncognitive skills play a central role in labor market success across rapidly developing East Asian economies undergoing structural transformation.

2.3. Gaps in the Literature

Despite extensive evidence on the importance of noncognitive abilities, several gaps remain. First, most wage studies rely on cross-sectional data, limiting the ability to control for unobserved individual heterogeneity and to trace how evolving cognitive and noncognitive skills shape wage trajectories over time (Bound, Brown, & Mathiowetz, 2001). Few studies simultaneously model cognitive test scores, self-reported noncognitive traits, and formal educational attainment within a longitudinal framework, raising concerns that the returns to schooling may be overstated when noncognitive skills and measurement error are not explicitly accounted for (Bowles et al., 2001).

Second, much of the empirical literature focuses on Western economies, particularly the United States and Europe, where institutional settings, education systems, and labor market structures differ substantially from those in East Asia (Almlund et al., 2011). East Asian evidence is growing but remains relatively fragmented, often based on small samples, single cohorts, or narrow occupational groups (Chen, 2002; Liu, 2026; Yamamoto & Brinton, 2010). Taiwan, specifically, has experienced rapid globalization, technological upgrading, and expansion of higher education, all of which may alter the relative importance of cognitive and noncognitive skills in wage determination.

Third, systematic longitudinal evidence from Taiwan that jointly considers cognitive test scores, noncognitive traits (such as perseverance, teamwork, and norm compliance), and education is scarce. Existing Taiwanese evidence emphasizes the importance of teamwork and other soft skills for performance evaluation and pay (Chen, 2002), but it does not exploit longitudinal survey data that jointly measure cognitive and noncognitive traits and link them to wage dynamics. Longitudinal datasets such as the Taiwan Education Panel Survey (TEPS), which contain repeated measures of both cognitive performance and noncognitive indicators across schooling and early labor market entry, offer a unique opportunity to address these gaps by modeling how diverse abilities interact with education to shape wage dynamics.

2.4. Summary

The literature indicates that formal education and cognitive skills remain central determinants of wages, but noncognitive skills, such as interpersonal ability, self-discipline, and norm compliance, play independent and economically meaningful roles in shaping labor market outcomes. Dynamic models of skill formation and evidence

from early interventions further suggest that both cognitive and noncognitive traits are malleable and that early investments can generate persistent earnings gains. However, longitudinal evidence from East Asian economies, especially Taiwan, remains limited, particularly regarding how cognitive and noncognitive abilities jointly contribute to wage determination in rapidly changing, high-education, export-oriented labor markets.

By disaggregating cognitive and noncognitive dimensions and exploiting the panel structure of TEPS, this study provides new evidence on how diverse abilities interact with schooling to shape wage outcomes in Taiwan's evolving labor market. In doing so, it contributes to both the international literature on the economics of personality and skills and the regional debate on how education systems and labor market institutions can better foster and reward the full range of competencies required in a knowledge-intensive economy.

3. Data and Methodology

3.1. Data Sources and Sample

The primary data source for this study is the Taiwan Education Panel Survey (TEPS) and its follow-up component, TEPS-B. The TEPS is a nationally representative survey that collects detailed information on the family environment, school experiences, and academic performance of students. Administered initially in 2001 to a cohort of middle school, high school, and vocational school students, TEPS also includes a battery of standardized tests that measure various aspects of cognitive ability. TEPS-B, a subsequent follow-up survey, tracks these individuals into young adulthood, collecting information on labor market outcomes, including full-time employment status, wages, and job characteristics.

Our analysis is based on data spanning six waves: TEPS 2001, TEPS 2003, TEPS 2005, TEPS 2007, TEPS-B 2010, and TEPS-B 2014. Specifically, we construct a sample of full-time workers, new entrants to the labor force, with a total sample size of 3,014 individuals. The sample is balanced by gender and covers a variety of educational backgrounds and occupational skill levels. Table 1 summarizes the descriptive statistics for the primary variables used in our analyses. These descriptive statistics indicate a diverse sample in terms of education, occupational skill categories, and family background. A substantial proportion of respondents have attended college, consistent with Taiwan's expanded higher education system.

Table 1. Descriptive statistics of variables for full-time workers (N = 3,014).

Variable name	Mean	S.D.	Min.	Max.
Wage (NT$)	33365.69	9558.537	18418.25	79940.31
Cognitive Ability	0.0215	0.9351	-3.0785	2.9376
Noncognitive Ability				
Interpersonal	0.0078	0.9617	-3.5168	3.5027
Self-Discipline/ Diligence	0.0758	0.9591	-4.7705	2.5861
Norm Compliance	0.0706	0.8678	-8.6838	0.9850
Gender (Male=1)	0.4390	0.4963	0	1
Married (Yes=1)	0.0259	0.1588	0	1
Family SES (standardized)	-0.0857	0.9331	-2.0635	3.4178
Source of Income-Self	0.9977	0.0481	0	1
Source of Income-Relatives	0.0066	0.0812	0	1
Health Status (0-4)	2.6765	0.8240	0	4
BMI	22.0160	3.7383	15.2416	52.7344
College/University (Yes=1)	0.8268	0.3785	0	1
Postgraduates	0.1334	0.3400	0	1
Public University (Yes=1)	0.3407	0.4740	0	1
Work Experience (months)	28.7432	19.1831	0	177
Seniority (months)	16.4045	14.6176	1	159
Job Change (frequency)	1.1891	1.3031	0	11
Middle/Lower Management (Yes=1)	0.1374	0.3443	0	1
High-Level Manager (Yes=1)	0.0040	0.0630	0	1
Public servant (Yes=1)	0.1234	0.3290	0	1
Work place				
Northern Region (Yes=1)	0.5100	0.5000	0	1
Central Region (Yes=1)	0.3013	0.4589	0	1
Occupational Skill Intensity				
High-Skilled Occupation	0.4751	0.4995	0	1
Mid-Skilled Occupation	0.4983	0.5001	0	1
Low-Skilled Occupation	0.0133	0.1145	0	1

Note: For cognitive ability, a transformation was applied so that scores range from 0 to 100. All dummy variables are coded as 1 for yes and 0 for no.
Sources: TEPS and TEPS-B.

3.2. Measurement of Abilities and Other Variables

3.2.1. Cognitive Ability

Cognitive ability is assessed using a comprehensive analytical ability test administered as part of TEPS 2001 and TEPS 2005. The original test scores range from approximately -3 to +3. For ease of interpretation and to facilitate comparisons with other measures, these scores are linearly transformed to a scale ranging from 0 to 100. This measure is designed to capture a broad array of cognitive functions, including problem solving, quantitative reasoning, and language ability.

3.2.2. Noncognitive Ability

We distinguish noncognitive skills across three main dimensions. Detailed measurement items and variable definitions are provided in Appendix Table A.1.

1. Interpersonal Skills
- Measured using both self-assessment items and tutor evaluations.
- Items assess traits such as extroversion, communication skills, leadership, and the ability to collaborate.
- For example, survey questions include one's ability to work well with peers and to give clear oral presentations.

2. Self-Discipline and Diligence
- Measured via self-reported responses on persistence, time management, and the capacity to focus on tasks even under adverse conditions.
- Items include statements such as "I never let other tasks delay my work" and "Even when I encounter difficulties, I push through to complete my work."

3. Norm Compliance
- Assessed by both self-response and tutor evaluations regarding adherence to rules and social norms.
- Items include behaviors such as punctuality, obedience in academic settings, and a low frequency of rule violations (e.g., truancy, cheating on tests).

Table 2 presents the correlation matrix for cognitive ability and the three noncognitive measures. As expected, the correlations among these dimensions are low, indicating that each captures a distinct facet of ability.

Table 2. Correlation matrix for ability measures.

Variable name	Cognitive Ability	Interpersonal Ability	Self-Discipline/ Diligence Ability	Norm Compliance Ability
Cognitive Ability	1.0			
Interpersonal Ability	0.1452	1.0		
Self-Discipline/ Diligence Ability	-0.1047	-0.0035	1.0	
Norm Compliance Ability	0.1684	-0.0101	-0.0121	1.0

3.2.3. Control Variables

In addition to abilities, our analysis controls for several variables typically associated with wage determination.
- Education: Dichotomized into whether an individual attended college/university (Undergraduate) or attained a postgraduate degree.
- Family Socioeconomic Status (SES): A composite index reflecting parental education, occupational status, and family income.
- Demographic Variables: Gender, marital status, and health status (Self-reported).
- Body Mass Index (BMI): As a proxy for physical appearance and health, which might affect wages.
- Work Market Variables: Work experience (Months), seniority (Months in current full-time employment), and number of job changes.
- Job Characteristics: Dummy variables for holding a managerial position, working in the public sector, region of employment (Northern, Central, or Other), and occupational skill intensity (high, medium, or low).

3.3. Empirical Strategy and Model Specification

3.3.1. Addressing Sample Selection

Workers are not randomly selected from the population; rather, individuals self-select into full-time employment. To address potential selection bias, we employ a Heckman (1979) two-stage estimation procedure. In the first stage, a binary probit model estimates the probability of full-time labor market participation. An instrumental variable, the "source of income" indicator (whether the respondent relies on self-generated income or relatives' support), serves as an exclusion restriction. This variable is hypothesized to affect the decision to work (due to financial necessity) but not directly influence wages.

After estimating the probit model, we compute the inverse Mills ratio (IMR), which is then included as an additional regressor in the second-stage wage equation.

3.3.2. Wage Equation Specification

The second-stage model is specified as follows:

$$\ln(w_i) = \alpha_i + \beta A_i^T + X_i^T \gamma + \eta \lambda_i + \varepsilon_i \qquad i = 1, \ldots, n.$$

where:
- $\ln(w_i)$ is the natural logarithm of the wage of individual i.
- A_i includes the set of cognitive and noncognitive measures.
- X_i is the vector of control variables (Education, family SES, demographic factors, work experience, etc.).
- λ_i is the inverse Mills ratio from the first-stage probit model.
- ε_i is the error term.

We also experiment with including interaction terms between cognitive and noncognitive abilities to assess potential complementarities. The estimation is carried out using maximum likelihood techniques.

4. Estimation Results

In this section, we present detailed results from our estimation exercises. We begin with the estimation of the employment selection model (First stage), then present the wage regression results (Second stage), and finally discuss subgroup analyses.

4.1. Heckman First-Stage: Employment Selection Model

To correct for potential selection bias due to nonrandom entry into full-time employment, we estimate a probit model. The estimated coefficients are presented in Table 3.

Table 3. Estimation of employment choice: Heckman First-Stage Probit Model.

Variable	Coefficient	Std. Error
Gender (Male)	-0.1451**	0.0522
Marital Status	0.0496	0.1604
Health Status	0.0184	0.0295
BMI	-0.0016	0.0066
College/University	0.4419***	0.1113
Postgraduates	-0.2943**	0.1230
Source of Income-Self	3.1224***	0.1460
Source of Income-Relatives	-1.0067***	0.2200
Family SES	-0.1092***	0.0250
Cognitive Ability	-0.0228	0.0281
Noncognitive Ability		
Interpersonal	0.0175	0.0244
Self-Discipline and Diligence	0.0322	0.0242
Norm Compliance	0.0566*	0.0254
Constant	-2.4724***	0.2458
pseudo R^2	0.4071	
Sample Size (N)	4668	

Note: *, **, *** indicate significance at the 5%, 1%, and 0.1% levels respectively.

The probit results reveal that individuals who depend on personal (self-generated) income are much more likely to work full-time, whereas those with family income support are less pressed to seek employment. Interestingly, cognitive ability does not significantly predict employment participation, whereas the noncognitive measure of norm compliance shows a weak but statistically significant positive effect.

The inverse Mills ratio (IMR) calculated from this first-stage model is later incorporated into our wage regression to correct for sample selection.

4.2. Heckman Second-Stage: Wage Determination Model

The second-stage wage equation is estimated using the natural logarithm of wages as the dependent variable. Table 4 presents three main models: (1) a baseline model with ability and controls; (2) a model that further introduces interaction terms; and (3) an extended model incorporating all ability measures and selected interactions.

Table 4. Estimation of the Wage Determination: Heckman Second-Stage Model.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Interpersonal Ability		0.0121**	0.0100*	0.0099*	0.0098*	0.0100*
		(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Cognitive Ability			0.0303***	0.0305***	0.0328***	0.0324***
			(0.0051)	(0.0051)	(0.0051)	(0.0051)
Interpersonal Ability*Cognitive Ability				0.0036		0.0033
				(0.0045)		(0.0045)
Self-discipline/Diligence Ability					0.0142**	0.0141**
					(0.0043)	(0.0043)
Norm Compliance Ability					-0.0092	-0.0047
					(0.0050)	(0.0054)
Self-Discipline/Diligence *Cognitive Ability						0.0006
						(0.0044)
Norm Compliance*Cognitive Ability						0.0108*
						(0.0048)
College/University	0.0406	0.0389	0.0201	0.0209	0.0174	0.0158
	(0.0233)	(0.0232)	(0.0233)	(0.0233)	(0.0233)	(0.0233)
Postgraduates	0.1563***	0.1518***	0.1323***	0.1323***	0.1298***	0.1280***
	(0.0270)	(0.0271)	(0.0271)	(0.0271)	(0.0271)	(0.0271)
Public University	0.0618***	0.0607***	0.0468***	0.0466***	0.0467***	0.0461***
	(0.0095)	(0.0095)	(0.0097)	(0.0097)	(0.0097)	(0.0097)
Gender (Male)	0.0878***	0.0882***	0.0881***	0.0878***	0.0853***	0.0854***
	(0.0096)	(0.0096)	(0.0096)	(0.0096)	(0.0097)	(0.0097)
Marital status	0.0230	0.0232	0.0325	0.0329	0.0322	0.0318
	(0.0262)	(0.0262)	(0.0261)	(0.0261)	(0.0260)	(0.0260)
Family SES	0.0204***	0.0197***	0.0158**	0.0157**	0.0156**	0.0158**
	(0.0049)	(0.0049)	(0.0049)	(0.0050)	(0.0049)	(0.0049)
Health Status	0.0121*	0.0111*	0.0127*	0.0127*	0.0111*	0.0110*
	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)
BMI	-0.0037**	-0.0037**	-0.0036**	-0.0036**	-0.0036**	-0.0036**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Work Experience	0.0041***	0.0040***	0.0040***	0.0040***	0.0040***	0.0040***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Work Experience²	-2.92e-5***	-2.83e-5***	-2.65e-5***	-2.65e-5***	-2.62e-5***	-2.61e-5***
	(7.28e-6)	(7.28e-6)	(7.24e-6)	(7.24e-6)	(7.23e-6)	(7.23e-6)
Seniority	0.0029***	0.0028***	0.0027***	0.0027***	0.0028***	0.0027***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Seniority²	-4.01e-5***	-3.94e-5***	-3.73e-5***	-3.74e-5***	-3.81e-5***	-3.74e-5***
	(9.55e-6)	(9.54e-6)	(9.49e-6)	(9.49e-6)	(9.47e-6)	(9.48e-6)
Job Change	-0.0107*	-0.0106*	-0.0096*	-0.0096*	-0.0099*	-0.0099*
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Middle/Low-level manager	0.0876***	0.0860***	0.0863***	0.0863***	0.0829***	0.0827***
	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)
High-Level Manager	0.1588*	0.1592*	0.1661*	0.1664*	0.1645*	0.1631*
	(0.0655)	(0.0654)	(0.0650)	(0.0651)	(0.0649)	(0.0649)
Public Servant	0.1919***	0.1921***	0.1861***	0.1860***	0.1859***	0.1838***
	(0.0131)	(0.0131)	(0.0131)	(0.0131)	(0.0131)	(0.0131)
Northern Region	0.0954***	0.0946***	0.0870***	0.0872***	0.0858***	0.0860***
	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)
Central Region	0.0008	0.0004	0.0008	0.0009	0.0007	0.0010
	(0.0122)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0120)
High-Skilled Occupation	0.1023***	0.0975***	0.0909***	0.0906***	0.0894***	0.0906***
	(0.0267)	(0.0267)	(0.0266)	(0.0266)	(0.0265)	(0.0265)
Mid-Skilled Occupation	-0.0043	-0.0080	-0.0103	-0.0105	-0.0109	-0.0094
	(0.0266)	(0.0266)	(0.0265)	(0.0265)	(0.0264)	(0.0264)
IMR	-0.0058	-0.0059	-0.0135	-0.0129	-0.0143	-0.0149
	(0.0347)	(0.0346)	(0.0345)	(0.0345)	(0.0351)	(0.0351)
Constant	10.0881***	10.0990***	10.1215***	10.1203***	10.1333***	10.1323***
	(0.0522)	(0.0523)	(0.0521)	(0.0521)	(0.0521)	(0.0521)
Wald χ^2 test (df)	1044.76***(20)	1055.32***(21)	1103.64***(22)	1104.55***(23)	1123.87***(24)	1131.69***(27)
Sample Size (N)	3014	3014	3014	3014	3014	3014

Note: The coefficient interpretation of cognitive ability, interpersonal ability, and other non-cognitive ability variables can be interpreted as the ratio of salary increase for each standard deviation increase of the ability.
Reference group: gender is female; education is below college; management positions are those who do not hold management. positions; work areas are the southern and eastern regions and offshore islands; skilled occupations are low-skilled occupations.
*, **, *** indicate significance at the 5%, 1%, and 0.1% levels respectively.

In Model (1), the coefficients for cognitive ability and interpersonal ability are positive and significant, indicating that each additional standard deviation of cognitive ability is associated with an approximate 3.03%–3.28% increase in wages, while interpersonal skills contribute about 1.2% per unit increase. Model (3), which includes additional controls for self-discipline and norm compliance, shows that self-discipline contributes an additional 1.42% premium. Moreover, the inclusion of ability measures substantially reduces the estimated coefficients on education and family SES, implying that these variables had been partly capturing unobserved individual ability.

4.3. Subgroup Analyses

To explore whether the effects of cognitive and noncognitive skills vary by gender, educational attainment, and occupational skill intensity, we estimate separate models for distinct subgroups. Tables 5 and 6 summarize these results.

Table 5. Job selection for different classified samples: Probit model estimates.

Group	Gender		Education		Occupational skill intensity	
Subgroup	Male	Female	Undergraduates	Postgraduates	High-skilled	Mid-skilled
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Gender (Male)			-0.0865	-0.3234**	0.0101	-0.1855***
			(0.0597)	(0.1090)	(0.0466)	(0.0476)
Marital Status	0.3055	-0.0582	-0.0434	0.5635	0.0388	0.0860
	(0.2767)	(0.2067)	(0.1631)	(0.6396)	(0.1452)	(0.1407)
Health Status	0.0534	-0.0092	0.0100	0.0439	-0.0027	0.0005
	(0.0433)	(0.0408)	(0.0331)	(0.0654)	(0.0261)	(0.0266)
BMI	-0.0031	-0.0005	-0.0032	-0.0034	0.0003	-0.0024
	(0.0090)	(0.0101)	(0.0074)	(0.0151)	(0.0060)	(0.0061)
College/University	-0.0428	0.9691***			0.5272***	-0.3677**
	(0.1629)	(0.1613)			(0.1316)	(0.1124)
Postgraduates	-0.8794***	0.3612*			0.5944***	-1.1775***
	(0.1766)	(0.1814)			(0.1406)	(0.1291)
Source of Income-Self	3.0892***	3.2124***	3.1541***	3.0419***	2.6784***	2.1117***
	(0.1925)	(0.2306)	(0.1632)	(0.3234)	(0.2314)	(0.1737)
Source of Income-Relatives	-0.9458	-0.9442***	-0.8775***		-0.5333*	-0.4195
	(0.4790)	(0.2581)	(0.2272)		(0.2462)	(0.2207)
Family SES	-0.0998**	-0.1245***	-0.1101**	-0.0978*	0.0588**	-0.1508***

Group	Gender		Education		Occupational skill intensity	
Subgroup	Male	Female	Undergraduates	Postgraduates	High-skilled	Mid-skilled
Variable	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0364)	(0.0348)	(0.0293)	(0.0479)	(0.0225)	(0.0238)
Cognitive Ability	0.0209	-0.0736	-0.0123	0.0298	0.1263***	-0.1286***
	(0.0391)	(0.0410)	(0.0302)	(0.0694)	(0.0260)	(0.0260)
Noncognitive Ability						
Interpersonal	0.0540	-0.0184	0.04887	-0.0580	0.0415	-0.0191
	(0.0341)	(0.0354)	(0.0284)	(0.0477)	(0.0218)	(0.0226)
Self-Discipline/Diligence	0.0427	0.0258	0.0230	0.0648	0.0486*	-0.0151
	(0.0345)	(0.0344)	(0.0278)	(0.0490)	(0.0218)	(0.0224)
Norms Compliance	0.0495	0.0684	0.0752**	0.0045	0.0082	0.0307
	(0.0296)	(0.0508)	(0.0273)	(0.0676)	(0.0244)	(0.0243)
Constant	-2.1720***	-3.0291***	-2.0571***	-2.6212***	-3.5693***	-1.7020***
	(0.3476)	(0.3740)	(0.2428)	(0.4971)	(0.3066)	(0.2534)
Pseudo R^2	0.4329	0.3659	0.3415	0.3790	0.1450	0.2007
Sample Size (N)	2312	2356	3555	1095	4581	4581

Note: The variable of Source in income from relatives was removed for the post-graduate group due to the collinearity problem.
Reference group: gender is female; education is below college.
*, **, *** indicate significance at the 5%, 1%, and 0.1% levels respectively.

Due to space constraints, only a summary is presented here. Full results are provided in Appendix Table A.2. For example, subgroup estimates reveal that among female respondents and those with undergraduate qualifications, the wage returns to cognitive ability are lower than for male respondents and those in high-skilled occupations. Specifically, cognitive ability is a more robust predictor of full-time employment in high-skilled occupations than in mid-skilled ones.

Table 6. Wage Determination for Different Classified Samples: Heckman Second-Stage Estimation.

Group	Gender		Education		Occupational skill intensity	
Subgroup	Male	Female	Undergraduates	Postgraduates	High-Skilled	Mid-Skilled
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Interpersonal Ability	0.0177*	0.0512***	0.0298***	0.0674***	0.0489***	0.0343***
	(0.0081)	(0.0074)	(0.0053)	(0.0195)	(0.0102)	(0.0081)
Cognitive Ability	0.0065	0.0102	0.0110*	0.0280	-0.0021	0.0256***
	(0.0070)	(0.0055)	(0.0046)	(0.0178)	(0.0069)	(0.0061)
Interpersonal*Cognitive. Ability	0.0044	-0.0003	0.0054	-0.0278	0.0082	0.0057
	(0.0066)	(0.0062)	(0.0048)	(0.0173)	(0.0073)	(0.0060)
Self-Discipline/Diligence	0.0168*	0.0119*	0.0160***	0.0170	0.0190**	0.0157*
	(0.0072)	(0.0054)	(0.0046)	(0.0155)	(0.0070)	(0.0063)
Norms Compliance	-0.0037	-0.0118	-0.0072	0.0093	-0.0002	-0.0057
	(0.0068)	(0.0095)	(0.0057)	(0.0193)	(0.0081)	(0.0074)
Self-Discipline/Diligence *Cognitive Ability	-0.0073	0.0075	0.0031	-0.0138	-0.0036	0.0032
	(0.0066)	(0.0058)	(0.0047)	(0.0150)	(0.0068)	(0.0063)
Norms Compliance*Cognitive Ability	0.0107	-0.0115	0.0076	0.0223	0.0067	0.0141*
	(0.0060)	(0.0104)	(0.0049)	(0.0262)	(0.0082)	(0.0065)
College/University	0.0509	0.0025			0.1612**	0.02038
	(0.0314)	(0.0388)			(0.0591)	(0.0276)
Postgraduates	0.1861***	0.0874*			0.2887***	0.1508**
	(0.0438)	(0.0390)			(0.0635)	(0.0567)
Public University	0.0722***	0.0276*	0.0427***	0.0543	0.0487**	0.0689***
	(0.0157)	(0.0120)	(0.0102)	(0.0289)	(0.0158)	(0.0153)
Gender (Male)			0.0851***	0.0668*	0.0667***	0.1088***
			(0.0101)	(0.0336)	(0.0146)	(0.0145)
Marital Status	0.0277	0.0245	0.0348	-0.0794	0.0316	0.0235
	(0.0441)	(0.0323)	(0.0264)	(0.1240)	(0.0444)	(0.0323)
Family SES	0.0070	0.0202**	0.0179***	0.0068	0.0152*	0.0281**
	(0.0078)	(0.0064)	(0.0053)	(0.0140)	(0.0072)	(0.0088)
Health Status	0.0150	0.0074	0.0077	0.0243	0.0109	0.0088
	(0.0084)	(0.0062)	(0.0053)	(0.0163)	(0.0077)	(0.0069)
BMI	-0.0017	-0.0056***	-0.0028*	-0.0093*	-0.0042*	-0.0024
	(0.0018)	(0.0016)	(0.0012)	(0.0039)	(0.0019)	(0.0015)
Work Experience	0.0062***	0.0023**	0.0043***	0.0035	0.0050***	0.00304**
	(0.0014)	(0.0009)	(0.0007)	(0.0041)	(0.0011)	(0.0011)
Work Experience^2	-5.07e-5***	-9.69e-6	-2.94e-5***	-8.23e-5	-3.43e-5***	-1.79e-5
	(1.48e-5)	(8.27e-6)	(7.32e-6)	(5.44e-5)	(9.79e-6)	(1.22e-5)
Seniority	0.0010	0.0028***	0.0029***	0.0005	0.0017	0.0038***
	(0.0015)	(0.0008)	(0.0007)	(0.0043)	(0.0011)	(0.0011)
Seniority^2	-1.36e-5	-3.87e-5***	-4.07e-5***	5.02e-5	-3.06e-5*	-4.95e-5**
	(2.32e-5)	(9.98e-6)	(9.51e-6)	(6.47e-5)	(1.25e-5)	(1.79e-5)
Job Change	-0.0138*	-0.0085	-0.0099*	0.0093	-0.0189*	-0.0047
	(0.0070)	(0.0053)	(0.0043)	(0.0195)	(0.0075)	(0.0052)

Group	Gender		Education		Occupational skill intensity	
Subgroup	Male	Female	Undergraduates	Postgraduates	High-Skilled	Mid-Skilled
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Middle/Low-level Manager	0.0447*	0.1104***	0.0817***	0.0961*	0.1076***	0.0469**
	(0.0190)	(0.0157)	(0.0125)	(0.0468)	(0.0192)	(0.0165)
High-Level Manager	0.2238	0.1468*	0.1652**		0.1755*	0.1264
	(0.1708)	(0.0665)	(0.0638)		(0.0838)	(0.1065)
Public Servant	0.2266***	0.1542***	0.2136***	0.0277	0.1670***	0.1816***
	(0.0225)	(0.0161)	(0.0142)	(0.0345)	(0.0183)	(0.0210)
Northern Region	0.0554**	0.1065***	0.0907***	0.0393	0.0694***	0.1090***
	(0.0180)	(0.0142)	(0.0118)	(0.0337)	(0.0171)	(0.0152)
Central Region	-0.0168	0.0144	0.0058	-0.0306	-0.0133	0.0182
	(0.0194)	(0.0152)	(0.0125)	(0.0418)	(0.0192)	(0.0158)
High-Skilled Occupation	0.0975**	0.1055*	0.0889**	0.1588		
	(0.0359)	(0.0425)	(0.0270)	(0.1141)		
Mid-Skilled Occupation	0.0144	-0.0090	-0.0074	0.0235		
	(0.0357)	(0.0423)	(0.0269)	(0.1153)		
IMR	-0.0471	0.0328	-0.0099	-0.0717	0.1168	-0.0835
	(0.0519)	(0.0498)	(0.0385)	(0.0970)	(0.0715)	(0.0543)
Constant	10.1240***	10.2017***	10.1231***	10.3899***	9.9921***	10.1417***
	(0.0767)	(0.0765)	(0.0454)	(0.1715)	(0.1297)	(0.0625)
Wald χ^2 test (DOF)	441.10***(26)	762.34***(26)	1063.36***(25)	102.16***(24)	311.38***(25)	388.03***(25)
Sample Size (N)	1323	1691	2612	402	1432	1502

Note: The low-skilled sample was only 40 people and was removed due to the collinearity problem.
The variable of senior management positions in the postgraduate group was removed due to the collinearity problem.
Reference group: gender is female; education is below college; management position is not a management position; work area is the southern and eastern regions and offshore islands; occupational skill intensity is low-skilled occupations.
*, **, *** indicate significance at the 5%, 1%, and 0.1% levels respectively.

Note that a summary version is shown here; see Appendix Table A.3 for full details. These estimates from Table 6 indicate that the wage premiums for cognitive ability are strongest among postgraduates and those in high-skill occupations. Interpersonal abilities are particularly important for mid-skilled positions where teamwork and service orientation are vital.

The subgroup analyses reinforce the main findings and suggest that while cognitive ability remains the dominant predictor of wages, noncognitive skills, especially interpersonal skills, affect wage outcomes differently across groups. For example, interpersonal skills appear to yield a statistically significant effect among female workers in mid-skilled jobs, consistent with the service-oriented nature of many such occupations.

5. Discussion

5.1. Interpretation of Main Findings

Our results underscore several important points. First, cognitive ability is a robust determinant of early-career wages. A one-standard-deviation increase in cognitive ability translates into roughly a 3.24% increase in wages, even after controlling for education, family background, and other demographic factors. This finding aligns with the long-established notion that cognitive skills substantially contribute to productivity.

Second, noncognitive skills also play a significant role, albeit with a smaller magnitude. Our measure of self-discipline and diligence is associated with a 1.41% wage premium per standard deviation increase, while interpersonal skills yield an approximately 1% increase. Although the wage differences attributable to noncognitive skills appear modest in the overall sample, their effects are more pronounced in certain subgroups. For instance, interpersonal skills show a stronger wage effect among female workers and employees in mid-skilled occupations. These results suggest that noncognitive competencies may be particularly valued in job settings that require frequent interpersonal interaction and teamwork.

Third, the conventional returns to education and family SES are attenuated once ability measures are included. In our analysis, the inclusion of cognitive and noncognitive variables reduces the estimated returns to education by about 60% and the impact of family SES by about 23%. This finding implies that prior literature that did not control for these individual ability dimensions might have overstated the roles of education and family background.

5.2. Complementarity Between Cognitive and Noncognitive Skills

A key question we set out to answer is whether cognitive and noncognitive skills interact synergistically to boost wages. We included interaction terms between cognitive ability and interpersonal as well as self-discipline skills. Across our full-sample estimations, the interaction effects were small and statistically insignificant. One potential explanation for this finding is the limited work experience and relatively low seniority of our sample; many respondents are new entrants working in positions where the full complexity of job responsibilities, where complementarities might be more pronounced, has not yet materialized. Subgroup analyses provide tentative evidence that, in higher-skilled occupations or among individuals with greater job tenure, the synergy between cognitive and noncognitive skills might eventually emerge. Future research with longitudinal data tracking panel members as they advance in their careers will be crucial to better detect and understand these dynamics.

5.3. Robustness and Limitations

Our use of a Heckman two-stage model is critical for controlling labor market selection, and the insignificance of the inverse Mills ratio (IMR) in our wage equations suggests that selection bias is not a major concern in our sample. Nonetheless, limitations remain. First, our measurements of noncognitive skills, while multidimensional, rely partly on self-reports and tutor evaluations, which may be subject to reporting bias. Second, our sample comprises new labor market entrants; the influence of abilities on wages might evolve as workers gain experience

and job responsibilities change. Finally, the cross-sectional nature of parts of our analysis cautions against strong causal inferences.

5.4. Implications for Policy and Future Research

Our findings carry significant policy implications. If cognitive and noncognitive skills are crucial drivers of wage outcomes, then educational policy should not solely emphasize formal degrees and traditional academic tests. Instead, curricula should also incorporate programs that foster self-discipline, social interaction, and communication skills. Policymakers and educational administrators could, for example, introduce leadership training, group projects, and self-regulation workshops into secondary and tertiary education curricula.

Furthermore, employer training programs might benefit from recognizing the role of noncognitive skills in productivity. Investing in employee development that improves interpersonal interactions and self-management may yield benefits in terms of increased productivity and higher wages over time.

Future research should extend our analysis by tracking these cohorts over longer periods. Longitudinal studies that follow workers as they advance into higher-skilled and managerial roles will help clarify whether the complementarities between cognitive and noncognitive skills become more pronounced with career progression. Investigating additional channels, such as industry-specific demands and regional variations in skill premiums, could also provide valuable insights.

6. Conclusion and Policy Implications

This study set out to explore the influence of cognitive and noncognitive abilities on the wages of new entrants to the Taiwanese labor market. Using data from the TEPS and TEPS-B surveys and employing a Heckman two-stage estimation framework, we find that cognitive ability commands significant wage returns, with self-discipline and interpersonal skills also contributing to earnings, albeit to a lesser extent. Importantly, the inclusion of individual ability measures substantially diminishes the estimated effects of traditional proxies of human capital, such as formal education and family SES.

The results underscore the need for educational and training policies that develop both hard and soft skills. In today's rapidly evolving labor market, where routine tasks are increasingly automated, the noncognitive abilities that enable effective interpersonal communication and personal initiative are becoming ever more crucial. Policymakers should invest in talent development programs that address both types of skills and consider fostering environments where the synergy between cognitive and noncognitive skills can flourish.

In conclusion, the study contributes to the literature by providing robust evidence that skill formation is multidimensional and that both cognitive and noncognitive competencies are essential in determining early-career wages. The implications extend beyond wage determination into broader discussions about social mobility and economic policy in an era characterized by rapid technological change and structurally shifting labor markets.

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Appendix

Table A1. Variable name and description.

Variable Name	Description
Gender	1 for male, 0 for female.
Marital Status	1 for married, 0 otherwise.
Education	The reference group is high school or below
College/University	1 for undergraduate, 0 otherwise.
Postgraduate	1 for postgraduate, 0 otherwise.
Public University	1 for graduates from a public university, 0 otherwise.
Family Socioeconomic Status (SES)	A standardized composite index of parents' education, parents' occupations, and family income; the higher the number, the higher the socioeconomic status.
Health Status	Self-report physical health condition for the last year, five grades from 0 to 4. The larger the number, the better the health.
BMI	Body mass index (BMI) is a person's weight in kilograms divided by the square of height in meters.
Source of Income	
Self	From your own income.
Relatives	From relatives.
Seniority	Total number of months in current full-time employment.
Work experience	Total number of months of employment since the first job.
Managerial Position	The reference group currently does not hold a management position.
Middle/Lower-Level manager	Currently holds a middle- and low-level management position.
High-Level manager	Currently holds a senior management position.
Public Servant	1 for work in the government sector; 0 for the private sector.
Job Change	The total number of jobs changed.
Work Area	The reference group is the southern and eastern regions of the country, and on offshore islands.
Northern Region	Work in the northern region.
Central Region	Work in the central region.
Others Region	Work in the southern and eastern regions of the country and on offshore islands.
Occupational Skill Intensity	According to the occupational classification of ISCO08, the nine main occupations are divided into three groups according to the required skill levels, which are dummy variables.
High-Skilled Occupation	Work classified as executives and managers, professionals and technicians, and associate professionals.
Middle-Skilled Occupation	Work classified as office staff, service staff, store and market sales staff, technical agricultural, forestry, fishery, and animal husbandry staff, technical workers and other related staff, and machine operators and assembly staff members.
Low-Skilled Occupation	Work classified as manual and unskilled labor.

Table A2. The content of the questions on the measurement of interpersonal skills.

Questionnaire item	Measurement object	Measurement method
I have always been calm and steady, rarely impatient.	Self-report	The original variable is a self-response score on an equidistant scale ranging from 1 to 4 points. The higher the score, the more disagreement there will be. In this study, the reverse scoring was used to facilitate interpretation. The higher the score, the better the interpersonal skills.
I do a good job of giving an opinion, report, or statement.	Self-report	Same as above
As for how to divide labor and coordinate in the event, I don't know how to do it.	Self-report	Same as above
I can work well with anyone.	Self-report	Same as above
Can give oral presentations clearly	Tutor evaluation	The original variable is a self-response score on an equidistant scale ranging from 1 to 5 points. The higher the score, the more disagreement there will be. In this study, the reverse scoring was used to facilitate interpretation. The higher the score, the better the interpersonal skills.
Able to collaborate with other students on a task	Tutor evaluation	Same as above
Have leadership	Tutor evaluation	Same as above

Table A3. The Content of The Questions on The Measurement of Self-Discipline/Diligence Ability.

Questionnaire item	Measurement Object	Measurement Method
You never let anything else delay your work or your studies.	Self-report	The original variable is a self-response score on an equidistant scale ranging from 1 to 5 points. The higher the score, the more disagreement there will be. In this study, the reverse scoring was used to facilitate interpretation. The higher the score, the better the interpersonal skills.
When you have trouble at work or at school, you try to figure it out.	Self-report	Same as above
Even in the face of things you don't like, you can still perform at your best.	Self-report	Same as above
Even if you are feeling a little sick, try to do your best for the day.	Self-report	Same as above
Although work takes a long time to see results, you can maintain consistent performance.	Self-report	Same as above

Table A4: The content of the questions on the measurement of the ability to comply with norms.

Table A4. The content of the questions on the measurement of the ability to comply with norms.

Questionnaire item	Measurement Object	Measurement Method
Cheating on a test	Self-report	The original variable is a self-response score on an equidistant scale ranging from 1 to 4 points. The higher the score, the more disagreement there will be. In this study, the reverse scoring was used to facilitate interpretation. The higher the score, the better the interpersonal skills.
Smoking, drinking, or eating betelnuts	Self-report	Same as above
Truancy or skipping class	Self-report	Same as above
Fights at school or clashes with teachers	Tutor evaluation	The original variable is a binary variable of 1 and 2, 1 indicates that the sample has performed the behavior, and 2 indicates that the sample has not performed the behavior. In this study, reverse scoring was used to facilitate interpretation, with higher scores indicating greater compliance with norms.
Smoking, drinking, or eating betel nut	Tutor evaluation	Same as above
Truancy or skipping class	Tutor evaluation	Same as above