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Returns to balance in cognitive skills for the self-employed: evidence from 18 countries

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Abstract Is there a positive contemporaneous association between balance in cognitive skills and self-employment earnings? In this paper, we extend past studies that draw on balance in cognitive skills tests administered at an early age and use the balance in scores on cognitive skills tests administered during 2011–2012 in the Programme for the International Assessment of Adult Competencies (PIAAC), a cross-sectional sample of 47,768 adult participants from 18 countries. Lowering concerns for cognitive skills measured at an early age, PIAAC's measure of cognitive skills provides a contemporaneous measure of cognitive skills also accumulated through past experiences. Using a standardized measure of cognitive skills across participating countries, PIACC also lowers concerns for measurement error resulting from cultural bias in country-specific cognitive skills tests. Extending the entrepreneurship earnings puzzle—lower average income for the self-employed relative to wage earners—a greater balance in cognitive skills among the self-employed helps close earnings gaps with wage earners. However, balance in cognitive skills is not associated with self-employment. The implications of the findings are discussed.

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1 Introduction

Building on the classical work by Mincer (1974), recent studies have found that cognitive skills influence earnings and economic growth (Hanushek et al. 2017; Hanushek and Woessmann 2008). Cognitive skills play an important role in increasing individual productivity and earnings and also explain differences in returns to human capital accumulation across countries. Cognitive skills are equally important for entrepreneurs who must address a variety of business challenges. Referring to cognitive skills as a general ability, Marshall (1890) highlighted the key role of cognitive abilities in managing a business. Building on Marshall (1890), Hartog et al. (2010) in their longitudinal sample drew on the coefficient of variation among four cognitive skills assessed through the Armed Forces Qualification Test administered between the ages of 15 and 23 in National Longitudinal Survey of Youth (NLSY) 1997. Aldén et al. (2017, p. 2) citing that Hartog et al. (2010) study does not measure cognitive skills of "people of the same age and level of education" used the standard deviation of cognitive skills assessed in a sample of 18–19-year-old males at the time of enlistment in the Swedish army. Both studies found support for a positive association between balance in cognitive skills and self-employment earnings.

We draw on the concept of balance from Lazear's (2004) jack-of-all-trades (JAT) and Marshall's proposition on the importance of cognitive skills for entrepreneurs to test for the association between the contemporaneous balance of cognitive skills and self-employment income in a multi-country sample. While our measure of balance in cognitive skills is not associated with the generally used measures of JAT,[1] we draw on the JAT literature to provide scaffolding for the hypothesis that balance in cognitive skills is positively associated with income for the self-employed.

Our sample, the 2011–2012 Programme for the International Assessment of Adult Competencies (PIAAC) survey, provides three advantages. First, albeit the cross-sectional nature of PIAAC data has its own limitations, the advantages of the large-scale PIAAC sample in studying the effects of cognitive skills on earnings are discussed in some recent studies using PIAAC (e.g., Hanushek et al. 2015, 2017).[2] By substantially extending "the depth and range of measured skills" (Hanushek et al. 2015, p. 104), PIAAC provides a richer measure of cognitive skills (Cingano 2014; Jerrim 2017; Hanushek et al. 2017; Hanushek et al. 2015). Cognitive skills measured in PIAAC allow for an improved assessment of human capital over "existing empirical evidence [that] has rested on crude and (almost certainly) biased estimates of [human capital]" (Hanushek et al. 2015, p. 120). The contemporaneous measure of cognitive skills in PIAAC is also more relevant to cognitive skills sought in current labor markets. Second, the use of identical cognitive skills tests across all participating countries provides a standard measure of cognitive skills, thereby lowering concerns for measurement error resulting from culturally biased cognition skills tests (Hanushek and Woessmann 2008). Third, standardized cognitive skills tests in PIACC also improve generalizability in inferences among countries included in the sample.[3] Although our sample from 18 countries includes most European countries and Chile, Israel, Japan, and South Korea, the sample helps improve the generalizability of our hypothesis in studying the importance of balance in cognitive skills for self-employed.

The proposed framework also contributes to the broader cognitive skills literature in labor economics that has generally focused on the effects of individual cognitive skills scores. In addition to the influence of individual cognitive scores, balance as a structural association among cognitive skills may explain additional variance in income outcomes. Balance in cognitive skills is a theoretically meaningful concept and was initially used by clinical psychologists who consider greater scatter, that is, a lower balance, in the subtests of the Wechsler intelligence tests as an indicator of brain pathology (Gregory 1987; Frank 1983). The scatter in scores of different components of an IQ test is similar to the coefficient of variance (Hartog et al. 2010) or standard deviation (Aldén et al. 2017) of scores on cognitive skills tests. Greater balance in test scores implies higher "all-roundedness." As such, the structure of interrelationships among the cognition scores could further inform studies in labor economics.

Our results show that balance in cognitive skills is not associated with self-employment; however, the self-employed with higher balance in cognitive skills could close income gaps with the employed. Lower income levels among the self-employed are not surprising and are discussed in the entrepreneurship earnings puzzle literature (Hyytinen et al. 2013; Hamilton 2000). Even though balance in cognitive skills helps close income gaps with wage earners, lower earnings among the self-employed in our sample could be due to the inclusion of diverse types of the self-employed. As our sample is representative of the general working population, it includes a relatively large proportion of the blue-collar self-employed, which may account for the lower income on average as compared to past JAT studies that draw on

[1] The exceptions are Hartog et al. (2010) and Alden et al. (2017) who used coefficient of variance and standard deviation respectively, and also drew on JAT as their theoretical framework.

[2] The three cognitive skills used in the study are literacy, numeracy, and problem-solving skills. From Hanushek et al. (2015, p. 108), literacy refers to the "ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential." Numeracy skills refer to "ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life." Problem-solving skills were measured in technology-rich context so as to assess the "ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks."

[3] While our study is not directly related to JAT theoretical framework, the notion of balance in experience and skills has been explored in the samples from the USA (Hartog et al. 2010; Lazear 2004), Germany (Tegtmeier et al. 2016; Wagner 2003, 2006; Lechmann and Schnabel 2011; Stuetzer et al. 2012), Italy (Silva 2007), or Canada (Åstebro and Thompson 2011).

samples of advanced degree holders, inventors, or Stanford MBA alumni.[4] While the white-collar self-employed rely on specific occupational skills (e.g., lawyers, accountants), to be self-employed, they must also draw on diverse cognitive skills to increase self-employment earnings. The blue-collar self-employed may generally rely on a specific occupational skill set (e.g., handyman, electrician); however, to be self-employed, they must also rely on literacy (e.g., to improve learning), numeracy (e.g., to manage accounting, to provide job estimates), and problem-solving (e.g., to meet varying customer demands, to manage time and resources) skills. To confirm the value of balance in cognitive skills across collar types, we performed an additional analysis wherein we split the sample into four subgroups by collar types. In this analysis, we found broad support for the proposed association across collar types.[5]

In this paper, we start by examining the literature on cognitive skills and JAT, specifically the balance in cognitive skills, and thereafter present our hypothesis against the backdrop of this literature. The second section describes data, measures, and results. The paper concludes with a discussion of results, implications for theory, and limitations.

2 Theoretical development and hypotheses

We examine Marshall's work discussed in Hartog et al. (2010) and recent work on cognitive skills by Hanushek and colleagues and draw on the cognitive skills literature first, followed by a review of findings on the balance in skills and experiences in the JAT literature. We then blend these reviews into Sections 2.1 and 2.2, in Section 2.3 to develop our hypothesis.

2.1 The value of cognitive skills

Human capital is central to entrepreneurial success (Unger et al. 2011). As proxies for human capital, labor economists have used "years of schooling, years of work experience, and the square of years of work experience" (Holzer and Lerman 2014, p. 2). While proxies of education and work experiences have contributed to our understanding of the importance of skills in a variety of settings, recently, economists have proposed the importance of cognitive skills (Holzer and Lerman 2014) as a proxy for human capital.

Using the recently available PIAAC data on cognitive skills, Hanushek and Woessmann (2013) and Hanushek et al. (2008) find that in addition to years of schooling, cognitive skills are positively associated with individual income and economic growth. Other studies have found support for the association between cognitive skills and higher earnings (Pena 2016; McGowan and Andrews 2017; Hanushek et al. 2015), higher education (Feinberg et al. 2016), and lower income inequality (Hanushek et al. 2017).

2.2 The importance of balance in skills and experience for self-employed—a review

Although our measure of balance in cognitive skills is not directly related to the theoretical underpinnings of JAT, the notion of balance in diverse skills is central to our hypothesis because compared to wage earners who must invest more intensively in one type of skill, the self-employed must focus on a more balanced human capital investment strategy (Lazear 2004). Hartog et al. (2010) and Aldén et al. (2017) also draw on JAT as a theoretical framework to test for the association between balance in cognitive skills and self-employment outcomes.

The underlying premise of the JAT hypothesis by Lazear (2004) is that compared to those who are employed, the self-employed must have a variety of skills to manage variegated demands in their business. The self-employed may have a comparative disadvantage in specialized skills; however, they must have a comparative advantage in the diversity of skills (Lazear 2004). Knowledge, skills, and experiences from a variety of areas form a complementary kaleidoscope of abilities that could drive higher entrepreneurial performance.

Since the conceptualization of JAT by (Lazear 2004), a series of studies has tested its association with likelihood of self-employment and self-employment-related outcomes (e.g., Tegtmeier et al. 2016; Spanjer and van Witteloostuijn 2017) drawing on cross-sectional and longitudinal samples using industry, educational, and/or cognitive skills as proxies for operationalizing jack-of-all-trades.

[4] 1—elementary occupation; 2—semi-skilled blue collar; 3—semi-skilled white collar; 4—white collar

[5] The effects are consistent for elementary occupations, semi-skilled white collar, and white collar, however, not significant for semi-skilled blue-collar self-employed.

Using JAT as a theoretical basis for diversity in skills and experiences, studies have found support for positive (Åstebro and Thompson 2011; Wagner 2003, 2006; Tegtmeier et al. 2016; Chen and Thompson 2016) or no association (Silva 2007; Åstebro and Thompson 2011) between JAT and self-employment. Wagner (2003, 2006) using balance in roles in labor markets as a proxy for JAT found a positive association between JAT and self-employment. A related study found that while professional training did not improve odds of self-employment, the number of changes in the profession was positively associated with self-employment (Lechmann and Schnabel 2011). Lechmann and Schnabel (2011), however, found no difference in human capital investment patterns between the self-employed and the employed. In a later study based on longitudinal survey of Italian families, Silva (2007) found that a more balanced educational focus and a number of prior roles are positively associated with self-employment only in cross-sectional but not in panel estimates. Using the Global Entrepreneurship Monitor data, Hessels et al. (2014) found that nascent entrepreneurs from the Netherlands and Germany realized more startup success when they had more job variety. More recently, Hsieh (2016) found that "experiencing business-related functions in parallel rather than sequentially [or] experiencing domains sequentially [sic] for those who are analytically disposed of" increases the likelihood of self-employment (p. 307).

Studies on the association of JAT on earnings have found support for a positive (Hartog et al. 2010; Bublitz and Noseleit 2014), a negative (Åstebro and Thompson 2011), or an inverted U-shaped (Spanjer and van Witteloostuijn 2017) association. Hartog et al. (2010) drawing on the NLSY 1979–2000 found that balance in general ability (measured as a coefficient of variance in scores on Armed Forces Qualifications Test (AFQT) "generates a higher income, but only for entrepreneurs" (p. 948). In a sample of 5670 participants in the Federal Institute for Vocational Education and Training's (BIBB) and Federal Institute for Occupational Safety and Health's (BAuA) 2006 Employment Survey, Bublitz and Noseleit (2014), who use a higher count of skills to proxy for balance in skills, find that the "relationship between skill balance and income is strongest for entrepreneurs" (p. 17). Åstebro and Thompson (2011), who draw on a sample of 830 independent inventors and 300 individuals from the general population, use the count of occupations and industries as a proxy for a variety of work experiences and infer that "inventor-entrepreneurs typically have a more varied labor market experience, and that varied work experience is associated with lower household income" (p. 637). Spanjer and van Witteloostuijn (2017: p. 147) draw on NLSY 1979 and use knowledge experience diversity (total number of unique knowledge fields associated with all past occupations) and skill experience diversity (total number of unique skills associated with all past occupations) as proxies for balance in skills. They find support for an inverted U-shaped association between skill experience diversity and income, but no support for knowledge experience diversity. While Åstebro and Thompson (2011) draw on a sample of inventor-entrepreneurs, our sampling frame, in line with the three population-level studies—Hartog et al. (2010), Bublitz and Noseleit (2014), and Spanjer and van Witteloostuijn (2017)— hypothesizes for a positive association.

Other contingencies tested in the JAT literature are as follows. A more balanced portfolio of skills and experiences is also positively associated with the number of activities completed during the venture creation process (Stuetzer et al. 2012; Hessels et al. 2014). Additional contingency factors such as sex (Tegtmeier et al. 2016), stage of firm development (Wagner 2006), other demographic factors (Silva 2007; Oberschachtsiek 2008), and sequential or parallel work experiences (Hsieh 2016) have also been proposed. Drawing on organizational sociology literature and extending work by Elfenbein et al. (2008), Bublitz and Noseleit (2014) assessed the value of skill balance for employees and self-employed contingent on firm size. They find that skill balance matters more for employees in smaller firms. Combining JAT and taste for variety theory, Åstebro and Thompson (2011) found that variety of experiences lowered income from self-employment. Extending Åstebro and Thompson (2011) and Åstebro and Yong (2016) and drawing on entrepreneurial learning and cognition literature, Spanjer and van Witteloostuijn (2017) found support for an inverted U-shaped relationship between experience diversity and self-employment income. Drawing on the venture life-cycle framework (Davidsson and Gordon 2012), Stuetzer et al. (2012) found that entrepreneurs with a broad skill set complete more venture creation activities. Building on Lazear (2004) and venture creation framework, Hessels et al. (2014) found that more varied work experiences are positively related to introducing innovations.

Challenging Lazear's assumption of JAT as a mode for maximizing lifetime earnings, Tegtmeier et al. (2016) drew on gender and entrepreneurship literature (Elam 2014) to find that the JAT framework could be applied to motivations of female entrepreneurs that differ from those of male entrepreneurs. Oberschachtsiek (2008), based on the occupational choice framework, found that duration of self-employment is not strongly associated with balanced skill sets.

In summary, studies on JAT have generally highlighted the importance of balance in endowments of self-employed. Combining the value of cognitive skills from labor economics with the value of balance in such skills from JAT, we propose our hypothesis below.

2.3 Balance in cognitive skills and self-employment earnings

Closely related to our empirical context, Hartog et al. (2010) draw on the intelligence literature and find support for a positive association between the coefficient of variation of cognitive skills and social ability on self-employment earnings. While diversity in industry and occupational experiences help directly influence business activities, based on recent developments in labor economics on the value of contemporaneously measured cognitive skills (Hanushek et al. 2015, 2017), and building on Hartog et al. (2010) and Aldén et al. (2017), we use the balance in three cognitive skills—literacy, numeracy, and problem-solving skills in technology-rich environments—to predict self-employment earnings.

Literacy score, or the "understanding, evaluating, using and engaging with written text to participate in society, to achieve one's goals and to develop one's knowledge and potential," (OECD 2013) could be central to entrepreneurial learning. Higher literacy scores could improve information processing capabilities of the self-employed in managing business activities. Ability to understand, evaluate, and integrate a wide range of information is pivotal not only in the early opportunity-seeking and opportunity-seizing stages but is central also in managing day-to-day business activities (Drayton 2002). For the self-employed, the managing of informational processing demands to not only acquire but also process and disseminate knowledge could be necessary for improving business performance. Enhanced information processing could, in turn, facilitate learning in the context of industry and markets (Minniti and Bygrave 2001; Politis 2005), or in managing a business, which requires scanning, acquiring, and synthesizing information from external sources (Cooper et al. 1995; Hansen and Allen 1992). These learning processes are further enhanced by single-, double-, and triple-loop learning (Chen and Thompson 2016).

Numeracy score, or "the ability to access, use, interpret, and communicate mathematical information and ideas, to engage in and manage mathematical demands of a range of situations in adult life" (OECD 2013), could also be central to managing a business. Ranging from scheduling to inventory management and from accounting to interpreting emerging business conditions using analytical tools, numeracy skills are essential to improving business performance (Vijverberg 1999; Martín-Rojas et al. 2013). Business owners are challenged on a range of issues from managing capacity to predicting sales forecasts. The multi-faceted and variegated analytical demands of running a business require higher numeracy skills.

Finally, problem-solving skills in today's technology-rich environment require "using digital technology, communication tools, and networks to acquire and evaluate information, communicate with others, and perform practical tasks" (OECD 2013). Entrepreneurial undertakings require significant problem-solving (Hsieh et al. 2007). In the increasingly digitalized world, the self-employed must seek and manage information from digital tools and media to not only acquire information but to also solve problems. With the emergence of crowdfunding platforms to the emergence of the networked organization of a venture to the emergence of the shared economy and online lending markets, ability to solve problems through digital medium and tools is necessary to ensure adaptability of a business.

The balance, akin to lower scatter, is considered as the "overriding quality that helps an individual deal with the environment (Binet and Simon 1911)" and based on Marshall (1890) necessary for "great success in any pursuit and especially in business" (Hartog et al. 2010, pp. 952–953). In line with the broader intelligence and ability literature where a lower deviation among the scores indicates a greater balance in abilities, the influence of balance in cognitive skills may not be orthogonal, but instead highly co-dependent in addressing variegated demands from different business functions (Cawley et al. 2001).

According to Gibbs (1997), entrepreneurs learn through imitation, from peers, through feedback from stakeholders, experimenting with resource bundles, and problem-solving. A balance in cognitive skills could also be central to managing trial-and-error necessary for first-order and higher-order learning in a multitude of business activities. The need for balance in literacy, numeracy, and problem-solving skills is important because being able to manage diverse information (literacy), leverage analytical skills (numeracy), and the ability to solve problems in practical tasks (problem-solving) could provide a unique combination of skills that could provide a unique bundle of resources (Barney 1991), allowing the self-employed to develop solutions and enhance adaptation. Balance in cognitive skills provides and nurtures an entrepreneurial mindset (Baron and Henry 2010) necessary to devise business solutions to problems.

Based on the past findings on JAT and the need for balance in cognitive skills, we propose the following:

Hypothesis: Balance in cognitive skills would be positively associated with income for the self-employed.

3 Method

3.1 Data

To test the hypothesis, we draw on The Programme for the International Assessment of Adult Competencies (PIAAC) 2011–2012. PIAAC is a comprehensive survey of adults between the ages of 16 and 65 located in Europe, Asia (Korea and Japan), Israel, and Chile. The data were collected between August 2011 and March 2012. The survey measured cognitive skills, education, labor market status, and demographic characteristics of the participants and is therefore particularly suited for testing the role of dispersion of cognitive skills on returns for the self-employed. A detailed description of the cognitive tests in PIACC is available in OECD (2013). PIACC cognitive skills tests use information and communication technologies at work and in everyday life to measure literacy, numeracy, and problem-solving skills, along with a “range of generic skills, such as collaborating with others and organizing one’s time, required of individuals in their work” (p. 25).

Cognitive skills in PIAAC, which were administered during 2011–2012, measured lower temporal mismatch between cognitive skills assessed during the early years and current cognitive skills necessary for job success. Individuals accumulate cognitive skills through their past experiences, and cognitive skills measured at an early age may not fully reflect the tapestry of early age cognitive skills and cognitive skills acquired over time through educational and occupational experiences. PIAAC assessments have discussed the advantages of contemporaneous measures of cognitive skills as a proxy for human capital (Carlsson et al. 2015; Boarini et al. 2012; Hanushek et al. 2017). The contemporaneous measure of cognitive skills is also less subject to upward bias induced by the measurement of cognitive skills at an early age. In other words, using early-age cognitive skills to predict outcomes at a later age does not control for the inter-temporal development of cognitive skills through the life-cycle, and possibly inflates the estimates of early-age cognitive skills. Standardized cognitive skills tests administered to large samples from multiple countries improve generalizability and reduce measurement error (Hanushek and Woessmann 2008). Related to lower measurement error, the Armed Services Vocational Aptitude Battery (ASVAB) test used in Hartog et al. (2010), and by extension the Swedish army enlistment test in Aldén et al. (2017), aim “to maximize the role of cultural knowledge” (Hartog et al. 2010, p. 953). PIAAC uses standard cognitive skills tests across participants from different countries that potentially lower measurement error and concerns about test items by culture-specific knowledge.

The total sample consists of 156,906 participants. However, information is not available for all the participants, and most of the missing values are for non-employed participants (that is, such participants did not provide employment wage information and were therefore excluded from the analysis). Description of rich details on sampling and data collection procedures are beyond the scope of this work and are available at http://www.oecd.org/skills/piaac/ and https://nces.ed.gov/surveys/piaac/index.asp.

Based on casewise deletion, the final sample consists of 47,768 participants. The 18 countries represented in the sample are Belgium, Chile, the Czech Republic, Denmark, Estonia, Finland, Greece, Ireland, Israel, Japan, Korea, Lithuania, the Netherlands, Norway, Poland, the Slovak Republic, Slovenia, and the UK.

3.2 Measures

Table 1 lists the variables and operationalizations.

The outcome of interest is the log of monthly average earnings. Self-employment is measured using the question "Current work employee or self-employed" (question "D_Q04' in PIAAC; 1 = self-employed, 0 = employed).

3.2.1 Balance in cognitive skills

Three cognitive skills were assessed in the PIAAC: literacy (the ability to understand, evaluate, use, and engage with written texts),[6] numeracy (the ability to access, use, interpret, and communicate mathematical information and ideas),[7] and problem-solving in technology-rich environment (the ability to use digital technology, communication tools, and networks to acquire and evaluate information, communicate with others),[8] which we will abbreviate as TPS (technological problem-solving). The test items were often framed as real-world problems, such as maintaining a driver's logbook (numeracy domain) or reserving a meeting room on a particular date using a reservation system (TPS). By default, all the three tests are carried out on computers but literacy and numeracy can also be assessed on paper for those who prefer to do so and for those who lack basic computer skills. TPS can only be carried out on computers and those who refuse or cannot use a PC are simply routed out. As a consequence, the number of missing values in TPS is relatively high in many countries (on average about 10% across all the participating countries but up to more than 20% in some).

The tests use a computerized adaptive testing (CAT) design that adapts questions to the examinee's ability. Not all respondents are administered all the questions and a routing algorithm guides respondents through a subset of the test items according to their previous answers. The scores are assigned on the basis of the item response theory (IRT) measure and are reported in terms of ten plausible values for each ability (Rutkowski et al. 2010). Each of the three skills is measured on a 500-point scale. To obtain a single score for each ability, we averaged these ten values. Finally, each of the three cognitive skills scores was standardized within each of the 19 countries. Each of the scores for cognitive skills was standardized to make the scores comparable between countries. Due to differences in educational, cultural, and institutional factors across countries, we standardized cognition scores at the country level because standardizing the scores across countries would not allow for variation around mean of cognitive scores within a country. This approach is consistent with Hanushek et al. (2015) (Åstebro and Thompson 2011; Jerrim 2017) who "standardize scores … to have a within-country mean of zero and a within-country standard deviation of one" (p. 108). Because we control for country dummies, the fixed effects of country-to-country differences are controlled for in the estimates.

Our measure of balance is based on the standard deviation of the (country-wise) standardized scores of the three cognitive skills; the lower the standard deviation, the higher the balance (see Ganzach 1995 for using the internal standard deviation as a measure of balance). Aldén et al. (2017) use "intra-individual standard deviation in test scores on the five tests" (p. 4) from the Swedish military enlistment test. To illustrate, consider two people and two cognitive skills. The cognitive skills of the first are non-balanced, that is, one cognitive skill is high and the other is low. The cognitive skills of the other are balanced, that the two cognitive skills are moderate. If the balance is important for performance and wage, then, ceteris paribus, the second person will be more successful and earn a higher wage. Therefore, we measure balance by subtracting the standard deviation of the three abilities from 3 (3 is the highest value of the abilities' standard deviation in our data).

3.2.2 Control variables

The current occupation type could systematically impact earning levels. We therefore control for occupation (1—elementary occupation; 2—semi-skilled blue collar; 3—semi-skilled white collar; 4—white collar). We include years of work experience as a control because the number of years in the labor force, as an additional proxy for human capital, could also impact earnings. To control for the effects of individual cognition skills scores on income, and thereby assess the effect of balance after controlling for the effects of these scores,

[6] Test items for literacy test are available at: https://nces.ed.gov/surveys/piaac/sample_lit.asp
[7] Test items for numeracy test are available at: https://nces.ed.gov/surveys/piaac/sample_num.asp
[8] Test items for problem-solving test are available at: https://nces.ed.gov/surveys/piaac/sample_pstre.asp

Table 1 Variable details

Variable	Operationalization	Number	Mean	sd	Min	Max
Log of monthly wage	Log of monthly wage	47,768	8.8259	2.5357	0	18.2776
Balance in cognitive skills	The reverse coded coefficient of variance of literacy, numeracy, and decision scores adjusted at country level; higher values indicate higher levels of balance in skills	47,768	2.6407	0.2100	0.1047	2.9985
Self-employed	"Current work employee or self-employed" (1 = self-employed; 0 = employed)	47,768	0.1047	0.3061	0	1
White collar	1—elementary occupation; 2—semi-skilled blue collar; 3—semi-skilled white collar; 4—white collar	47,768	3.2126	0.9159	1	4
Years of work experience	Years of work experience	47,768	17.0298	11.9182	0	55
Literacy score	Literacy score adjusted at country level	47,768	0.0793	0.9818	−4.5410	3.9334
Numeracy score	Numeracy score adjusted at country level	47,768	0.1048	0.9763	−4.5938	3.8003
Problem-solving score	Problem-solving score adjusted at country level	47,768	0.0479	0.9922	−4.6448	4.8054
Age	Age	47,768	38.8262	12.1767	16	65
Sex	Sex (1 = Male; 2 = Female)	47,768	1.5053	0.5000	1	2
Self-rated health	1—excellent; 2—very good; 3—good; 4—fair; 5—poor	47,768	2.4307	0.9769	1	5
Education	1: primary or less (ISCED 1 or less); 2: lower secondary (ISCED 2, ISCED 3C short); 3: upper secondary (ISCED 3A–B, C long); 4: post-secondary, non-tertiary (ISCED 4A–B–C); 5: tertiary—professional degree (ISCED 5B); 6: tertiary—bachelor degree (ISCED 5A); 7: tertiary—master/research degree (ISCED 5A/6); and 8: tertiary—bachelor/master/research degree (ISCED 5A/6) (standardized)	47,768	0.2009	0.9982	−2.2089	2.4340
Parent highest education	1—neither parent has attained upper secondary education; 2—at least one parent has attained secondary education; 3—at least one parent has attained tertiary	47,768	2.0063	0.7532	1	3
Multi-lingual	1—native-born and native language; 2—native-born and foreign language; 3—foreign-born and native language; 4—foreign-born and foreign language	47,768	1.2016	0.6889	1	4
Industry code	2-digit industry code of the current occupation	47,768	60.0805	24.1904	2	110
Occupation code	2-digit occupational code of the current occupation	47,768	29.2031	15.9811	6	58
Country	Country ID	47,768	415.2224	216.2652	56	826

Casewise deletion

consistent with Hanushek et al. (2015), we standardize scores to "have a within-country mean of zero and a within-country standard deviation of one" (p. 108).

We include age, sex, (1—male; 2—female), self-rated health (1—excellent to 5—poor), education (1—primary or less to 8—tertiary, bachelor/master/research; standardized), parental education, and language ability as additional controls. The rationale for including these controls is as follows. Studies in entrepreneurship have highlighted the influence of age on self-employment undertakings (Curran and Blackburn 2001) and have found systematic differences in motivation and prevalence for self-employment among males and females (Boden 1996). Related to control for self-reported health, increasingly, studies in entrepreneurship have highlighted the value of well-being in self-employment (Binder and Coad 2013). Also, significant stress associated with self-employment has both physical and psychological implications for health that could limit selection into or income from self-employment (Hessels et al. 2017b). Education, a proxy for human capital, is associated with accumulation of knowledge and ability for self-employment (Parker 2004).

Past research has shown that parental education influences early-life human capital development and higher household income associated with higher parental education also provides early-childhood development opportunities (Blumberg and Pfann 2016). Lower language barriers resulting from multi-lingual ability may lower labor market mobility constraints (Callahan and Gándara 2014). Controlling for language ability also allows for controls for immigrant acculturation levels. For immigrants and first-generation native-born, greater fluency in the local language among immigrants could offer more advantages in the labor market. We control for language ability as follows: 1—native-born and native language, 2—native-born and foreign language, 3—foreign-born and native language, and 4—foreign-born and foreign language.

Finally, we control for 2-digit industry code, 2-digit occupation code, and country dummies.

Table 1 provides the list of variables, operationalizations, and preliminary descriptives. Table 2 presents pairwise correlations.

Table 3 provides a country-wise description of the key variables of interest. Participants in the Slovak Republic and Greece had lower incomes and those from Japan, Norway, and Denmark were in the upper end of income distribution. On average, 10.47% participants were self-employed. Self-employment in Chile, Greece, and South Korea was among the highest, whereas Slovenia had the lowest prevalence of self-employment.

3.3 Results

To test the hypothesis, we use hierarchical ordinary least squares (OLS) regression. In Table 4, balance in skills is positively associated with income (Model 1: $\beta = 0.129$, $p < 0.001$). Because a one standard deviation increase is significant, a more viable increase of one-tenth of a standard deviation might provide a better interpretation of effect sizes. For a one-tenth standard deviation increase in balance in cognitive skills, monthly income increases by 1.29%.

To test the hypothesis that self-employed with higher balance in cognitive skills would have a higher income, we interact self-employment status (1 or 0) with the balance in cognitive skills to predict the reported monthly income. As the data is cross-sectional, the contemporaneous associations between self-employment status, income, and balance in cognitive skills during 2011–2012 are tested in an OLS specification. Due to the lack of longitudinal data, the results do not control for lagging effects of cognitive skills or self-employment and therefore, only a contemporaneous association can be inferred; causation is not inferred or implied.

The hypothesis is supported (Model 2: $\beta = 0.331$, $p < 0.001$), in other words, among the self-employed, for a one-tenth of standard deviation increase in balance in cognitive skills, monthly income increases by 3.31%. On the other hand, among employees, the increase in monthly income with a higher balance in cognitive skills is not present (the flat solid line in Fig. 1). Consistent with the entrepreneurship earnings puzzle (Hyytinen et al. 2013), in Fig. 1, the employed on average had higher income levels; however, the self-employed with greater balance in cognitive skills could close the earnings gaps with the employed. Thus, in Fig. 1, the steeper the slope of the line for the self-employed (dashed line) and the flatter the line for the employed (solid line) indicate the narrowing of the income gap between the employed and the self-employed with an increasing balance in cognitive skills (the gap between the lines is reduced as one moves from left to the right on x-axis). In Fig. 1, the solid line representing the employed has a very flat slope (a change from about 8.75 to 9 when moving from zero to three on the x-axis); however, the dashed line representing the self-employed has a very steep slope (a change from about 6.75 to about 8). Therefore, the self-employed seem to gain more from an increase in balance in cognitive skills. In other words, the gap in income between the employed and the self-employed at low levels of balance in cognitive skills is about 2 (about 6.75 for the self-employed vs. about 8.75 for the employed); however, as the balance in cognitive skills increases, the gap narrows to about 1 (about 8 for the self-employed and about 9 for the employed).

3.3.1 Multilevel model

We also test for the multilevel model (based on *mixed* routine in Stata 15) with the country at level 2. In Models 3 and 4 in Table 4, the results are similar to those of the ordinary least squares (OLS) estimates.

3.3.2 Matched-pair sampling

We further test for differences in income levels after matching employed and self-employed on the balance of cognitive skills and controls. We use three different matching techniques—one-to-one matching without replacement, one-to-one matching with replacement, and

Table 2 Correlation table

		1	2	3	4	5	6	7	8
1	Log of monthly wage	1							
2	Balance in cognitive skills	0.0014	1						
3	Self-employed	− 0.0586*	− 0.0449*	1					
4	Collar color	0.0631*	− 0.0057	0.0016	1				
5	Years of work experience	0.0339*	0.0247*	0.0728*	0.1183*	1			
6	Literacy score	0.0366*	0.0293*	− 0.0241*	0.3249*	− 0.1542*	1		
7	Numeracy Score	0.0540*	− 0.0006	0.0119*	0.3146*	− 0.0564*	0.8772*	1	
8	Problem-solving score	0.0289*	0.0525*	− 0.0557*	0.2878*	− 0.2611*	0.8180*	0.7708*	1
9	Age	0.0880*	0.0115*	0.1037*	0.1586*	0.9063*	− 0.1506*	− 0.0505*	− 0.2821*
10	Sex	− 0.1098*	0.0408*	− 0.1000*	0.1435*	− 0.0597*	− 0.0110*	− 0.1249*	− 0.0453*
11	Self-rated health	0.1401*	− 0.0192*	0.0288*	− 0.0775*	0.1423*	− 0.1321*	− 0.1074*	− 0.1509*
12	Education	0.0897*	− 0.0415*	− 0.0049	0.5065*	0.0066	0.4031*	0.4063*	0.3380*
13	Parent highest education	− 0.0225*	− 0.0092*	− 0.0223*	0.1614*	− 0.2820*	0.2824*	0.2439*	0.3100*
14	Multi-lingual	− 0.0468*	− 0.0162*	− 0.0179*	− 0.0213*	0.0032	− 0.0859*	− 0.0755*	− 0.0669*
15	Industry code	− 0.1637*	0.0239*	− 0.0421*	0.2735*	0.0599*	0.0787*	0.0348*	0.0367*
16	Occupation code	− 0.2258*	0.0289*	− 0.0283*	− 0.6253*	− 0.0789*	− 0.2237*	− 0.2203*	− 0.2024*
17	Country	− 0.2274*	0.0056	− 0.0223*	0.0090*	− 0.0316*	0.0109*	0.0073	0.0198*

	9	10	11	12	13	14	15	16
1								
2								
3								
4								
5								
6								
7								
8								
9	1							
10	− 0.0006	1						
11	0.1885*	0.0232*	1					
12	0.1097*	0.0776*	− 0.0812*	1				
13	− 0.2860*	0.0078	− 0.1066*	0.2398*	1			
14	0.0231*	0.0159*	− 0.0226*	0.0406*	0.0464*	1		
15	0.0988*	0.2403*	0.0156*	0.1889*	0.0607*	0.0023	1	
16	− 0.0976*	− 0.0666*	0.1028*	− 0.3463*	− 0.1039*	− 0.0147*	0.1877*	1
17	− 0.0562*	0.0123*	− 0.0614*	0.0021	0.0013	− 0.003	− 0.1490*	− 0.2294*

Casewise deletion

*$p < 0.05$ (two-tailed)

Table 3 Country-wise descriptives (casewise deletion)

		Log of monthly wage	Balance in cognitive skills	Self-employed
Belgium	Number	2527	2527	2527
	Mean	7.8509	2.6699	0.0780
	sd	0.8720	0.1809	0.2682
Chile	Number	1976	1976	1976
	Mean	12.6961	2.6056	0.2090
	sd	1.9915	0.2254	0.4067
Czech Republic	Number	2356	2356	2356
	Mean	9.6387	2.6172	0.1244
	sd	1.4780	0.2169	0.3301
Denmark	Number	4333	4333	4333
	Mean	10.0548	2.6787	0.0870
	sd	1.2496	0.1788	0.2819
Estonia	Number	3116	3116	3116
	Mean	6.4717	2.6564	0.0876
	sd	1.3845	0.1883	0.2828
Finland	Number	3136	3136	3136
	Mean	7.7710	2.6595	0.0890
	sd	1.0378	0.1936	0.2847
Greece	Number	1200	1200	1200
	Mean	6.5533	2.4446	0.2333
	sd	1.5401	0.3294	0.4231
Ireland	Number	2411	2411	2411
	Mean	7.6548	2.6462	0.1203
	sd	1.3199	0.1955	0.3254
Israel	Number	1963	1963	1963
	Mean	8.8379	2.6282	0.0667
	sd	1.1549	0.2072	0.2496
Japan	Number	2291	2291	2291
	Mean	12.4048	2.6100	0.0677
	sd	1.1180	0.2248	0.2512
Korea	Number	2894	2894	2894
	Mean	14.4647	2.6334	0.2087
	sd	1.3928	0.2130	0.4065
Lithuania	Number	2418	2418	2418
	Mean	7.4155	2.6371	0.0811
	sd	1.0402	0.2061	0.2730
Netherlands	Number	3272	3272	3272
	Mean	7.5515	2.6835	0.0972
	sd	1.1713	0.1788	0.2963
Norway	Number	3070	3070	3070
	Mean	10.1959	2.6608	0.0570
	sd	1.0430	0.1883	0.2319
Poland	Number	2775	2775	2775
	Mean	7.6235	2.5913	0.0688

Table 3 (continued)

		Log of monthly wage	Balance in cognitive skills	Self-employed
	sd	0.9548	0.2312	0.2532
The Slovak Republic	Number	1957	1957	1957
	Mean	6.5247	2.5902	0.1272
	sd	0.9572	0.2439	0.3333
Slovenia	Number	1914	1914	1914
	Mean	7.1633	2.6496	0.0590
	sd	0.7111	0.2097	0.2358
The UK	Number	4159	4159	4159
	Mean	7.2933	2.6747	0.1118
	sd	1.1207	0.1849	0.3152
Total	Number	47,768	47,768	47,768
	Mean	8.8259	2.6407	0.1047
	sd	2.5357	0.2100	0.3061

nearest-neighbor matching [with five closest neighbors and caliper = 0.1].

To assess differences in income between employed and self-employed at high and low levels of balance in cognitive skills, we split the sample into two groups: (i) below mean value of balance in cognitive skills and (ii) at or above mean value of cognitive skills. To be consistent with the inferences in Fig. 1—that self-employed with higher levels of balance in cognitive skills are able to close income gaps with the employed—the difference in income for those at or above mean of the balance of cognitive skills should be smaller than that for those below mean of balance in cognitive skills. As the bold and italicized values in Table 5 show, across all the three matching approaches, the income difference is lower (indicating closing income gap) for those at or above mean of the balance of cognitive skills than that for those below mean of the balance of cognitive skills.

3.3.3 Alternate income measures.

The outcome variable, log of monthly average earnings, has two possible limitations. First, the effects of balance in cognitive skills on income may be sensitive to income groups, especially with the greater prevalence of blue-collar self-employed who may have lower income in

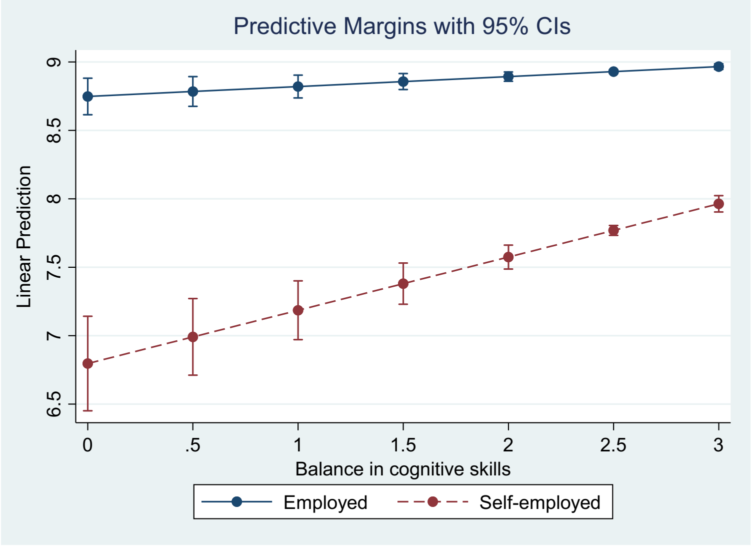


Fig. 1 Balance in cognitive skills and self-employment

Table 4 OLS and mixed model estimates

	OLS		Mixed model (country at level 2)	
Variables	(1) ln_wage3	(2) ln_wage3	(3) ln_wage3	(4) ln_wage3
Balance in cognitive skills	0.129***	0.0667**	0.129***	0.0667**
	(0.0250)	(0.0256)	(0.0250)	(0.0256)
Self-employed		− 1.962***		− 1.963***
		(0.186)		(0.185)
Balance in cognitive skills × self-employed		0.331***		0.331***
		(0.0705)		(0.0704)
White collar	0.0703***	0.0707***	0.0702***	0.0705***
	(0.0158)	(0.0152)	(0.0158)	(0.0151)
Work experience	0.0177***	0.0156***	0.0177***	0.0156***
	(0.00112)	(0.00108)	(0.00112)	(0.00108)
Literacy score	0.0193	0.0213+	0.0193	0.0213+
	(0.0127)	(0.0122)	(0.0126)	(0.0122)
Numeracy score	0.0146	0.0382***	0.0146	0.0382***
	(0.0120)	(0.0115)	(0.0119)	(0.0115)
Problem-solving score	0.0313**	0.00281	0.0313**	0.00283
	(0.00992)	(0.00958)	(0.00991)	(0.00956)
Age	− 0.00330**	0.00190+	− 0.00329**	0.00190+
	(0.00112)	(0.00108)	(0.00112)	(0.00108)
Sex	− 0.243***	− 0.297***	− 0.244***	− 0.297***
	(0.0122)	(0.0118)	(0.0122)	(0.0117)
Health	− 0.0351***	− 0.0373***	− 0.0350***	− 0.0372***
	(0.00577)	(0.00555)	(0.00576)	(0.00554)
Education	0.169***	0.160***	0.169***	0.160***
	(0.00696)	(0.00669)	(0.00694)	(0.00668)
Parent education	− 0.0320***	− 0.0162*	− 0.0320***	− 0.0162*
	(0.00779)	(0.00749)	(0.00778)	(0.00748)
Multi-lingual	0.00320	− 0.00219	0.00317	− 0.00223
	(0.00781)	(0.00751)	(0.00779)	(0.00749)
Constant	7.532***	8.089***	8.698***	9.190***
	(0.130)	(0.128)	(0.554)	(0.566)
Industry code dummies (2-digit)	Included	Included	Included	Included
Occupational code dummies (2-digit)	Included	Included	Included	Included
Country dummies/random-effects	Included	Included	Level 2	Level 2
Observations	47,802	47,768	47,802	47,768
R-square	0.807	0.821		
F	1184	1288		
$p <$	0.001	0.001	0.001	0.001
Number of groups			18	18
Chi-square			8641	13,291

Standard errors in parentheses

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, +$p < 0.1$

Table 5 Matched-pair sampling

		Less than mean of balance in cognitive skills (< 2.64)					Greater than or equal to the mean of balance in cognitive skills (≥ 2.64)				
Variable	Sample	Treated	Controls	Difference	S.E.	*T*-stat	Treated	Controls	Difference	S.E.	*T*-stat
Matching method: one-to-matching with no replacement											
Log of monthly wage	Difference in means for unmatched sample	8.3249	8.9072	− 0.5823	0.0568	− 10.26	8.4469	8.8468	− 0.3998	0.0504	− 7.94
	Difference in means for matched sample	8.3249	9.5284	***− 1.2035***	0.0811	− 14.85	8.4469	9.5849	***− 1.1380***	0.0743	− 15.31
Matching method: one-to-matching with replacement											
Log of monthly wage	Difference in means for unmatched sample	8.3249	8.9072	− 0.5823	0.0568	− 10.26	8.4469	8.8468	− 0.3998	0.0504	− 7.94
	Difference in means for matched sample	8.3249	9.5139	***− 1.1890***	0.1179	− 10.09	8.4469	9.5699	***− 1.1230***	0.1008	− 11.14
Matching method: nearest-neighbor matching with caliper = 0.1											
Log of monthly wage	Difference in means for unmatched sample	8.3249	8.9072	− 0.5823	0.0568	− 10.26	8.4469	8.8468	− 0.3998	0.0504	− 7.94
	Difference in means for matched sample	8.3249	9.5576	***− 1.2327***	0.0982	− 12.55	8.4469	9.5360	***− 1.0891***	0.0856	− 12.73

Matching covariates: balance of cognitive skills and controls

general. Using income deciles may also lower variance in the measure of income, allowing for a more robust test of effects of balanced cognitive skills. Second, the outcome variable does not adjust for differences in purchasing power across countries.

To address these limitations, we use two additional income measures to test for the robustness of findings: (i) log of monthly income deciles and (ii) log of monthly income adjusted for purchasing power parity.

In Table 6 and Fig. 2, findings are consistent with the main inferences.

3.3.4 Variation in inferences between blue- and white-collar occupations

Although in the main analysis we include a control on the extent to which a participant's work is white-collar work, the inferences may vary across blue- and white-collar workers. Using the Eurobarometer data (2008–2012), Hessels et al. (2017a) proposed that the blue-collar self-employed may differ systematically from their white-collar counterparts in "terms of physical demands, mental challenges and the degree of routineness" (p. 2); their results showed the white-collar self-employed had a higher life satisfaction, whereas the blue-collar self-employed had a negative to non-significant association with life satisfaction.

We split the sample into each collar type, creating four subsamples. The results in Table 7 show that the association is not supported for the semi-skilled, blue-collar self-employed; however, it is positive and significant across all other occupational types (the interaction plots for the three significant moderation estimates, available from the authors, were similar to the effects in Fig. 1).

3.3.5 Auxiliary analysis—balance in cognitive skills and self-employment

Although not directly related to our theoretical motivation nor to the main inferences, we conducted an auxiliary analysis to test whether balance in cognitive skills is associated with self-employment since Lazear's (2004) work on JAT and self-employment association has been of interest. To provide the readers with an understanding of the association between balance in cognitive skills

Table 6 OLS estimates—alternate income measures

Variables	(1) Log of monthly income deciles	(2) Log of monthly income deciles	(3) Log of monthly income adjusted for purchasing power parity	(4) Log of monthly income adjusted for purchasing power parity
Balance in cognitive skills	0.0965***	0.0795***	0.119***	0.0665**
	(0.0122)	(0.0127)	(0.0228)	(0.0233)
Self-employed		− 0.589***		− 1.766***
		(0.0938)		(0.170)
Balance in cognitive skills × self-employed		0.0637+		0.286***
		(0.0357)		(0.0646)
Controls	Included	Included	Included	Included
Industry code dummies (2 digits)	Included	Included	Included	Included
Occupational code dummies (2 digits)	Included	Included	Included	Included
Country dummies	Included	Included	Included	Included
Constant	1.461*	1.601**	7.527***	7.871***
	(0.569)	(0.556)	(1.031)	(0.990)
Observations	51,563	51,518	48,732	48,687
R-square	0.336	0.365	0.266	0.323
F	149.6	167.4	101.9	132.1
$p <$	0.001	0.001	0.001	0.001

Standard errors in parentheses

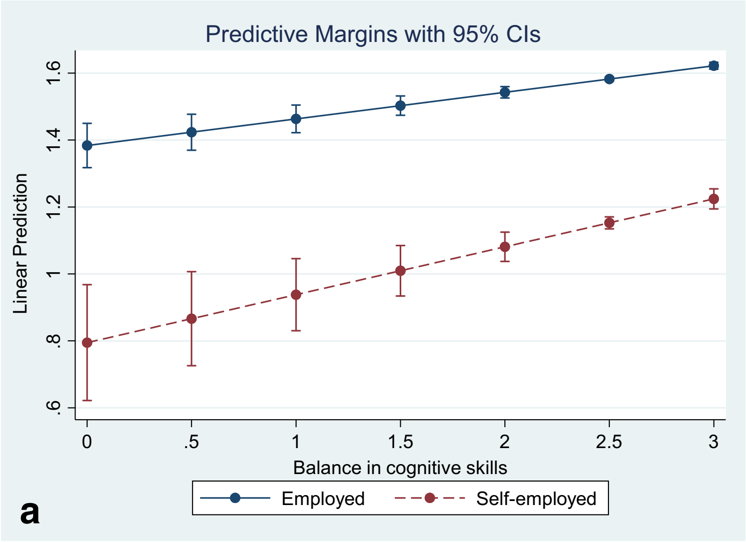
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, +$p < 0.1$

and self-employment in our sample, we conduct this additional analysis only for informative purposes and as ancillary to our theoretical framework.

Using income and controls from the main specification, in Table 8, balance in cognitive skills is not associated with self-employment ($\beta = -0.0072$, $p > 0.10$). Assessing the effects of individual skills literacy score is not associated with the likelihood of self-employment. Numeracy score is positively associated; however, problem-solving skills were negatively associated with the likelihood of self-employment. Problem-solving skills "involves using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks [and, focuses] on the abilities to solve problems for personal, work and civic purposes by setting up appropriate goals and plans, accessing and making use of information through computers and computer networks" (PIAAC Expert Group in Problem Solving in Technology-Rich Environments 2009, p. 15). Due to the generalized nature of these skills, they may not specifically influence self-employment choice and these broader skill sets pertaining to non-business domains, by itself, may lower the comparative advantage in setting up a business. Conversely, as found in the main analysis, the positive and significant association of problem-solving skills and self-employment income may be related to the need for ongoing engagement of a wide range of stakeholders in business and non-business domains.

4 Discussion

The self-employed represent about 10 to 15% of the labor force in developed countries. With an increasing focus on promoting self-employment, understanding earnings implications for the self-employed are important. Drawing on a multi-country sample, we tested the influence of balance in cognitive skills on earnings for the self-employed. First, confirming the "returns to entrepreneurship puzzle" (Hyytinen et al. 2013), the self-employed have lower earnings across 18 countries in our sample; however, the greater balance in cognitive skills seems to help close the earnings gaps with the employed. That is, with an increasing balance in



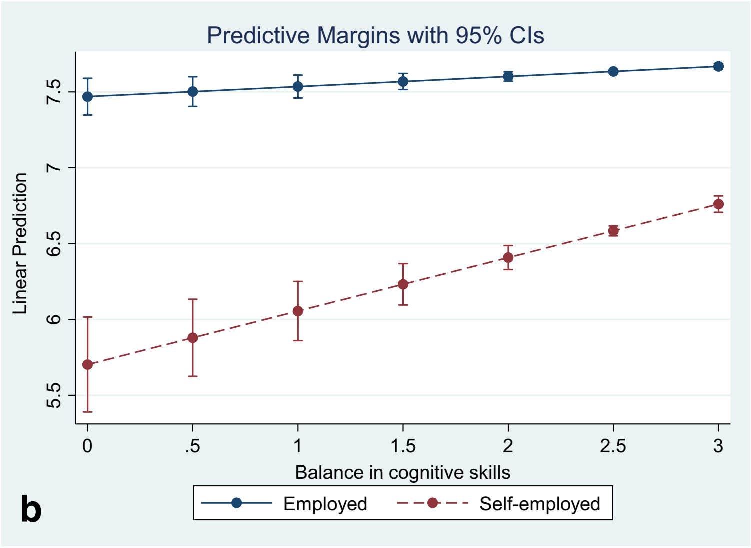


Fig. 2 Moderation effects for alternate income measures. (a) Moderation effects for log of monthly income deciles. (b) Moderation effects for log of monthly income adjusted for purchasing power parity

cognitive skills, the earnings increase for the self-employed; however, they remain unaffected for the employed. In contrast to previous findings (Aldén et al. 2017; Hartog et al. 2010), those with balanced cognitive skills are not more likely to be self-employed. Compared to Hartog et al. (2010) who find that "expected earnings *levels* in entrepreneurship relative to wage employment are higher only for the upper echelon of the general ability distribution," (p. 985), we find that earnings levels are lower than those of wage earners across all levels of balance in the cognitive skills for the self-employed.

The lower income among the self-employed was observed in a number of studies that were based on representative samples similar to ours and were labeled "the returns to entrepreneurship puzzle" (e.g., Hyytinen et al. 2013). It could be construed that lower income would result from inclusion of a variety of self-employed types, i.e., a significant portion of our sample includes the "entrepreneurs" who are self-employed workers, a mix of less educated, blue-collar workers, such as carpenters and electricians. Additional analysis in Table 7 shows that while there is heterogeneity in effect sizes, workers in elementary skills occupations also seem to realize income benefits from a greater balance in cognitive skills. The returns to balance in cognitive skills are somewhat consistent across the self-employed of different collar types.

Table 7 OLS estimates for blue and white collars

Variables	(1) Blue collar—elementary occupation	(2) Blue collar—semi-skilled blue collar	(3) White collar—semi-skilled white collar	(4) White collar—white collar
Balance in cognitive skills	0.0774	0.0165	0.0768+	0.0613+
	(0.0961)	(0.0732)	(0.0454)	(0.0367)
Self-employed	− 2.830**	− 0.494	− 1.948***	− 2.468***
	(0.931)	(0.445)	(0.377)	(0.255)
Balance in cognitive skills × self-employed	0.696*	− 0.200	0.344*	0.507***
	(0.353)	(0.169)	(0.143)	(0.0967)
Work experience	0.0125***	0.0135***	0.0168***	0.0196***
	(0.00342)	(0.00321)	(0.00176)	(0.00168)
Literacy score	0.0105	− 0.0124	0.0357	0.0370*
	(0.0469)	(0.0335)	(0.0217)	(0.0173)
Numeracy score	− 0.0280	0.0636+	− 0.0170	0.0632***
	(0.0443)	(0.0325)	(0.0208)	(0.0163)
Problem-solving score	− 0.0282	− 0.0129	0.0239	0.00598
	(0.0378)	(0.0264)	(0.0171)	(0.0136)
Age	0.0114***	− 0.00320	0.00405*	− 0.00293+
	(0.00336)	(0.00330)	(0.00171)	(0.00171)
Sex	− 0.392***	− 0.381***	− 0.292***	− 0.240***
	(0.0449)	(0.0434)	(0.0210)	(0.0160)
Health	− 0.0267	− 0.0346*	− 0.0309**	− 0.0358***
	(0.0206)	(0.0151)	(0.00974)	(0.00799)
Education	0.135***	0.0713**	0.146***	0.178***
	(0.0298)	(0.0230)	(0.0119)	(0.00904)
Parent education	− 0.0393	0.0150	− 0.0527***	− 0.000616
	(0.0301)	(0.0221)	(0.0136)	(0.0102)
Multi-lingual	0.0263	− 0.0273	0.0257+	− 0.0111
	(0.0231)	(0.0214)	(0.0137)	(0.0107)
Industry code dummies (2 digits)	Included	Included	Included	Included
Occupational code dummies (2 digits)	Included	Included	Included	Included
Country dummies/random-effects	Included	Included	Included	Included
Constant	6.474***	8.236***	8.024***	8.508***
	(0.592)	(1.230)	(0.752)	(0.177)
Observations	2699	7942	13,631	23,496
R-square	0.867	0.794	0.858	0.806
F	139.3	226.4	630.2	710.5
p <	0.001	0.001	0.001	0.001

Standard errors in parentheses

$***p < 0.001$, $**p < 0.01$, $*p < 0.05$, $+p < 0.1$

The findings extend recent studies on cognitive skills and earnings among those active in the labor force (Hanushek et al. 2015). By extending these studies, we add a dimension of self-employment and find that the

Table 8 Logit estimates

Variables	(1) DV = self-employed
Balance in cognitive skills	− 0.00715
	(0.0857)
Work experience	− 0.00757*
	(0.00346)
White collar	0.0392
	(0.0536)
Log of monthly earnings	− 0.582***
	(0.0159)
Literacy score	0.0392
	(0.0422)
Numeracy score	0.248***
	(0.0409)
Problem-solving score	− 0.264***
	(0.0340)
Age	0.0535***
	(0.00349)
Sex	− 0.830***
	(0.0427)
Health	− 0.0639**
	(0.0197)
Education	− 0.00260
	(0.0233)
Parent education	0.163***
	(0.0262)
Multi-lingual	− 0.0592*
	(0.0289)
Industry code dummies (2 digits)	Included
Occupational code dummies (2 digits)	Included
Country dummies	Included
Constant	3.845***
	(0.412)
Observations	47,444
Chi-square	8957
$p <$	0.001

Standard errors in parentheses

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $+p < 0.1$

self-employed have systematically lower earnings despite a balanced cognitive skills portfolio. Focusing on occupation-specific differences could further help develop a more fine-grained understanding of the value of cognitive skills.

Spanjer and van Witteloostuijn (2017), using experience diversity as a proxy for JAT found that skill experience diversity, measured as "the number of skills linked to an entrepreneur's past jobs (*skill experience diversity*)" (p. 147), had an inverted U-shaped relationship with performance. While Spanjer and van Witteloostuijn (2017) draw on O*NET skills indices, in the current study, we focus on cognitive skills that could vary among individuals despite job memberships in similar occupational classes. While skills accumulated from work experiences differ from cognitive skills, we call for future research to further delve into this association.

Hsieh et al. (2017), proposing risk-aversion as an antecedent to JAT, in a sample of Dutch university students found that risk-averse individuals are more likely to invest in diverse skills (proxied by industry diversity and education diversity). In the current study, we do not focus on antecedents to balance in cognitive skills; however, it is possible that biological or psychological factors could influence investments into or development of diverse cognitive skills. To parse out social, professional, genetic, and psychological factors, twin studies could shed more light on these competing drivers of balance in cognitive skills.

4.1 Limitations and future research directions

The findings of the study must be interpreted in light of their limitations. First, we use cross-sectional data and as such, our measure of the cross section is a snapshot of cognitive skills at given point in time. However, to assuage concerns about omitted variables, we controlled for the industry, occupation, and country effects, and our findings were robust to the matched-pair sampling analysis. As early years are formative in skill development, we controlled for parental education and language ability. Furthermore, Hartog et al. (2010) combine both work experiences and cognitive skills (based on ASVAB) in a longitudinal setting. In the current data, we lack the job history data to operationalize sector and functional diversity in an individual's work history. We call for future research to combine the measures of cognitive skills with job histories to derive a much richer understanding of the interplay between cognitive skills and work experiences. While Aldén et al. (2017) draw on cognitive tests administered during Swedish Army enlistment, their data provides opportunities for assessing co-evolution of early-age cognitive skills and its complex interactions with educational, work, and life experiences.

Hsieh (2016) using the National Science Foundation's private Scientists and Engineers Statistical Data Systems panel database found that those who simultaneously (instead of sequentially) experienced business functions were more likely to be self-employed. However, those who were analytically pre-disposed (proxied by the level of education) were more likely to be self-employed when experiencing business functions sequentially. Cognitive skills measured in a longitudinal panel setting could further help parse out the accumulation of sequential and simultaneous experience of business functions.

Second, our findings are not generalizable beyond the countries included in the sample. Future research could consider additional skills such as occupational and employability skills to further sharpen our understanding of balance in skills and self-employment. Studies could also consider balance in traits such as personality and how these could influence self-employment choices.

Cognitive skills have been used to understand country-level differences in educational systems, labor markets, and knowledge capital (Hanushek et al. 2017; Hanushek and Woessmann 2008). Cognitive skill is generally positively associated with growth and spread of education at the country level increases the prevalence of cognitive skill levels that in turn is associated with higher income at the country level (Hanushek et al. 2008). These cross-country variations in cognitive skills and antecedents that drive differences in cognitive skills at the country level could further explain differences in cross-country self-employment levels or self-employment-driven economic growth. We call for future research to address these issues at the country level.

In conclusion, we aimed to extend Hartog et al. (2010) and Aldén et al. (2017) by drawing on a large multi-country sample with a more recent and richer cognitive ability tests with greater generalizability and lower measurement errors. Consistent with those two studies, the self-employed with more balanced cognitive skills have a higher income; however, the income levels do not exceed those of the wage earners. The self-employed with a higher balance of cognitive skills are better able to close income gaps with the employed. Inconsistent with both studies, we do not find that those with higher balance in cognitive skills are more likely to be self-employed. The findings leave much food for thought for future research in understanding the role of balance in cognitive skills in self-employment outcomes.

References

Aldén, L., Hammarstedt, M., & Neuman, E. (2017). All about balance? A test of the jack-of-all-trades theory using military enlistment data. *Labour Economics, 49*, 1–13.

Åstebro, T., & Thompson, P. (2011). Entrepreneurs, jacks of all trades or hobos? *Research Policy, 40*(5), 637–649.

Åstebro, T., & Yong, K. (2016). Invention quality and entrepreneurial earnings: the role of prior employment variety. *Entrepreneurship Theory and Practice, 40*(2), 381–400.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Baron, R. A., & Henry, R. A. (2010). How entrepreneurs acquire the capacity to excel: insights from research on expert performance. *Strategic Entrepreneurship Journal, 4*(1), 49–65.

Binet & Simon (1991/1916). New investigation upon the measure of the intellectual level among school children.In H.H Goddard (Ed.), Development of inteligence in children (the Binet-Simon Scale) (pp.274–328). Baltimore: Williams & Wilkins.

Binder, M., & Coad, A. (2013). Life satisfaction and self-employment: a matching approach. *Small Business Economics, 40*(4), 1009–1033.

Blumberg, B. F., & Pfann, G. A. (2016). Roads leading to self-employment: comparing transgenerational entrepreneurs and self-made start-ups. *Entrepreneurship Theory and Practice, 40*(2), 335–357.

Boarini, R., d'Ercole, M. M., & Liu, G. (2012). Approaches to measuring the stock of human capital: a review of country practices. *OECD Statistics Working Papers, 2012*(4), 0_1.

Boden, R. J. (1996). Gender and self-employment selection: an empirical assessment. *The Journal of Socio-Economics, 25*(6), 671–682.

Bublitz, E., & Noseleit, F. (2014). The skill balancing act: when does broad expertise pay off? *Small Business Economics, 42*(1), 17.

Callahan, R. M., & Gándara, P. C. (2014). *The bilingual advantage: language, literacy and the US labor market* (Vol. 99): Multilingual Matters.

Carlsson, M., Dahl, G. B., Öckert, B., & Rooth, D.-O. (2015). The effect of schooling on cognitive skills. *Review of Economics and statistics, 97*(3), 533–547.

Cawley, J., Heckman, J., & Vytlacil, E. (2001). Three observations on wages and measured cognitive ability. *Labour Economics, 8*(4), 419–442.

Chen, L. W., & Thompson, P. (2016). Skill balance and entrepreneurship evidence from online career histories. *Entrepreneurship Theory and Practice, 40*(2), 289–305.

Cingano, F. (2014). Trends in income inequality and its impact on economic growth.

Cooper, A. C., Folta, T. B., & Woo, C. (1995). Entrepreneurial information search. *Journal of Business Venturing, 10*(2), 107–120.

Curran, J., & Blackburn, R. A. (2001). Older people and the enterprise society: age and self-employment propensities. *Work, Employment and Society, 15*(4), 889–902.

Davidsson, P., & Gordon, S. R. (2012). Panel studies of new venture creation: a methods-focused review and suggestions for future research. *Small Business Economics, 39*(4), 853–876.

Drayton, W. (2002). The citizen sector: becoming as entrepreneurial and competitive as business. *California Management Review, 44*(3), 120–132.

Elam, A. B. (2014). Gender and entrepreneurship. Edward Elgar Publishing.

Elfenbein, D. W., Hamilton, B. H., & Zenger, T. R. (2008). The entrepreneurial spawning of scientists and engineers: stars, slugs, and the small firm effect. Working paper.

Feinberg, I., Frijters, J., Johnson-Lawrence, V., Greenberg, D., Nightingale, E., & Moodie, C. (2016). Examining associations between health information seeking behavior and adult education status in the US: an analysis of the 2012 PIAAC data. *PLoS One, 11*(2), e0148751.

Frank, G. (1983). *The Wechsler enterprise: an assessment of the development, structure and use of the Wechsler tests of intelligence*. Elmsford, NY: Pergamon Press.

Ganzach, Y. (1995). Attribute scatter and decision outcome: judgment versus choice. *Organizational Behavior and Human Decision Processes, 62*(1), 113–122.

Gibbs, A. (1997). Small firms training and competitiveness: building upon the small business as a learning organization. *International Small Business Journal, 15*(3), 13–29.

Gregory, R. J. (1987). *Adult intellectual assessment*. Allyn & Bacon.

Hamilton, B. H. (2000). Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy, 108*(3), 604–631.

Hansen, E. L., & Allen, K. R. (1992). The creation corridor: environmental load and pre-organization information-processing ability. *Entrepreneurship: Theory and Practice, 17*(1), 57–66.

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

Hanushek, E. A., & Woessmann, L. (2013). The role of international assessments of cognitive skills in the analysis of growth and development. In *The role of international large-scale assessments: perspectives from technology, economy, and educational research* (pp. 47–65). Springer.

Hanushek, E. A., Woessmann, L., Jamison, E. A., & Jamison, D. T. (2008). Education and economic growth. *Education Next, 8*(2).

Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2015). Returns to skills around the world: evidence from PIAAC. *European Economic Review, 73*, 103–130.

Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2017). Coping with change: international differences in the returns to skills. *Economics Letters, 153*, 15–19.

Hartog, J., Van Praag, M., & Van Der Sluis, J. (2010). If you are so smart, why aren't you an entrepreneur? Returns to cognitive and social ability: entrepreneurs versus employees. *Journal of Economics & Management Strategy, 19*(4), 947–989.

Hessels, J., Brixy, U., Naudé, W., & Gries, T. (2014). Skill variety, innovation and new business formation.

Hessels, J., Arampatzi, E., van der Zwan, P., & Burger, M. (2017a). Life satisfaction and self-employment in different types of occupations. *Applied Economics Letters,* 1–7.

Hessels, J., Rietveld, C. A., & van der Zwan, P. (2017b). Self-employment and work-related stress: the mediating role of job control and job demand. *Journal of Business Venturing, 32*(2), 178–196.

Holzer, H. J., & Lerman, R. I. (2014). Cognitive skills in the US labor market: for whom do they matter. In *Presentation at Taking the Next Step with PIAAC: A Research-to-Action conference, American Institutes for Research, Arlington, VA*.

Hsieh, C. (2016). Do the self-employed more likely emerge from sequential or parallel work experience in business-related functions? *Entrepreneurship Theory and Practice, 40*(2), 307–334.

Hsieh, C., Nickerson, J. A., & Zenger, T. R. (2007). Opportunity discovery, problem solving and a theory of the entrepreneurial firm. *Journal of Management Studies, 44*(7), 1255–1277.

Hsieh, C., Parker, S. C., & van Praag, C. M. (2017). Risk, balanced skills and entrepreneurship. *Small Business Economics, 48*(2), 287–302.

Hyytinen, A., Ilmakunnas, P., & Toivanen, O. (2013). The return-to-entrepreneurship puzzle. *Labour Economics, 20*, 57–67.

Jerrim, J. (2017). The link between family background and later lifetime income: how does the UK compare with other countries? *Fiscal Studies, 38*(1), 49–79.

Lazear, E. P. (2004). Balanced skills and entrepreneurship. *The American Economic Review, 94*(2), 208–211.

Lechmann, D., & Schnabel, C. (2011). Are the self-employed really jacks-of-all-trades? Testing the assumptions and implications of Lazear's theory of entrepreneurship with German data.

Marshall, A. (1890). *Principles of political economy*. New York: Maxmillan.

Martín-Rojas, R., García-Morales, V. J., & Bolívar-Ramos, M. T. (2013). Influence of technological support, skills and competencies, and learning on corporate entrepreneurship in European technology firms. *Technovation, 33*(12), 417–430.

McGowan, M. A., & Andrews, D. (2017). Labor market mismatch and labor productivity: evidence from PIAAC data. In *Skill mismatch in labor markets* (pp. 199–241). Emerald Publishing Limited.

Mincer, J. (1974). Schooling, experience, and earnings. *Human Behavior & Social Institutions No., 2*.

Minniti, M., & Bygrave, W. (2001). A dynamic model of entrepreneurial learning. *Entrepreneurship: Theory and Practice, 25*(3), 5–5.

Oberschachtsiek, D. (2008). Founders' experience and self-employment duration: the importance of being a 'Jack-of-all-trades'. An analysis based on competing risks. Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg [Institute for Employment Research, Nuremberg, Germany].

OECD (2013). OECD skills outlook 2013: first results from the survey of adult skills. In O. Publishing (Ed.) Organization for Economic Cooperation and Development. doi:https://doi.org/10.1787/9789264204256-en.

Parker, S. C. (2004). *The economics of self-employment and entrepreneurship*. Cambridge: Cambridge University Press.

Pena, A. A. (2016). PIAAC skills and economic inequality. *Journal of Research and Practice for Adult Literacy, Secondary, and Basic Education, 5*(2), 17.

PIAAC Expert Group in Problem Solving in Technology-Rich Environments (2009). PIAAC problem solving in technology-rich environments: a conceptual framework. *OECD Education Working Papers* (Vol. 36). Paris.

Politis, D. (2005). The process of entrepreneurial learning: a conceptual framework. *Entrepreneurship Theory and Practice, 29*(4), 399–424.

Rutkowski, L., Gonzalez, E., Joncas, M., & von Davier, M. (2010). International large-scale assessment data: issues in secondary analysis and reporting. *Educational Researcher, 39*(2), 142–151.

Silva, O. (2007). The jack-of-all-trades entrepreneur: innate talent or acquired skill? *Economics Letters, 97*(2), 118–123.

Spanjer, A., & van Witteloostuijn, A. (2017). The entrepreneur's experiential diversity and entrepreneurial performance. *Small Business Economics, 49*(1), 141–161.

Stuetzer, M., Goethner, M., & Cantner, U. (2012). Do balanced skills help nascent entrepreneurs to make progress in the venture creation process? *Economics Letters, 117*(1), 186–188.

Tegtmeier, S., Kurczewska, A., & Halberstadt, J. (2016). Are women graduates jacquelines-of-all-trades? Challenging Lazear's view on entrepreneurship. *Small Business Economics, 47*(1), 77.

Unger, J. M., Rauch, A., Frese, M., & Rosenbusch, N. (2011). Human capital and entrepreneurial success: a meta-analytical review. *Journal of Business Venturing, 26*(3), 341–358.

Vijverberg, W. P. (1999). The impact of schooling and cognitive skills on income from non-farm self-employment. In *The economics of school quality investments in developing countries* (pp. 206–252). Springer.

Wagner, J. (2003). Testing Lazear's jack-of-all-trades view of entrepreneurship with German micro data. *Applied Economics Letters, 10*(11), 687–689.

Wagner, J. (2006). Are nascent entrepreneurs 'jacks-of-all-trades'? A test of Lazear's theory of entrepreneurship with German data. *Applied Economics, 38*(20), 2415–2419.