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What Skills Lead to Entrepreneurial Success? Evidence from Non-Farm-Household Enterprises in Indonesia

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I. Introduction

Entrepreneurs are often considered to be a significant driver of growth because, in creating a new product or producing an existing one more efficiently, they combine human capital with physical capital and ideas (Lazear, 2005). Carree and Thurik (2010) stated that entrepreneurship generated growth because it served as a vehicle for innovation and change and therefore as a conduit for knowledge spillovers. In advanced economies, the prevailing model is self-selection (Roy, 1951; Lucas, 1978), according to which individuals with higher entrepreneurship skills choose to become entrepreneurs while those with lower skills become wageworkers.

A number of empirical studies (Wong, Ho & Autio, 2005; Naudé, 2009, e.g.) found that opportunity-motivated or high-growth-potential entrepreneurship drove economic growth, but necessity-motivated entrepreneurship did not. One reason for this is that dynamic entrepreneurs are more likely to create positive externality through innovation while necessity entrepreneurs are usually accustomed to conventional ways of doing business (Fossen & Buttner, 2013). Finally, Vial and Hanoteau (2015) showed that entrepreneurship had a high potential for reducing poverty.

In this paper, we investigate the returns of cognitive skills of Indonesian non-farm household-enterprise operators to their business performance. Specifically, we compared the returns of fluid and crystallized intelligence to the business performance of non-farm-households, taking into account that these types of intelligence are correlated with each other and with educational attainment.

Analysis of the types of skills and characteristics important for success among entrepreneurs can inform entrepreneurship-training programs and educational curricula designed to increase the number of successful entrepreneurs. In addition, such information can enable programs designed to support small businesses—for example training or microcredit—and identify enterprise owners who have greater potential for future success. On the other hand, low-potential entrepreneurs may benefit more from absorption into low-skilled wage jobs in the manufacturing or service sectors.

Workers' cognitive skills, based on evidence drawn largely from cross-country comparisons, play an important causal role in economic growth (Hanushek & Woessmann, 2009). A study by Bargain and Zeidan (2017) found that the impact of cognitive skills on the earnings of Indonesian workers was generally modest compared to what is typical of developed countries. The central argument of the study was that physical growth and skill development reflected general conditions during respondents' childhoods: for example, people whose height was above average also tended to possess greater cognitive capacity. Bargain and Zeidan (2017) further reported that the impact of height on earnings dropped significantly once cognitive skill was introduced into the equation. In Mexico, Vogl (2014) found a similar effect when height and cognitive skills were introduced into an earnings model.

What about the effects of cognitive skills on entrepreneurs' success? One way they may do so is by making household enterprises more productive, and a number of studies have shown a significant and positive relationship between human capital and entrepreneurial success (Unger et al., 2011). In addition, Barron (2007, cited in Sambasivan, Abdul, and Yusop, 2009), stated that alertness to opportunities depended upon an individual's cognitive ability. Van Praag and Cramer (2001) found that, together with educational attainment, childhood intellectual capacity (as measured by IQ at age 12) was positively and significantly correlated with the number of employees employed in an enterprise. Meisenberg (2012) argued that individuals with higher-than-average cognitive skills were able to start and run businesses more effectively and were better able to innovate continuously.

In addition to overall cognitive skills, other types of skills may also have different returns. Lazear (2004) found that individuals who became entrepreneurs chose a more varied curriculum during their college years than did their peers who became salaried workers. This study provides insight into the premise that entrepreneurs employ a different strategy in their education than do wageworkers. Hartog, van Praag, and van der Sluis (2010) compared the role of cognitive skills for entrepreneurs and wage workers. Using longitudinal data from the United States, their study found that general ability provided a 30%-higher return for entrepreneurs compared to salaried workers. According to the authors, specific abilities that contributed to the earnings premium for entrepreneurs were mathematical, technical, and social abilities. Furthermore, the authors explained that entrepreneurs who earned a premium relative to wage employees were those who belonged to the upper part of the general or specific ability distribution.

Indonesia is classified as a low-middle-income country, and its economic growth averaged around 5% annually between 2001 and 2014 (World Bank Group, 2019). A continuing decline in poverty has accompanied this stable and relatively high growth rate. According to official statistics, headcount poverty declined from 18% in 2001 to 10.7% in 2016. As a result, Indonesia is on the cusp of launching itself into high-middle-income status, and the Indonesian government has identified self-employment as a development strategy. The Ministry of Cooperatives and Small and Medium Enterprises, for example, provides training and start-up capital for entrepreneurs. The Ministry of Finance has decreed that specific government tenders be open only to micro- and small enterprises. In addition, the Ministry of Education and Culture provides seed funding and has created an entrepreneurship curriculum for senior secondary students and an internship program.

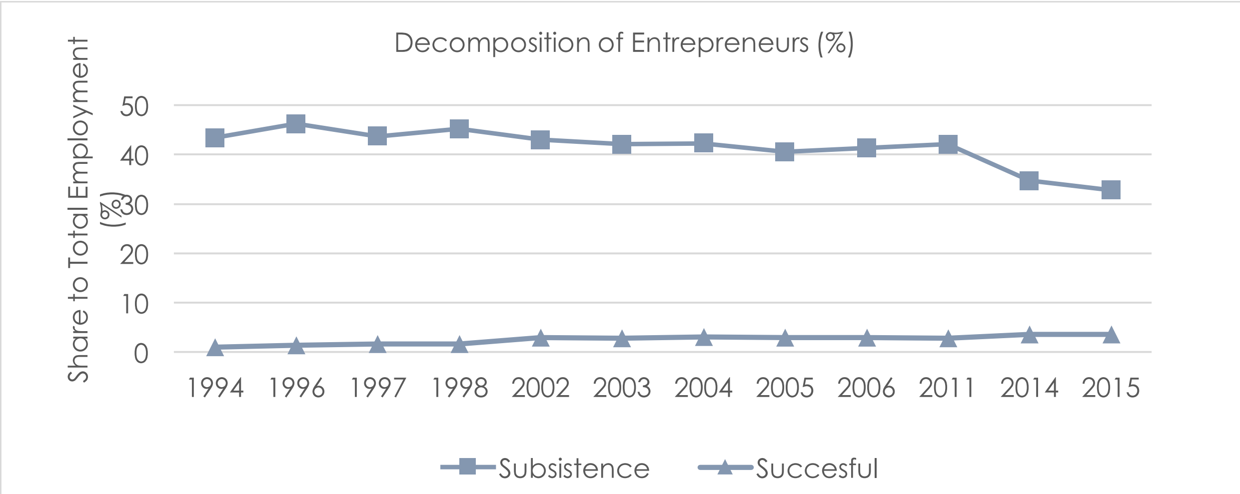
In the last two decades, official reports from Indonesia note that a sizable share of the workforce is self-employed. The percentage of self-employed workers in the total workforce remained stable at between 45% and 48% during the 1994-2011 period before dipping in 2014 and 2015 (Figure 1).

Figure 1. Entrepreneurs in Indonesia, 1994-2015

Source: National Labor Force Survey (Sakernas) (1994-2015)

Following de Mel, McKenzie, and Woodruff (2008) and Djankov et al. (2005), who measured entrepreneurial success by the single indicator of whether an enterprise had at least one paid employee, we found that the majority of Indonesia's self-employed workers were subsistence entrepreneurs (Figure 2). The share of successful entrepreneurs continued to increase between 1994 and 2001, from less than 1% in 1994 to around 3% two decades later. While the trend was encouraging, the share of subsistence entrepreneurs has remained extremely large for quite a long period of time, consistent with the observations of Hsieh and Olken (2014) who reported that almost all firms in Indonesia hired fewer than ten workers. The fraction of firms with fewer than ten workers in Indonesia is higher than it is in Mexico, which is also considered a developing country despite a higher GDP per capita than Indonesia (Hsieh & Olken, 2014).

Figure 2. Breakdown of Entrepreneurs, 1994-2015



Source: National Labor Force Survey (Sakernas) (1994-2015)

Using rich longitudinal data from 2007 and 2014 from Indonesia, we found that fluid intelligence had a positive, sizeable, and statistically significant effect on business profits and value. The statistically significant returns to higher fluid intelligence appeared to be robust even when time-invariant unobserved heterogeneity was taken into account. A one standard deviation increase in performance on the Raven's test led to a higher profit of around 5.7% and a higher business value of about 7%. On the other hand, we found no evidence that crystallized intelligence, once we had controlled for fluid intelligence and educational attainment, had any impact on business performance. Quantile regressions revealed some heterogeneous effects of fluid intelligence on the size of business. Finally, our results were robust to possible individual selection into non-farm entrepreneurship.

II. Conceptual Framework

Literature in psychology is divided regarding the definition of ability. While early psychologists argued that ability was a unitary concept, others believed that ability was divided into specific components. These two paradigms created the terms "general ability" and "specific ability." Cattell (1971) further broke general ability into two different components. The first was crystallized intelligence, defined as intelligence acquired and accumulated through interaction with the environment, level of education, and experience. This form of intelligence was often measured as knowledge and appeared to be linked with education, physical environment, and health. Crystallized intelligence was usually assessed through tests of vocabulary, analogies, and general knowledge. Because it was strongly influenced by experience and environment, crystallized intelligence could continually be improved and generally increased with age.

The second component of general ability was fluid intelligence, which was related to an individual's capacity to think logically and solve problems in novel situations, to acquire knowledge, and to adapt to changes. Generally, fluid intelligence was measured using tests of cognitive functioning that relied on working memory and abstract reasoning. Fluid intelligence was independent of acquired knowledge and highly influenced by genetics and biological factors. Targeted training could increase fluid intelligence but only to a small extent. Au et al (2015) conducted a meta-study on the effect of n-back training on fluid intelligence and concluded that the effect was statistically significant but small—around 3-4 points on a standardized IQ test. In terms of the relationship between fluid and crystallized intelligence, Thorsen, Gustafsson, and Cliffordson (2014) found that fluid intelligence played a role in the formation of crystallized intelligence. Finally, Salthouse (2004) reported that fluid intelligence had a negative and linear correlation with age. This implied that controlling for age in our model was important.

Among various individual determinants of labor-market outcomes, earnings are influenced by fluid cognitive skills and height (Vogl, 2014; LaFave & Thomas, 2017; Bargain & Zeidan, 2017) or by physical strength (i.e., "brawn") (Rosenzweig & Zhang, 2013). We relied on a similar assumption: that the labor market rewarded various types of intelligence differently, depending on the context or a country's level of development. One key departure

on fluid intelligence.

In estimating the effects of different types of intelligence on labor-market outcomes, we used findings from the research cited above to select control variables. Specifically, we included height and ethnicity as controls for in-utero disease environment, nutrition, and genetics. We also controlled for educational attainment and infrastructure conditions in respondents' home districts.

III. Data

We used data from the Indonesia Family Life Survey (IFLS), a multi-level and multi-topic longitudinal household survey that was conducted five times between 1993 and 2014. In addition to collecting household-level information, the IFLS sampled at the individual level and was also a community-facility survey. The 1993 IFLS-1 covered 7,224 households across 321 sampling areas in thirteen provinces with a tracking rate greater than 90%. The 2014 IFLS-5 successfully retained 6,647 households that had been surveyed since 1993 (Strauss, Witoelar & Sikoki, 2016). We focused on the most recent IFL surveys, conducted in 2007 (IFLS-4) and 2014 (IFLS-5), which collected a significantly richer set of information on cognitive skills.

3.1. Household Businesses in the IFLS

Because it was a household survey, the IFLS was not specifically designed to collect information on entrepreneurs and firms. It did provide information on household businesses, however. The IFLS collected data for farm and non-farm businesses owned by the household, including information on business profits, assets, capital, and ownership. Furthermore, a separate question identified the household member who was primarily responsible for the business (which we defined as an entrepreneur), enabling us to link individual characteristics to the business. It was not always true, however, that the owner of the household business was also primarily responsible for daily operations.

The attempt to identify owners of farm businesses only appeared in IFLS-3. One possible way to include farm-household business in our analysis was to use average characteristics of adult household members for the farm-business analysis. The lack of information linking farm-household business with individual-level information in IFLS-4 and -5 led to our decision to include only non-farm-household businesses, which did allow us to link individual-level information with entrepreneurs.

Each household in the IFLS was asked to provide detailed information regarding all non-farm businesses they operated. Approximately 84% of households in our dataset managed only a single non-farm business. The IFLS did not create an identifier for household business that could be used to link household business across survey years, however. This meant that we were unable to identify which household businesses identified in IFLS-4 were still operating in IFLS-5. We could, however, link entrepreneurs across the two surveys. Considering the seven-year gap between the IFLS-4 and IFLS-5, and the nature of businesses in Indonesia, it is highly probable that the majority of the household business in IFLS-4 had changed their work sector, changed businesses but remained in the same sector, or closed their businesses by the time of IFLS-5. These considerations may not pose a significant problem, however, given that only 10% of our sample was derived from IFLS-4 (see Tables 3 and 4 below).

Additionally, while the majority of entrepreneurs in our dataset ran a single non-farm-household business, some apparently ran more than one at the same time. Table 1 summarizes non-farm-household businesses and unique entrepreneurs in our dataset. We included all entrepreneurs regardless of the number of businesses they operated.

Table 1. Non-farm-household businesses in the IFLS

	IFLS-4	IFLS-5
Number of non-farm-household businesses	6,197	6,724
Number of unique entrepreneurs	5,714	6,311

Source: Authors' estimations based on the IFLS-4 and IFLS-5.

3.2. Measurement of Cognitive Skills in IFLS

In a section called EK, the IFLS-4 and IFLS-5 collected information that could be used as a proxy for cognitive skills. The section was first introduced in the third wave of IFLS in 2000 and included two sets of skills modules, EK1 and EK2, administered to 7-14 and 15-24 year-olds, respectively. The former contained five numeracy problems and twelve shape-matching problems (Raven's Progressive Matrices Test), while the latter contained five numeracy problems and eight shape-matching problems. The numeracy problems in EK2 were significantly more complicated than those in EK1.

In IFLS-4, the enumerators used the following procedure (Suryadarma, 2015): EK1 was administered to individuals who were 7-14 years old in 2007. Individuals who had taken the EK1 module in 2000 retook it in 2007. In addition, if these individuals were already at least 15 years old in 2007, they were also asked to respond to the EK2 module. Note that individuals who had been 7-14 years old in 2000 were around 14-21 years old in 2007. Similarly, individuals who had answered the EK2 in 2000 were also asked to respond to the same module in 2007 even if they had been older than 24 in 2007. The dataset showed that respondents to the EK2 module could have been as old as 35 in 2007. We decided to use EK2 test scores rather than EK1 scores as one indicator of cognitive skills because the EK2 was more difficult and, arguably, more relevant to the kinds of numeracy needed to operate a business.

The age cutoff for EK2 test participants changed in IFLS-5. In IFLS-5, the Raven's test from the EK2 module was given to everyone aged 15 or older, while the numeracy test from EK2 was given to respondents who were 15-60 years old (Strauss, Witoelar & Sikoki, 2016). The result was that respondents to the EK2 modules were not necessarily in a similar age range: some might have taken the tests as youth while others might have taken them during their 30s or even older.

We believe that the EK2 numeracy test measured a different dimension of cognitive ability than did the Raven's test. Following Cattell's breakdown of general intelligence (1971), the numeracy test in EK2 captured crystallized intelligence because knowledge in math is usually acquired and accumulated through schooling. On the other hand, the Raven's Progressive Matrices Test is a reasoning test more fitted to the concept of fluid intelligence, which depends on innate ability rather than education or acculturation. In addition to the EK section, the IFLS also asked individuals younger than 30 for their national examination scores. In Indonesia, students have to sit for national examinations at the end of each school level: primary (sixth grade), junior secondary (ninth grade), and senior secondary (12th grade). Given that primary education is universal, but that the average adult educational attainment in Indonesia is slightly below eight years, national examination scores at the junior and senior secondary levels are largely missing. In addition, significant recall bias was likely for primary-level national examination scores. Consequently, we did not use national examination scores as a proxy for cognitive skills.

Table 2 summarizes the number of respondents who took the EK2 tests. As discussed above, there were significantly more respondents to IFLS-5 than to IFLS-4.

Table 2. EK2 Tests in IFLS

	IFLS-4	IFLS-5
Number of respondents of EK2	11,825	36,380
Number of respondents who refused to participate in EK2 test	742	5,041
Number of respondents for whom EK2 scores were available	11,083	31,339

Source: Authors' estimations based on the IFLS-4 and IFLS-5.

The correlation in performance between mathematics and Raven's score was 0.41, an expected result given that the literature we have cited reports that crystallized intelligence is a function of fluid intelligence. While sizeable, the correlation was not sufficiently high to make multicollinearity a concern.

3.2.1 Sample Construction

Respondents to the IFLS who identified themselves as owners of non-farm businesses were asked to respond to additional questions regarding their single or multiple non-farm businesses. Each observation in our sample reflects a non-farm entrepreneur and the non-farm-household business(es) for which she or he was responsible.

Our dataset combines the two latest IFLS waves and contains information on 12,256 non-farm businesses that reported profit information (Table 3, second row). When divided into the two IFLS waves, the number of non-farm businesses slightly increased over the seven years between surveys: 6,010 in 2007 and 6,246 in 2014. Because of the IFLS's age limitations for administering sections EK, only a subsample of non-farm entrepreneurs reported cognitive-skills information. When we combined entrepreneurs' information with their cognitive test scores, we ended up with 6,465 non-farm businesses (964 from IFLS-4 and the rest from IFLS-5).

Table 3 summarizes information regarding the number of non-farm entrepreneurs who reported cognitive scores from EK2 tests. The number of entrepreneurs without cognitive scores was much lower in IFLS-5 than in IFLS-4 because, starting with IFLS-5, age limitations for the EK2 changed, allowing more respondents to participate and increasing the number of non-farm entrepreneurs whose cognitive scores were reported. For each IFLS respondent who was eligible to take the EK2 tests but refused to do so, the IFLS also recorded the reason for the refusal. Table 4 summarizes these results.

Table 3. Linking Entrepreneur Dataset with Cognitive Test Scores Dataset

	IFLS-4	IFLS-5
Non-farm businesses (Table 1)	6,197	6,724
Non-farm businesses with profit data	6,010	6,246
Among those with profit data :		
Have complete cognitive scores	964	5,501
Missing at least one cognitive score, of which:	5,046	745
Supposed to take the EK2 test but did not	26	474
Have missing score due to survey design	5,020	271

Source: Authors' estimations based on the IFLS-4 and IFLS-5.

Among the reasons for not taking EK2 tests, "refused," "cannot read," and "unable to answer" seemed to be of greatest concern because they may have signaled lower cognitive ability or self-selection. Individuals who rejected the EK2 test for these reasons constituted only a small part of our whole entrepreneur sample in both IFLS waves, however. Consequently, the proportion of entrepreneurs who were supposed to take the EK2 tests but refused due to cognitive reasons seemed negligible.

Table 4. Reason for Not Taking EK2 Tests

Reason	IFLS-4	IFLS-5
Refused	14	223
Cannot read	1	12
Unable to answer	0	6
Not enough time	1	5
Proxy respondent	8	156
Other	0	14
Couldn't be contacted	2	58
Total	26	474

Source: Authors' estimations based on the IFLS-4 and IFLS-5.

In addition to entrepreneurs' cognitive test scores, we also used the IFLS's community-facility module to collect information on local infrastructure at the district level. Because the IFLS did not administer the community-facility module in all areas, we were only able to match 6,001 non-farm entrepreneurs with their community information (from a set of 6,465 non-farm entrepreneurs whose cognitive scores were reported).

Based on the description above, the major reason for the reduction in sample size was missing cognitive-skills reports. It is also worth reiterating that in 2007, the EK2 test was only administered to 15-35 year-olds. In consequence, the results are dominated by youth, many of whom would have had no responsibility for a non-farm business. To check for the correlates of missing cognitive scores, we estimated a probit model in which the dependent variable was equal to one if at least one of the entrepreneur's cognitive scores was missing and zero otherwise. Because of the way the EK module was administered, we expected both that age would be a significant correlate and that there would be fewer missing cognitive scores in later IFLS waves. Table 5 shows estimated coefficients and average marginal effects.

Table 5. Correlates of Probability of Missing Cognitive Scores

Business Characteristics		Coefficient	Average Marginal Effects
Ln (profit)		0.020 (0.025)	0.006 (0.008)
Ln (business value)		-0.007 (0.016)	-0.002 (0.005)
Number of employees		-0.002 (0.007)	-0.001 (0.002)
Age of business (years)		0.001 (0.004)	0.000 (0.001)
Sector (excluded category: sector requiring brawn)			
	Brain	0.172 (0.135)	0.053 (0.042)
	Social	0.084 (0.133)	0.025 (0.040)
Entrepreneur Characteristics			
Educational attainment (ref: elementary)			
	Junior secondary	0.082 (0.093)	0.025 (0.029)
	Senior secondary / tertiary	0.102 (0.086)	0.031 (0.027)
Height (cm)		-0.004 (0.004)	-0.001 (0.001)
Age (years)		0.375*** (0.026)	0.114 (0.007)
Age squared		-0.003*** (0.000)	-0.001 (0.000)

Male (Yes = 1)	0.145*	0.044
	(0.081)	(0.024)
Ethnic Javanese (Yes = 1)	-0.269**	-0.081
	(0.114)	(0.034)
Dependency ratio	0.002***	0.000
	(0.001)	(0.000)
Household size	-0.069***	-0.021
	(0.014)	(0.004)
Household headed by man (Yes = 1)	0.188**	0.054
	(0.094)	(0.026)
Urban (Yes = 1)	-0.032	-0.010
	(0.087)	(0.027)
District and survey year characteristics		
Proportion of households with access to grid electricity	0.004	0.001
	(0.003)	(0.001)
Proportion of villages with factories or cottage industry	0.155*	0.047
	(0.092)	(0.028)
Number of non-farm-household businesses at district level	-0.000	0.000
	(0.001)	(0.000)
IFLS Wave 5 (2014), Yes = 1	-4.701***	-0.971
	(0.159)	(0.005)
Constant	-7.611***	
	(0.898)	
Province fixed effects	Yes	
Number of observations	7,349	
Predicted probability at mean	0.230	

Source: Authors' estimations based on the IFLS-4 and IFLS-5.

Notes: *** 1% significance, ** 5% significance, * 10% significance. Robust standard errors clustered at individual level in parentheses. Dependent variable (missing cognitive scores) = 1 for observations with missing values on at least one cognitive test score and = 0 for observations with non-missing values on both cognitive test scores.

Table 5 shows that missing cognitive scores had no statistically significant correlation with any business characteristics. In addition, average marginal effects were very small. Among the characteristics of entrepreneurs, only age, ethnicity, household size, dependency ratio, and whether the household was headed by a man were significantly correlated with the probability of missing cognitive scores; here again, average marginal effects were relatively small. As expected, age was positively correlated with the probability of missing cognitive scores. Javanese ethnicity (the Javanese are the largest ethnic group in Indonesia) was negatively correlated with missing cognitive scores. Larger household size also reduced the probability of missing scores. In addition to the characteristics of entrepreneurs, we found that the scores of entrepreneurs in the 2014 IFLS-5 were less likely to be missing by 97.1 percentage points with respect to the 2007 IFLS-4.

IV. Empirical Strategy

Our reduced-form specification is shown in Equation 5:

$$Y_{ijt} = \beta_z X_j + \beta_i I_{jt} + \beta_E E_{jt} + \beta_C C_{it} + \beta_D D_t + \varepsilon_{ijt} \tag{5}$$

where Y_{ijt} was the main indicator of interest for enterprise *i* associated by entrepreneur *j* in year *t*. We used annual profit and total value of business to measure enterprise performance. The latter comprised real value of land, buildings, equipment, and vehicles.

X_j were predetermined characteristics of the entrepreneur: sex, age, ethnicity, and height. I_{jt} represented the crystallized and fluid intelligence of the entrepreneur as measured through the mathematics and Raven's tests in the EK2 module. For entrepreneurs who took both the IFLS-4 and the IFLS-5, the variable was time-variant. Meanwhile, EI_{jt} was the educational attainment of entrepreneur *j*.

C_{it} were characteristics of the community in which enterprise *i* was located (the presence of infrastructure, for example) at the district level. We also included province fixed effects. D_t was a vector of dummy variables indicating the year of the survey. A binary indicator represented the survey year 2014, with 2007 acting as the reference year.

Table 6 shows the descriptive statistics. The average profit of non-farm-household businesses over the previous twelve months was 11.9 million Rupiahs, indicating a small but healthy profit. With regard to assets, only slightly more than 10% of the non-farm businesses in our sample owned land. The number of non-farm businesses who possessed buildings or vehicles was also low, but the majority owned equipment, indicating that non-farm businesses invested mainly in equipment or tools. Taken together, we found that the value of non-farm businesses in Indonesia was an average of 23 million Rupiahs, implying that businesses were operated with very little capital or use of technology.

Entrepreneurs who were primarily in charge of the business had completed ten years of education on average, with a sizeable variation: 46% had at least twelve years of education (senior secondary/tertiary) while 33% had a maximum of six years of education (elementary or below). These entrepreneurs were still relatively young, with an average age of 40, and 54% were men. Slightly less than half of the entrepreneurs were Javanese.

Table 6. Descriptive Statistics

Variable	Number of observations	Mean	Std Dev
Outcome variables			
Profit in the past 12 months (in 10,000s of Rupiahs)	5,196	1193.19	2974.89
Total value of business (in 10,000s of Rupiahs)	4,928	2299.13	8912.87
Entrepreneur characteristics			
Math score (standardized)	5,286	-0.09	0.99
Raven's score (standardized)	5,286	-0.10	0.98
Height (cm)	5,286	157.35	8.43
Age (years)	5,286	40.45	11.98
Educational attainment			
Elementary or below	5,286	0.33	0.47
Junior secondary	5,286	0.21	0.41
Senior secondary / tertiary	5,286	0.46	0.50
Male (Yes = 1)	5,286	0.54	0.50
Ethnic Javanese (Yes = 1)	5,286	0.45	0.50
Household characteristics			
Dependency ratio	5,286	67.00	67.57
Household size	5,286	5.26	2.43
Household headed by man (Yes = 1)	5,286	0.88	0.33
Urban (Yes = 1)	5,286	0.65	0.48
Community characteristics—district level			
Proportion of households with access to grid electricity	5,286	0.96	0.07
Proportion of villages with factory or cottage industry	5,286	0.63	0.39
Proportion of villages where a formal financial institution provides business loan	5,286	0.36	0.15
Number of non-farm household enterprises	5,286	63.81	44.50
Business characteristics			
Sector mainly requiring brawn (Yes = 1)	5,286	0.03	0.18
Sector mainly requiring brain (Yes = 1)	5,286	0.37	0.48
Sector mainly requiring social skills (Yes = 1)	5,286	0.59	0.49

Source: Authors' estimations based on the IFLS-4 and IFLS-5.
Notes: These descriptive statistics are based on the sample estimated in Table 7

We also separated businesses into sectors based on the main skills required, following the three-category approach suggested by Bargain and Zeidan (2017). In the IFLS, Section TK collected information on employment and asked respondents whether their jobs required much physical effort, lifting of heavy loads, intense concentration or attention, work with computers, or skill in dealing with people for all or almost all the time. We used these responses to calculate brain, brawn, and social scores for each work sector. The brawn score was the average of "lots of physical effort" and "lifting heavy loads." The brain score was the average of “intense concentration/attention” and “work with computers.” The social score was obtained from the percentage of workers who noted that their jobs required “skill in dealing with people all or almost all the time.”

Work sectors were then classified as, “brawn,” “brain,” or “social” depending upon which score was greater than the other two. Among nine work sectors in Section TK, three could be classified as brawn sectors: agriculture, forestry, fishing, hunting; mining and quarrying; and construction, while the brain sectors were manufacturing; electricity, gas, water; and transport, storage, and communication. The social sector included wholesale, retail, restaurant, hotels; finance, insurance, real estate, and business services; and social services.

Table A1 in the Appendix shows the mapping. Table 6 shows that six out of ten entrepreneurs in our sample were in sectors that required mainly social skills. Because of our focus on non-farm businesses, only 3% of the businesses were in sectors that required mainly brawn. About 65% of non-farm businesses were in urban areas, also reflected in the fact that non-farm businesses were in communities that had almost universal access to electricity. On average, however, only 36% of villages in the communities where these businesses were located had a formal financial institution that provided business loans. In contrast, it appeared that many of these communities had factories or cottage industries, which is an indicator of economic progress.

Given the way that the IFLS sampled for the EK module and our focus on non-farm enterprises, our concern was that our estimation results might not represent Indonesia’s entrepreneurs. Appendix A2 compares the basic characteristics of entrepreneurs in our data with those in the TK module, which focused on all types of workers by occupation. From the TK module, we focused specifically on self-employed individuals, in a sense comparing the characteristics of our sample with all entrepreneurs who responded to the IFLS. We found statistically significant differences in all characteristics except height and age, although most of the magnitude differences were small. Our sample had lower cognitive skills and included a lower proportion of males and a higher proportion of ethnic Javanese. In addition, a higher proportion of entrepreneurs in our sample lived in urban areas. Our focus on non-farm entrepreneurs was also reflected in the fact that the proportion of individuals who worked in sectors that required brawn was twenty-five percentage points lower in our sample, while the proportion working in brain-intensive and social-skills-intensive sectors was higher by twelve and fifteen percentage points, respectively. Therefore, our results are unlikely to represent the entire self-employed sector in Indonesia.

V. The Effect of Crystallized and Fluid Intelligence on Non-Farm Business Outcomes

We estimated the model in Equation 5 using least squares. Both profit and value of total business were deflated using the 2007 consumer price index, and we further transformed them into their log values as has been the practice in previous related studies.

Cognitive skill was our main variable of interest and was measured using math scores (intended to capture crystallized intelligence) and Raven's scores (proxying fluid intelligence). In order to get comparable estimates across skills, we standardized all scores by subtracting the overall sample mean and dividing by its standard deviation. Table 7A and 7B show the estimation results, first using cognitive scores alone and then with the control variables included step-wise.

When profit was regressed on math score alone, that score had a positive and significant effect (as shown in Column 1). Similar to Hartog, van Praag, and van der Sluis (2010), we considered this our upper-bound estimate. Similarly, regressing profit on Raven's score alone yielded a positive and statistically significant effect (Column 2). Adding both scores (Column 3) or educational attainment to the equation (Column 4), however, resulted in a substantial decline in math-score estimates or the disappearance of their statistically significant effect on profit. In contrast, the effect of Raven's score remained statistically significant and robust when controlling for math score (Column 3). Its effect was reduced by half when educational attainment was included (Column 5), however. In the specification in which we included all control variables (Column 8), we found that the effect of math scores was relatively small at 3% and not statistically significant.

On the other hand, a one standard deviation increase in Raven's score improved business profit by 5.7%. Similarly, the effect of education was positive, large, and statistically significant. When we considered the results for business value, our findings were similar with regards to math, Raven's score, and educational attainment (Columns 9-14). After we included all control variables (Column 16), we found that the direct effect of Raven's score was sizeable at 7% but only weakly significant. Math score had a small and statistically insignificant effect, while educational attainment had a large and positive effect.

Other individual-level variables showed positive and statistically significant effects on most of the business-performance indicators. We found that entrepreneurs who were taller, older men had higher profits and business value. The finding on height corroborates Vogl (2014) in Mexico and Bargain and Zeidan (2017) in Indonesia. Examining household-level variables, we found that entrepreneurs residing in a household headed by a man earned a profit that was around 19% higher. Household size also had a positive effect on business value.

Examining district-level characteristics, the availability of factories, a proxy for economic progress, had a positive effect on profit but not on business value. In contrast, the number of non-farm-household businesses in a district, a measure of competition, had a negative but essentially zero effect on profit or business value.

Taken together, the results shown in Tables 7A and 7B corroborated our first two hypotheses. The reasons for our findings could be many. For example, because fluid intelligence reflects problem-solving abilities and quick adaptation to change, it could be more useful than crystallized intelligence in a developing country like Indonesia, where the economic environment may change quickly and regulations are incomplete. Second, non-farm businesses in Indonesia are relatively small with few assets or employees. This implies that these business do not need a high level of crystallized intelligence to operate and that higher levels of crystallized intelligence would not lead to increased business performance.

Table 7A. Intelligence and Non-Farm Business Profit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Math test score (std)	0.114***		0.069***	0.041*		0.026	0.031	0.030
	(0.023)		(0.024)	(0.024)		(0.025)	(0.024)	(0.024)
Raven's test score (std)		0.149***	0.123***		0.068***	0.060**	0.059**	0.057**
		(0.023)	(0.025)		(0.025)	(0.026)	(0.026)	(0.026)
Educational attainment (ref: elementary)								
Junior secondary				0.250***	0.225***	0.221***	0.252***	0.237***

				(0.060)	(0.061)	(0.061)	(0.060)	(0.060)
Senior secondary / tertiary				0.463***	0.432***	0.418***	0.373***	0.357***
				(0.053)	(0.055)	(0.056)	(0.055)	(0.055)
Age (years)							0.146***	0.145***
							(0.012)	(0.012)
Age squared							-0.002***	-0.002***
							(0.000)	(0.000)
Height (cm)							0.015***	0.015***
							(0.004)	(0.004)
Male (Yes=1)							0.470***	0.479***
							(0.060)	(0.061)
Ethnic Javanese (Yes=1)							-0.098	-0.100
							(0.061)	(0.063)
Dependency ratio							-0.000	-0.000
							(0.000)	(0.000)
Household size							0.012	0.011
							(0.009)	(0.009)
Household headed by man (Yes=1)							0.195***	0.192***
							(0.069)	(0.069)
Urban (Yes=1)							0.132***	0.095*
							(0.047)	(0.049)
Proportion of households with access to grid electricity								0.599*
								(0.349)
Proportion of villages with factories or cottage industry								0.217***
								(0.061)
Number of non-farm-household businesses at district								-0.001*
								(0.001)
Constant	15.005***	14.962***	14.957***	14.655***	14.659***	14.666***	9.032***	8.534***
	(0.106)	(0.107)	(0.107)	(0.114)	(0.114)	(0.114)	(0.609)	(0.683)
Survey year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Number of observations	5,196	5,196	5,196	5,196	5,196	5,196	5,196	5,196
R-squared	0.037	0.040	0.042	0.051	0.052	0.052	0.138	0.141

Source: Authors' estimations based on the IFLS-4 and IFLS-5.
Notes: *** 1% significance, ** 5% significance, * 10% significance. Dependent variable is ln (annual business profit). Robust standard errors clustered at individual level in parentheses; specifications are estimated using OLS.

Table 7B. Intelligence and Non-Farm Business Value

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Math test score (std)	0.238***		0.145***	0.044		0.022	0.032	0.029
	(0.036)		(0.038)	(0.037)		(0.039)	(0.037)	(0.037)
Raven's test score (std)		0.311***	0.258***		0.095**	0.089**	0.070*	0.070*
		(0.037)	(0.039)		(0.039)	(0.040)	(0.040)	(0.040)
Educational attainment (ref: elementary)								
Junior secondary				0.583***	0.544***	0.540***	0.579***	0.565***
				(0.094)	(0.096)	(0.096)	(0.093)	(0.093)
Senior secondary / tertiary				1.210***	1.157***	1.145***	1.079***	1.060***
				(0.085)	(0.087)	(0.089)	(0.087)	(0.088)
Age (years)							0.131***	0.131***
							(0.018)	(0.018)
Age squared							-0.001***	-0.001***
							(0.000)	(0.000)
Height (cm)							0.031***	0.031***
							(0.006)	(0.006)
Male (Yes=1)							0.746***	0.745***
							(0.093)	(0.093)
Ethnic Javanese (Yes=1)							-0.204**	-0.154
							(0.093)	(0.097)
Dependency ratio							-0.002***	-0.002***
							(0.001)	(0.001)
Household size							0.030**	0.029**
							(0.014)	(0.014)
Household headed by man (Yes=1)							0.090	0.084
							(0.108)	(0.108)
Urban (Yes=1)							-0.081	0.055
							(0.072)	(0.076)
Proportion of households with access to grid electricity								-0.194
								(0.533)
Proportion of villages with factories or cottage industry								0.022
								(0.096)
Number of non-farm-household								-0.002**

businesses at district								
								(0.001)
Constant	14.115***	14.023***	14.017***	13.211***	13.221***	13.228***	5.404***	5.648***
	(0.161)	(0.161)	(0.161)	(0.171)	(0.171)	(0.171)	(0.938)	(1.014)
Survey year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Number of observations	4,928	4,928	4,928	4,928	4,928	4,928	4,928	4,928
R-squared	0.027	0.033	0.036	0.069	0.069	0.070	0.146	0.147

Source: Authors' estimations based on the IFLS-4 and IFLS-5.
Notes: *** 1% significance, ** 5% significance, * 10% significance. Dependent variable is ln (annual business value). Robust standard errors clustered at individual level in parentheses; specifications are estimated using OLS.

Our third hypothesis involved self-sorting into sectors and posited that individuals with a higher type of specific intelligence would choose a sector in which that intelligence would bring the highest return. Table 8 shows the correlates of occupation sectors, with brawn-intensive sectors as the base category. In contrast to our hypothesis, we found no evidence that entrepreneurs sorted based on intelligence or educational attainment. As mentioned, this finding may be driven by local economic environments and labor-market constraints that impede skills-sectors match. A one standard deviation increase in math score increased the probability of working in brain-intensive sector by only 0.8 percentage points and reduced the probability that the entrepreneur would work in a brawn-intensive or social-intensive sector by 0.2 and 0.7 percentage points, respectively. On the other hand, a one standard deviation increase in Raven's score increased the probability that the entrepreneur would work in a brain- or brawn-intensive sector by 0.3 and 1.0 percentage points, respectively, and reduced the probability of working in a social-intensive sector by 1.3 percentage points. In contrast, we found that male entrepreneurs were more likely to work in brawn-intensive sectors and that those in urban areas were more likely to choose brain-intensive or social-intensive sectors.

Table 8. Cognitive Skills and Non-Farm Sector Choice

	Brain-intensive Sector (1)	Social-intensive Sector (2)
Math test score (standardized)	0.071	0.036
	(0.093)	(0.093)
Raven's test score (standardized)	-0.056	-0.110

	(0.099)	(0.098)
Educational attainment (ref: elementary)		
Junior secondary	0.164	0.087
	(0.236)	(0.234)
Senior secondary / tertiary	0.131	0.034
	(0.209)	(0.207)
Age (years)	-0.060	-0.090**
	(0.045)	(0.044)
Age squared	0.001	0.001*
	(0.000)	(0.000)
Height (cm)	-0.019	-0.021*
	(0.013)	(0.013)
Male (Yes=1)	-1.168***	-1.989***
	(0.261)	(0.258)
Ethnic Javanese (Yes=1)	0.212	0.114
	(0.263)	(0.261)
Dependency ratio	0.002	0.002*
	(0.001)	(0.001)
Household size	-0.038	-0.026
	(0.034)	(0.034)
Household headed by man (Yes=1)	-0.136	0.166
	(0.344)	(0.341)
Urban (Yes=1)	0.562***	0.536***
	(0.182)	(0.181)
Proportion of households with access to grid electricity	1.528	1.029
	(1.331)	(1.321)
Proportion of villages with factories or cottage industry	-0.379	-0.178
	(0.248)	(0.247)
Number of non-farm-household businesses at district	-0.000	-0.002
	(0.003)	(0.003)
Constant	6.632***	9.150***
	(2.460)	(2.429)
Survey year fixed effects	Yes	
Province fixed effects	Yes	
Number of observations	5495	
R-squared	0.060	

Source: Authors' estimations based on the IFLS-4 and IFLS-5.

Notes: *** 1% significance, ** 5% significance, * 10% significance; estimates are regression coefficients. Robust standard errors clustered at individual level in parentheses; specification estimated using multinomial logit with brawn-intensive sector as the base sector.

Once entrepreneurs were in particular sectors, however, we found that higher crystallized intelligence had a positive and statistically significant effect on profit. As shown in Table 9, a one-standard deviation increase in math score increased profit by about 9.2% for entrepreneurs in brain-intensive sectors. We found no evidence that math score had any effect on entrepreneurial profit in other sectors. We also found, however, that fluid intelligence had, on average, a positive and statistically significant effect (Table 7) but did not seem to be concentrated in any particular sector.

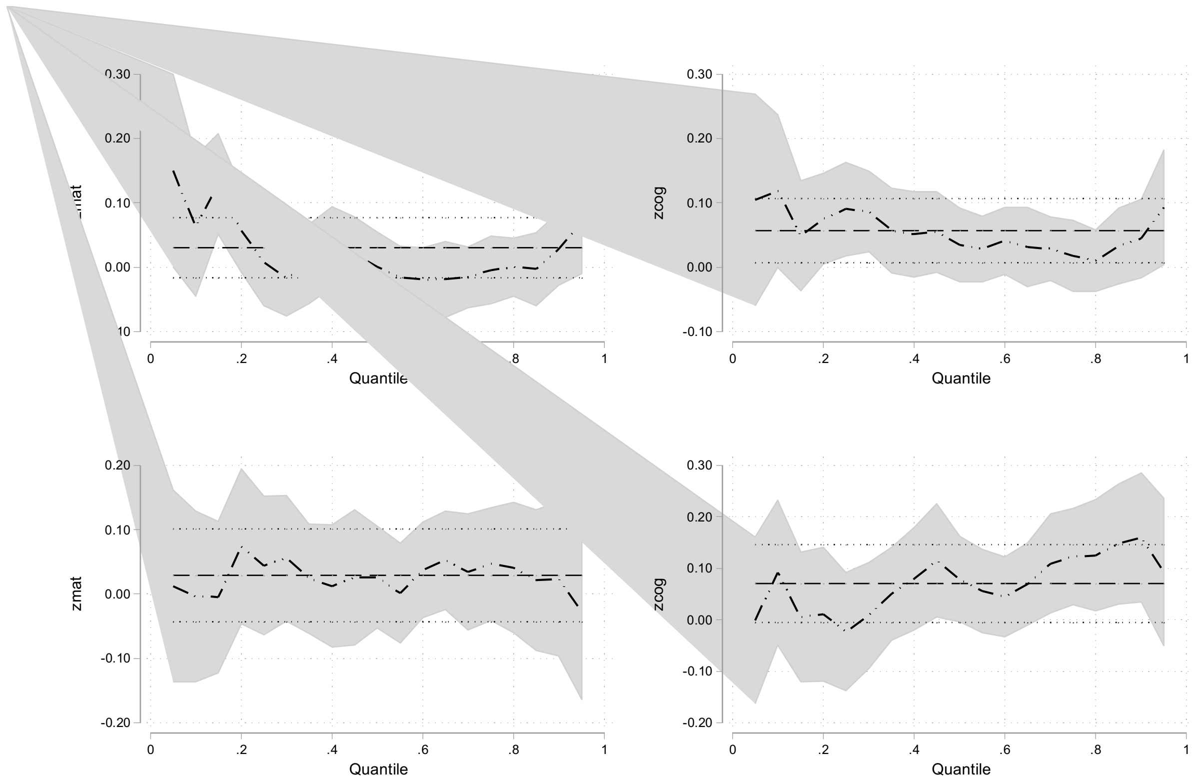
Table 9. Cognitive Skills and Non-Farm Business Performance, Subsample by Sector

	ln (profit)			ln (business value)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Brawn Sector Subsample						
Math test score (standardized)	0.056		0.048	0.057		0.063
	(0.164)		(0.164)	(0.223)		(0.223)
Raven's test score (standardized)s		0.106	0.103		-0.084	-0.089
		(0.148)	(0.147)		(0.259)	(0.261)
Number of observations	176	176	176	174	174	174
R-squared	0.368	0.370	0.370	0.260	0.261	0.261
Panel B. Brain Sector Subsample						
Math test score (standardized)	0.099***		0.088**	0.046		0.027
	(0.037)		(0.038)	(0.057)		(0.059)
Raven's test score (standardized)		0.072*	0.051		0.096	0.090
		(0.040)	(0.041)		(0.061)	(0.063)
Number of observations	1,936	1,936	1,936	1,839	1,839	1,839
R-squared	0.185	0.183	0.185	0.197	0.198	0.198
Panel C. Social Sector Subsample						
Math test score (standardized)	0.003		-0.007	0.026		0.013
	(0.030)		(0.031)	(0.048)		(0.049)
Raven's test score (standardized)		0.051	0.053		0.067	0.064
		(0.033)	(0.034)		(0.050)	(0.052)
Number of observations	3,084	3,084	3,084	2,915	2,915	2,915
R-squared	0.134	0.135	0.135	0.129	0.129	0.129

Source: Authors' estimations based on the IFLS-4 and IFLS-5.
Notes: *** 1% significance, ** 5% significance, * 10% significance. All control variables, survey year fixed effects, and province fixed effects are included; robust standard errors clustered at individual level in parentheses; specifications estimated using OLS.

We next tested our fourth hypothesis, according to which returns on intelligence should vary at different levels of business outcomes. We estimated quantile regression to see whether cognitive skills had differential effects across the distribution of business performance (profit and business value). Figure 3 shows the OLS and quantile regression estimates of math scores and Raven's score on profit (top panel) and business value (bottom panel). The horizontal axes indicate the quantiles of the corresponding business performance, and the vertical axes are the coefficients of math score and Raven's score at each quantile. The dashed lines represent the coefficient in the OLS model with confidence intervals in dotted lines, corresponding to Columns 8 and 16 of Table 7. The dashed bold lines represent the coefficient from quantile regression with corresponding confidence intervals in grey areas.

Figure 3. OLS and Quantile Regression Estimates of Math Score and Raven's Score, ln (Profit) (Top) and ln (Business Value) (Bottom)



Source: Authors' estimations based on the IFLS-4 and IFLS-5.

In the for profit area (top panel), the quantile regression estimate shows the generally decreasing effects of math scores between quantiles 0 and 0.3, after which the effects are relatively flat. For the Raven's score, the trend slopes negatively except at higher profit quantiles. Note that, along the distribution of profit, the effects of both types of intelligence were not statistically different from zero except at q0.1 for math and q0.3 and q0.9 for Raven's.

For business value (bottom panel), we found few statistically significant effects of math score along the distribution except at q0.7. Overall, the trend was flat. For the Raven's score, the overall trend was positive with statistically significant estimates at around q0.5 and between q0.7 and q0.9. Our fourth hypothesis, therefore, appears to be correct, particularly for the Raven's score in business value.

Finally, we were interested to find out whether selection into entrepreneurship drove our results. As mentioned earlier, our specifications were estimated from pooled 2007 and 2014 data. Our panel dataset was strongly imbalanced, however, for two reasons. First, as explained earlier, the questionnaire changed between 2007 and 2014 (in 2007, the EK2 modules covered only individuals between 15 and 35 years of age; in 2014 it covered respondents up to 60 years old), so that we could retain fewer observations from 2007. As argued in section IV, we were confident that this imbalance would not bias our results. The second reason is related to eventual selection into entrepreneurship between 2007 and 2014, as some non-farm entrepreneurs in 2007 could no longer be classified as such in 2014 (they moved to the farm or the wage sectors, they became unemployed, or they exited the labor market for various reasons, making the direction of the bias that resulted from unobservables unclear). They represent about 5% of our sample.

For the reasons discussed earlier, unfortunately, the cognitive test scores were largely missing in 2007. Hence, to investigate this second issue, we implemented a standard Heckman selection model on the 2014 data, in which selection was identified by a binary variable (a value of 1 if the individual was a non-farm entrepreneur in both years and zero otherwise—i.e., only in 2007).[1] The exclusion variable was the proportion of villages in the district in which a financial institution provided business loans. We argue that this characteristic would be correlated with the decision to continue owning a non-farm business over the span between IFLS-4 and IFLS-5, hence appearing in our panel sample. As shown in Table 10, once the selection into non-farm entrepreneurship was taken into account, we found much larger effects of Raven's test on business performance even with the selection correction. A one standard deviation increase in Raven's score resulted in a 9.7% higher profit and a 13.6% higher business value. In contrast, we found no evidence of statistically significant returns to higher crystallized intelligence. Therefore, we continued to find that fluid

[1] If test scores for 2007 had also been available, we could have adopted the methodology proposed by Semykina and Wooldridge (2010), which corrected selection with individual panel fixed effects.

intelligence provided a benefit to the performance of non-farm-household businesses.

Table 10. Intelligence and Non-Farm Business Performance, Corrected for Self-Selection

	ln (profit)	ln (business value)
Math test score (standardized)	0.0344	0.099
	(0.042)	(0.069)
Raven's test score (standardized)	0.097***	0.136**
	(0.042)	(0.069)
All control variables included	Y	Y
Number of observations	1,650	1,564

Source: Authors' estimations based on the IFLS-4 and IFLS-5.
Notes: *** 1% significance, ** 5% significance, * 10% significance. Robust standard errors clustered at individual level in parentheses; excluded variable used in the selection equation: proportion of villages where at least one financial institution provided business loans.

VI. Conclusion

Knowing whether skills affect entrepreneurial success is relevant to policy and could inform decisions regarding the kinds of training programs to deliver, the kinds of entrepreneurs who should be given priority for business loans, and whether some individuals are better off as wage workers than as entrepreneurs.

In this paper, we estimated and compared the returns to fluid and crystallized intelligence on the performance of non-farm household enterprises in Indonesia. Our conceptual framework examined the relationship of these types of intelligence to educational attainment, noting both direct and indirect effects of fluid intelligence on business outcomes.

Using a model that controlled for individual, household, enterprise, and district characteristics, we found that fluid intelligence had a positive, sizeable, and statistically significant effect on business profits. The statistically significant returns to higher fluid intelligence appeared to be robust even when selection into entrepreneurship was taken into account. A one standard deviation increase in performance in Raven's test led to higher profits of around 5.7% and a higher business value of about 7%. On the other hand, we found no evidence that crystallized intelligence, once we had controlled for fluid intelligence and educational attainment, had any effect on business performance.

Further examination by separating non-farm businesses into skills-based sectors showed that crystallized intelligence led to higher profits exclusively in brain-intensive sectors in which higher fluid intelligence seemed to provide no significant benefit. In other words, crystallized intelligence led to higher profits only when the entrepreneur was engaged in the sector that was most appropriate for the skills associated with that type of intelligence. At the same time, we found little sorting into sectors based on intelligence, educational attainment, or most other variables that we used.

We conjecture that our findings are consistent with the developing-country context and with the kinds of business in which entrepreneurs in those contexts are engaged. In developing countries, where businesses rules and regulations are still relatively incomplete, problem-solving skills and the ability to adapt quickly to change are generally more important than formally acquired knowledge. In addition, the majority of household businesses in Indonesia appear to be labor-intensive ones that use low capital and simple technology. For them, high levels of crystallized intelligence would be of no significant advantage.

Given that fluid intelligence is innate rather than taught, it appears that policies favoring increased training programs would not be an effective tool to support most entrepreneurs in Indonesia. Instead, our findings point to the need for policymakers to invest in improvements in environmental conditions and in long-term health outcomes, including in-utero care. In addition, the government could support entrepreneurs with high levels of crystallized intelligence either in finding jobs as wageworkers or in operating a business in the brain-intensive sector. This naturally implies that both policymakers and entrepreneurs must first discover the skills entrepreneurs possess before they choose a sector in which to engage. Policymakers should also reduce constraints on the full effectiveness of the intelligence factor in the non-farm entrepreneurial sector in Indonesia. Contrary to expectations, we found that sorting into specific sectors did not depend on the type of intelligence requested in a particular sector, possibly limiting returns to each type of intelligence. A better functioning labor market would help increase these returns.

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Appendix Tables

Table A1. Mapping Occupation Sectors to Brawn, Brain, Social Sectors

Sector	Category
Agriculture, forestry, fishery	Brawn
Mining and quarrying	Brawn
Electricity, gas, water	Brain
Construction	Brawn
Transportation and communication	Brain
Finance, insurance, real estate	Social
Restaurant, food sales	Social
Industry: food processing	Brain
Industry: clothing	Brain
Industry: other	Brain
Sales: non food	Social
Services: government	Brain
Services: teacher	Brain
Services: professionals	Brain
Services: transportation, tricycle, motorcycle taxi	Brain
Services: other (tailor, hairdressing)	Brain
Other	Brain

Source: Authors' estimations based on the IFLS-4 and IFLS-5.

Table A2. Comparing Study Sample with Sample of All Entrepreneurs in IFLS 2007 & 2014	Study Sample (Merging NT, EK)			IFLS TK & EK			Mean difference	p-value of mean difference = 0
Variable	Number of observations	Mean	Std Dev	Number of observations	Mean	Std Dev		
Entrepreneur characteristics								
Math score (standardized)	5,286	-0.09	0.99	9,296	-0.02	0.95	-0.07	0.000
Raven's score (standardized)	5,286	-0.10	0.98	9,296	0.09	0.83	-0.19	0.000
Height (cm)	5,286	157.35	8.43	9,296	157.31	8.59	0.04	0.785
Age (years)	5,286	40.45	11.98	9,296	40.81	13.33	-0.36	0.104
Male (Yes = 1)	5,286	0.54	0.50	9,296	0.58	0.49	-0.04	0.000
Ethnic Javanese (Yes = 1)	5,286	0.45	0.50	9,296	0.43	0.50	0.02	0.020
Household characteristics				9,296				
Dependency ratio	5,286	67.00	67.57	9,296	61.58	53.93	5.42	0.000
Household size	5,286	5.26	2.43	9,296	4.39	2.05	0.87	0.000
Household headed by man (Yes = 1)	5,286	0.88	0.33	9,296	0.89	0.32	-0.01	0.073
Urban (Yes = 1)	5,286	0.65	0.48	9,296	0.50	0.50	0.15	0.000
Business characteristics								
Sector mainly requiring brawn (Yes = 1)	5,286	0.03	0.18	9,296	0.28	0.45	-0.25	0.000
Sector mainly requiring brain (Yes = 1)	5,286	0.37	0.48	9,296	0.26	0.44	0.12	0.000
Sector mainly requiring social skills (Yes = 1)	5,286	0.59	0.49	9,296	0.44	0.50	0.15	0.000

Source: Authors' estimations based on the IFLS-4 and IFLS-5.