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Wages, mental abilities and assessments in large scale international surveys: Still not much more than *g*

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A B S T R A C T

We examine the role of General Mental Ability (GMA or *g*), versus specific abilities, in predicting wages among 69,901 participants from 19 countries in the Programme for International Assessment of Adult Competencies (PIAAC). We define GMA as the first principal component in a battery of three ability tests, and specific abilities as the low order components. Our initial results – a difference of 52%, between a *g* only model and a *g* + specific abilities model (R^2s of 0.061 and 0.093, respectively) – is considerably different from earlier results suggesting that "there is not much more than *g*" in predicting performance. However, further analyses show that this difference is reduced to 0.5% when crucial non-cognitive individual differences (age and sex) are controlled for (R^2s of 0.0763 and 0.0767, respectively). Path models of the relationships between individual differences, specific abilities, GMA and wage shed light on these results. Implications for the understanding of the relationship between mental abilities and wage, and to the understanding of cognitive test scores as representing various skills versus general ability, are discussed.

1. Introduction

In the last 30 years there have been extensive efforts via large-scale international surveys to assess adults' proficiency in key information-processing skills and to gather information and data on how adults use their skills at home, at work and in the wider community. The largest of these surveys is the PIAAC (Programme for International Assessment of Adult Competencies) which was conducted starting in 2008 and ended recently, and included 36 countries with an average of about 5000 participants per country. Subjects in the programme completed three cognitive tests: a test of numeracy, a test of literacy and a test of problem solving in technology-rich environments, via extensive computerized, as well as paper and pencil, tests. Two predecessors of the PIAAC are the Adult Literacy and Lifeskills (ALL) survey, which was conducted between 2002 and 2008, and the International Adult Literacy Survey (IALS), which was conducted between 1994 and 1996.

One difference between the approach of these surveys to understanding cognitive test scores and the common approach to test scores in applied psychology is that in the former approach, which we label the *skills approach*, test scores are viewed as measures of different skills, whereas in the second, which we label the abilities-intelligence approach, test scores are viewed as indicators of abilities. The difference between skills and abilities is rarely discussed in the literature, perhaps because it is practically impossible to construct tests that differentiate between the two concepts (see, however, Widdowson, 1998 and Arvey, Salas, & Gialluca, 1992, for a discussion). Conceptually, however, skills are the proficiencies developed through training or experience and abilities are the potential qualities of being able to do something. The two are likely to be almost indistinguishable because the development of skills strongly depends on abilities. Note also that often the same tests are viewed as intelligence tests by researchers using the intelligence approach and as skills tests by researchers using the skills approach. Examples are the tests in the Armed Services Vocational Aptitude Battery (Deary, Irwing, Der, & Bates, 2007 and Light & McGee, 2015, respectively) and the tests in the Adult Literacy Survey (Gottfredson, 1997 and Leuven, Oosterbeek, & Van Ophem, 2004, respectively). For convenience, in the current paper we label these tests "ability tests", and the concepts measured by the tests "abilities". However, this terminology should be viewed as neutral vis-a-vis the two approaches.

A second difference between the two approaches is that in the abilities-intelligence approach, but not in the skills approach, test scores are viewed to a large extent as indicators of a single General Mental Ability (GMA), intelligence, or *g*. This difference, unlike the first one, has analytical implication. While researchers in the abilities-intelligence approach usually aggregate the various test scores into a single measure of GMA (e.g., Jensen, 1998; Schmidt & Hunter, 2004),

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researchers in the skills approach avoid the use of such an aggregated measure. For example, of the 21 articles that refer to the PIAAC in the PsychNet database, none aggregated the three skill measures of the PIAAC into a single measure. We also observed the same phenomenon in Google Scholar when examining the first 100 most cited papers that refer to the PIAAC.[1]

In the current paper we contrast the skills approach with the intelligence approach by comparing their predictive validity in predicting economic performance on the basis of the PIAAC. Fig. 1 depicts the relationships between abilities and performance within the skills approach for a case in which there are two ability measures and a measure of performance. Within the skills approach, performance is viewed as a function of correlated abilities that affect performance. In this approach the estimation of the effects of abilities on performance is achieved by regressing performance on the two abilities. The coefficients of this regression represent the marginal effect of each ability on performance, keeping the other ability constant. Fig. 2 depicts the relationships between abilities and performance within the abilities-intelligence approach. Here abilities are viewed primarily as indicators of GMA, though they may also be influenced by specific abilities – the residual abilities after GMA is partialled out. In this approach performance is believed to be affected primarily by GMA, though some effects of specific abilities may also exist. Ideally, to estimate performance models in the abilities-intelligence approach one needs both a measure of GMA and measures of abilities. However, since independent measures of GMA are hard to find, and such measures are never collected in large-scale international databases, it is not possible to rely on this procedure to examine the effect of GMA versus specific abilities on performance in any existing database.

Yet, a method developed by Ree and co-authors overcomes this difficulty (Ree, Earles, & Teachout, 1994; Olea & Ree, 1994; Ree & Earles, 1992. See also Ree & Earles, 1991). These researchers conceptualized GMA as the first unrotated principal component of a battery of mental ability tests, and specific abilities as the lower order components of this analysis. (This conceptualization of GMA is the common conceptualization of GMA in the literature. See for example, Jensen & Weng, 1994).They then estimated two regressions. In the first, performance was regressed on only the first principal component, labeled the *g* factor, and in the second it was regressed on both the first component and the lower order components (non-g factors). The results showed that "there is not much more than *g*" in predicting job performance: Relative to *g*, the contribution of the non-g factors was negligible.

In the current study we attempted to examine whether the "not much more than *g*" premise is valid for predicting wage. Underlying this attempt is the view that by and large wage is an indicator of economic performance: The process by which both individuals and firms seek to maximize their fortune leads to an equilibrium in which wages reflect the economic benefit of one's work (Gibbons, 2005; Lemieux, MacLeod, & Parent, 2009). Whether or not this is the case in the economic system, is an empirical question, of which one of the consequences is that the relationships between abilities and wage is similar to the relationships between abilities and performance.

To the best of our knowledge, the "not much more than *g*" premise was never examined using wage as a measure of performance. This is an unfortunate situation because wages are of much interest to social scientists, perhaps even more than job performance, and are of great social importance. Furthermore, using wage as an indicator for performance can dramatically increase the data available for applied psychologists interested in the relationship between abilities and performance: Job performance data are much more difficult to collect in large representative surveys than wages, and therefore in most, if not all, of these databases only wages can serve as indicators of performance. Thus, it is of interest to examine whether the dominant role of *g* in prediction of job performance, which is fundamental to research in applied psychology, also applies to the prediction of wage.

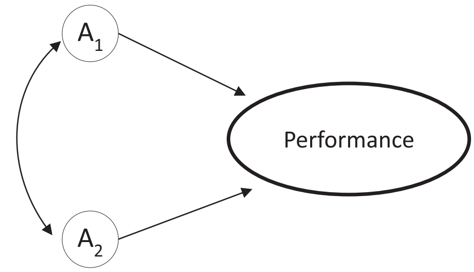

Fig. 1. The relationship between abilities and performance in the skills approach. A_1 and A_2 are two measured abilities.

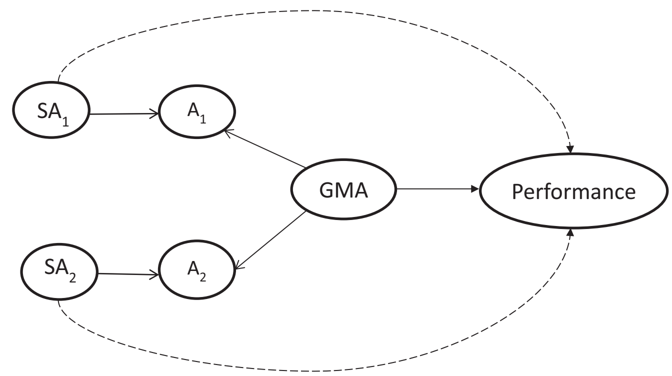

Fig. 2. The relationship between abilities and performance in the abilities-intelligence approach. A_1 and A_2 are two measured Abilities and SA_1 and SA_2 are two Specific Abilities. The broken lines suggest that Specific Abilities have a negligible effect on performance.

However, a major difference between wage and job performance is that whereas job performance is affected primarily by abilities, wage is affected not only by abilities but also by non-cognitive individual differences, particularly age and sex, that influence wage via remuneration policies that may be unrelated to ability (i.e., females earn less than males; and, in a seniority system, older workers earn more[2]). Ree and co-authors did not include such individual differences in their studies of job performance (see McClelland, 1993, for a discussion) but while this omission may have been of little significance with regard to job performance, it may be of considerable significance with regard to wage. To illustrate, consider Fig. 3 that depicts the relationships between performance and two ability variables. For the purpose of the current discussion these can be either the actual abilities or the derived principal components. The model includes also a non-cognitive individual difference (e.g., age) that may affect wage both indirectly through the mediation of the two abilities (e.g., through the effect of age on abilities), and directly without their mediation (e.g., through a seniority remuneration system). However, because performance depends mostly on ability and less on remuneration policies, the direct effect of the individual difference is relevant primarily to wage and less to performance. Therefore, omitting this individual difference will not distort the results of a performance model, but will distort the results of a wage model: It will bias the parameter estimates as well as the estimated fit of

[1] The difference between these two groups of papers is that the first included mainly psychology oriented papers whereas the second included mainly economics oriented papers.

[2] These policies are not necessarily signs of discrimination as females may work fewer hours and older workers may have valuable work experience that is not captured by the abilities measured in the PIAAC. However, including variables that attempt to directly capture these factors, such as job market experience and hours of work led to less powerful results vis a vis our theoretical framework. These substitution variables had more missing values and appeared to be less reliable than sex and age.

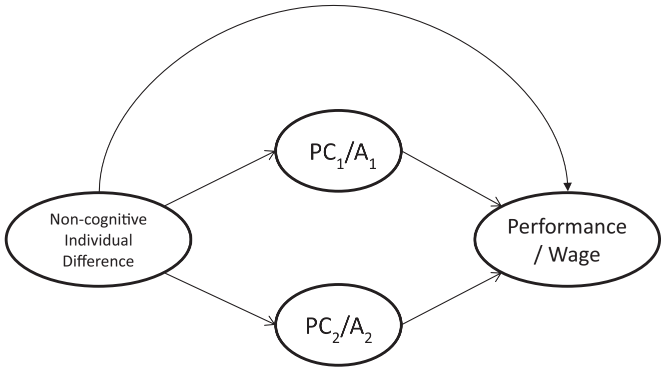

Fig. 3. The effect of a non-cognitive individual difference (e.g., sex, age) on abilities (either actual abilities, denoted by the A, or the derived principal components, denoted by PC) and performance/wage. When the outcome is performance, but not when it is wage, the direct effect of the non-cognitive individual difference is negligible.

the model. In particular, when this individual difference variable is not included in the model, the estimated effects of the abilities will be biased and the wage variance attributed to abilities will capture some of the variance due to the direct effect of the individual difference.

In the current paper we examine the relationships between abilities and wage from both the perspective of the abilities-intelligence approach and the perspective of the skills approach. First, we estimate the relationships between abilities and wage from the perspective of the skills approach, comparing bare-bones ability models to models that include our two individual difference variables. Second, we examine the role of GMA in predicting wage on the basis of the abilities-intelligence approach by estimating models similar to those estimated by Ree and co-authors for job performance, subsequently adding sex and age as individual differences controls. We conclude with a discussion of the implications of the results to the conceptualization of the relationships between abilities and performance and to the measurement of abilities in large scale international surveys.

2. Method

2.1. Data

We use data from 19 countries that participated in the first wave of the PIAAC (Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, Germany, Ireland, Japan, Korea, the Netherlands, Norway, Poland, Slovakia, Russia, Sweden, the United Kingdom, and the United States). The samples in each of the countries were designed to be representative of the adult population between the ages of 16 and 65 years. The same questionnaire, translated into the local language, was administered in all the countries. Altogether there were 156,906 participants interviewed. However, because of missing values, the analyses were performed only on 69,901. Most of the missing values were in the wage variable (non-employed participants) and in the measure of Technological Problem Solving (that was not administered to participants who lacked computer skills).

3. Measures

3.1. Abilities

Three content areas were assessed in the PIAAC: literacy (associated with the ability to understand, evaluate, use and engage with written texts), numeracy (associated with the ability to access, use, interpret, and communicate mathematical information and ideas), and problem solving in technology-rich environments (associated with the ability to use digital technology, communication tools and networks to acquire and evaluate information, and communicate with others), 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 three tests are carried out on computers but literacy and numeracy can also be assessed on paper for those who prefer it and for those lacking basic computer skills. TPS can only be assessed on computers and those who refuse or could not 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 participating countries and > 20% in some). The tests use a Computerized Adaptive Testing (CAT) design that adapts the questions to the examinee's ability. Not all respondents are administered all the questions and a routing algorithm guides respondents through a subset of 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 10 plausible values for each ability (Rutkowski, Gonzalez, Joncas, & von Davier, 2010). To obtain a single score for each ability we averaged these 10 values.[3] Finally, each of the three ability scores was standardized within each of the 19 countries.

3.2. GMA and specific abilities

GMA is the first principal component of a principal component analysis without rotation of the three abilities.[4] The two lower order components represent specific abilities.

3.3. Wage

The Monthly earnings, standardized within each country into a decile scale.

4. Results

4.1. Plan of the analyses

The first subsection of the Results presents a correlational analysis which provides rough, but intuitive, understanding of the relationship between each of the three abilities and wage, which is less obvious on the basis of the subsequent regression analyses. The following two sections analyze our data from the perspectives of the skills and abilities-intelligence approaches, respectively. In each of these two subsections we first examine the relationships between abilities and wage without controlling for sex and age and we then add sex and age to our models. Although this is a somewhat unconventional approach in which the "control" variables are added to the analysis *after* a preliminary analysis in which the effects of the focal independent variables are estimated, we chose this approach to highlight the difference between estimating ability-performance models in which the control for non-cognitive individual differences is unimportant to estimating ability-wage models in which the control for these individual differences in important.

[3] Although it is often recommended to conduct the analyses for each of the values and average the results of these 10 analyses, in practical use researchers conduct only one analysis, either by relying on only one of the values or by averaging the 10 values and analyzing this average. The latter method has the advantage of more accurate estimates of standard errors and the former has the advantage of more accurate parameter estimates (Rutkowski et al., 2010). We chose the second method for two reasons. First, as the sample size is very large, significance tests are of relatively little importance to us. Second, the models' fits (in terms of R^2) of the average plausible values is better than the average fits of the individual plausible values' models making reliance on the average plausible values better suited for analyses that focus on comparison between models' fit.

[4] Note that there is very little difference between using the first unrotated principal component and the first unrotated principal factor (Silks, 1938). Indeed, in our data the correlation between the two is 0.997.

Table 1
Zero order correlations.

	Wage	Age	Sex	Numeracy	Literacy
Wage	–				
Age	0.284	–			
Sex	−0.266	−0.004	–		
Numeracy	0.291	−0.043	−0.141	–	
Literacy	0.232	−0.123	−0.019	0.886	–
TPS	0.175	−0.280	−0.047	0.787	0.836

Note: Males are coded as 1, females coded as 2. Correlations above 0.002 in absolute value are significant ($p < .0001$).

Table 2
Partial correlation between sex and age and each of the three abilities controlling for the other two abilities.

	Sex	Age
Numeracy	−0.262	0.253
Literacy	0.201	−0.041
TPS	−0.008	−0.361

4.2. Correlational analysis

Table 1 presents the first order correlations of our study variables. As evident from the table, the correlations between the three abilities are very high, which is consistent with the idea that most of the variance in these abilities is explained by *g*. The correlation between numeracy and literacy is 0.886, which suggests that at least 79% of the variance in each of these two abilities is explained by *g* (the "true" correlation and the "true" explained variance are probably even large if the non-perfect reliabilities of the measure would be taken into account). The correlation between TPS and these two abilities is somewhat lower, suggesting that TPS is less g-saturated. Estimating the variance that is due to specific abilities (rather than GMA) is not possible with the current data. For example, the 21% of the variance in numeracy that is not explained by literacy could be attributed both to error and to specific numeracy (and vice versa regarding the prediction of literacy from numeracy). However, some evidence for the existence of specific abilities' variance can be obtained by estimating partial correlations of abilities with age and sex. As each pair of abilities could serve as a proxy for GMA, the partial correlation of age and sex with each ability controlling for the other two could be considered as a rough estimate for the correlation between the relevant specific ability and sex or age. Table 2 presents these partial correlations, indicating that age is negatively correlated with specific TPS and that females are higher on specific literacy scores and lower on specific numeracy. Our rough estimation of the relationships of age and sex with specific abilities is consistent with the literature showing that age is negatively correlated with computer skills (see Gist, Rosen, & Schwoerer, 1988) and that females are higher in literacy and lower in numeracy (Halpern, 2013). These relationships are in line with the notion that, despite the small number of tests in our data, the ability measures could be separated into general mental ability and specific abilities. Note, however, that whereas the partial correlation between sex and literacy was, as expected, positive (indicating higher literacy for females), the zero order correlation was negative (indicating higher literacy for males). This somewhat unexpected pattern of sex differences in literacy was already observed in the PIAAC as well as in other surveys, at least in the Nordic countries, and is attributed to the specific method of test construction in these surveys (Oddny & Lundetræ, in press). However, our view is that this unexpected sex difference in the zero order correlation is due to failure to control for GMA (see Brunner, Krauss, & Kunter, 2008 for a discussion on how raw ability scores change when GMA is controlled for).[5]

Table 3
Predicting wage from abilities, sex and age.

	Model 1			Model 2		
	b	stderr	β	b	stderr	β
Intercept	5.679	0.010	0.000	5.179	0.056	0.000
Numeracy	1.227	0.023	0.426	0.444	0.027	0.155
Literacy	−0.106	0.026	−0.037	0.121	0.029	0.042
TPS	−0.373	0.019	−0.130	0.315	0.023	0.110
Age				0.070	0.001	0.302
Sex				−1.469	0.025	−0.256
R^2	0.093			0.227		

Note: Age in years. Males are coded as 1, females coded as 2.

4.3. The prediction of wage from abilities

In this section we analyze the data from the perspective of the skills approach. Model 1 in Table 3 presents the results of regressing wage solely on the three abilities. The results of this model are surprising in that the coefficients of TPS and of literacy are negative. Strictly speaking this suggests that when numeracy and literacy are held constant, the higher the TPS, the lower the wage, and that when numeracy and TPS are held constant, the higher the literacy the lower the wage.

The surprising results of Model 1 could be explained by our discussion of the effects of omitted individual differences on the relationships between abilities and wage (Fig. 3). In the spirit of this discussion, we add to the model sex and age, two individual differences that have important direct effects on wage. Age is likely to have a positive effect on wage associated with the positive effect of seniority on monetary rewards in the job market (Suzuki, 1976; Poynton, 2005); females have lower wages because of factors, such as discrimination (Blau & Kahn, 2000), overall wage structure (Petersen & Morgan, 1995), and career centrality (Mayrhofer, Meyer, Schiffinger, & Schmidt, 2008). Our empirical results (Model 2 in Table 3) do indeed show that age and sex have strong direct effects on wage, and that their omission from the model results in severely biased parameter estimates: When these two individual differences are added to the model, the coefficients of all three abilities are positive.

Fig. 4 presents the parameter estimates of a path model that incorporates the effects of age and sex. The source of the sign switch of the parameter estimates between Model 1 and Model 2 in Table 3 is now apparent: when age and sex are omitted, there are spurious relationships between abilities and wage. For example, the negative effect of TPS in Model 1 is due to the negative relationship between TPS and age and the positive effect of age on wage. Note also that this path model also suggests that the sex and age wage gaps observed in our data (see Table 1) are not ability driven: They are associated with the relatively strong direct effects of sex and age on wage (−0.26 and 0.30, respectively), but not with their small indirect effects on wage, (−0.02, and − 0.05, respectively). For age, the wage gap is even the reverse of what is expected by age related differences in ability. Although the effect of age on wage mediated by ability is negative, its overall effect is positive.

4.4. The prediction of wage from principal components

The effects of abilities on wage in the skills approach confound the

[5] A somewhat different account for this sex difference is that the literacy score is influenced both by specific literacy and by GMA. The higher literacy of males is the result of a somewhat higher GMA (see Footnote 7 below) that "overcomes" the lower specific literacy.

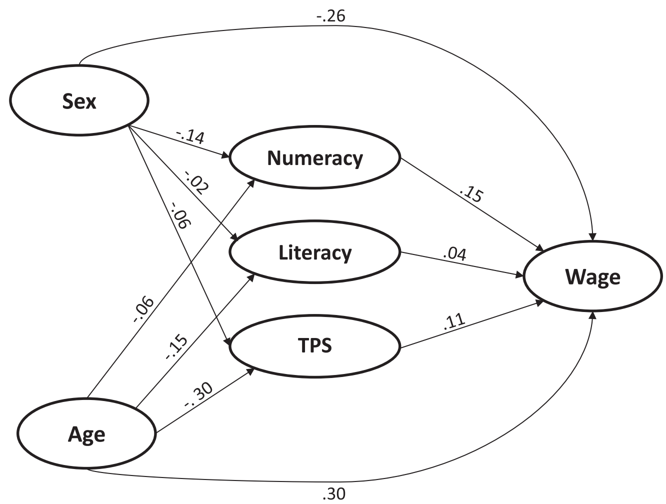

Fig. 4. A path model of the relationship between age, sex, principal components and wage.

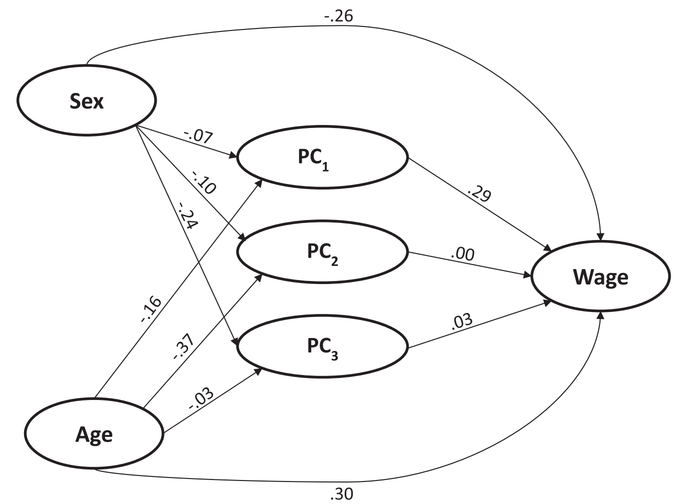

Fig. 5. Standardized coefficients of a path model of the relationship between wage and age, sex, *g* (PC_1) and specific abilities (PC_2 and PC_3).

Table 4
A principal component analysis of the three abilities.

	Principal component 1	Principal component 2	Principal component 3
Numeracy	0.961	−0.087	−0.262
Literacy	0.925	0.372	0.079
TPS	0.942	−0.276	0.190
Eigenvalue	2.666	0.223	0.111

effects of abilities as indicators of GMA with the effects of specific abilities. In this section we report the results of regressions in which wage is modeled on the basis of the unrotated principal components of the three abilities. This modeling scheme allows for a clear separation between the effect of GMA and the effects of specific abilities.

Table 4 presents the results of a principal component analysis on the three ability measures. The first principal component explained about 89% of the total variance, the second about 7.3%, and the third about 3.7%.

To test the "not much more than *g*" premise we estimated two regressions. In the first, wage was regressed solely on the first principal component, yielding an $R^2 = 0.061$. In the second, wage was regressed on all three components, yielding an $R^2 = 0.093$. Thus, in contrast to the “not much more than *g*” premise, there is a substantial increase in R^2, about 52%, when modeling wage with all the principal components instead of only the first one.

Some insight into these results is provided by Fig. 5 that presents a path model of the relationships between our two individual differences, the three principal components and wage. The results of this model suggest that the only important predictor of wage is PC_1 (the first Principal Component); the effects of PC_2 and PC_3 (the second and third Principal Components) on wage are very small. On the other hand, PC_2 and PC_3 are more strongly related to sex and age than PC_1.[6] As a result, omitting these individual differences results in a spurious relationship between wage and the non-g factors, but not between wage and *g*.

In order to appropriately examine the "not much more than *g*" premise it is necessary to control for this spurious relationship. One way to achieve this is to partial out the effect of sex and age on wage. To do this we first regressed wage on these two individual differences variables. We then performed two regressions. In the first, wage was regressed solely on the first principal component and in the second it was regressed on all three. The R^2s of the two regressions were, respectively, 0.0887 and 0.0888, suggesting that when age and sex are controlled for, there is a very small difference between the wage variance explained by the first principal component and the wage variance explained by all three components. Another way to demonstrate the negligible contribution of the non-g factors is to partial out the effects of sex and age on abilities. We first calculated the residual abilities by regressing each of the three abilities on age and sex. We then applied the standard method of estimating *g* by conducting principal component analysis on these residuals (resulting in explained variance of 90% for the first, second and third components, respectively). Finally we regressed wage on the first principal component, comparing the R^2 of this regression to the R^2 of the regression in which wage was regressed on all the three components. The R^2s of the two regressions were very similar, 0.0767 and.0763, respectively. Thus, consistent with the “not much more than *g*” premise, there is a very little increase in R^2, about 0.5%, when modeling the residual wage with all the principal components instead of only the first one. That is, the “not much more than *g*” premise holds when the effects of non-cognitive individual differences are partialled out either from wage or from abilities.[7]

Finally, the “not much more than *g*" premise can be evaluated by comparing the fit of models that have one, two or three abilities as well as a g-only model, using sex and age as a baseline model. The fit of the baseline model was 0.1509. Adding one of the abilities to the baseline model resulted in R^2 of 0.2233, 0.2207 and 0.2146 for numeracy, literacy and TPS, respectively. When two abilities are added, the R^2 are 0.2238, 0.2267 and 0.2261, depending on the ability pairs, and when all three abilities are added the R^2 is 0.2276. Thus, because of the commonality between the three ability measures there is considerable redundancy in using three measures of abilities rather than two or even one measure. This finding suggests that, consistent with the abilities-intelligence approach, all three ability measures in the PIAAC are, to a large extent, indicators of the same latent variable. Furthermore, in line with this approach, the R^2 of the *g* only model – 0.2272 – is very similar to the R^2 of the three abilities model.

[6] Yet, age and sex have small effects on PC_1·These small effects are consistent with the literature. See for example Flynn (1984) for previous results consistent with a negative effect of age on GMA, and Jackson and Rushton (2006) for previous results concerning the GMA advantage of males over females.

[7] Indeed, it is important to emphasize here that “not much more that *g*” does not mean to imply that *g* explains most of the variance in the criterion. Rather it means that most of the variance explained by cognitive abilities is attributed to *g* rather than specific abilities.

5. Discussion

Our initial attempt to examine whether the “not much more than *g*" premise applies to wage failed. We found that adding non-g factors adds about 50% to the variance explained by *g* alone. On the face of it, this finding is inconsistent with the "not much more than *g*" premise. Furthermore, we also found that in a simple model in which wage is regressed on the three abilities, the effects of two of the abilities – TPS and literacy – are negative. This finding appears to be inconsistent with what can be labeled the principle of marginal non-negativity, which suggests that when other abilities are held constant the effect of any ability on performance is non-negative (i.e., ability can only increase, but not decrease, performance). However, these two inconsistencies are cleared when individual differences that affect remuneration policies are taken into account. By adding these individual differences we control for the sex wage gap and the influence of seniority on wages, two ability-independent features of compensation in the labor market.

In the paper we draw on the literature that examined the relationship between GMA and job performance and the idea that wage is an indicator of performance showing that GMA, rather than specific abilities, is the principle determinant of wage. Yet, the difference between job performance and wage should be emphasized. Whereas job performance serves as an indicator of productivity within occupations, wage is an indicator of productivity both within and between occupations. A priori, this may suggest that specific abilities should be more powerful in predicting wage than in predicting performance. First, to some extent people are selected into occupations based on their specific abilities (e.g., engineers are high on numeracy ability, journalists high on literacy), which is likely to result in low variance in specific abilities within occupations and high variance between occupations. Second, specific abilities may be more important in determining performance in the job market as a whole than in individual occupations. For example, if people whose numeracy ability is high (relative to their GMA) receive extra compensation because numeracy is important for productivity within the entire economy more than in individual occupations, specific numeracy may be a powerful predictor of wage but not of job performance. As there is no information about job performance in our data, we cannot compare GMA to specific abilities as predictors of job performance vs. predictors of wage. However, by and large, our findings are consistent with the idea that both with regard to job performance and with regard to wage there is no much more than *g*.

In the paper we contrast two approaches to studying the relationship between abilities and wage. The first, the skills approach, suggests that wage depends on a number of different, though related, abilities. The second, the abilities-intelligence approach, suggests that various tests of mental abilities are simply different ways to measure one construct, General Mental Ability. Our analyses suggest that the abilities-intelligence approach has the same explanatory power as the skills approach, yet it is more parsimonious: It requires only a single concept (GMA) to describe the role of cognitive differences in wages. Furthermore, because of the large overlap between various abilities, trying to explain wage on the basis of a number of distinctive ability concepts is bound to lead to conceptual confusion, as it is not clear what ability is the appropriate explanatory variable. On the other hand, the abilities-intelligence approach, relying on GMA as a central construct, offers a clear conceptual framework for the study of the relationship between abilities and *wage*, suggesting that this relationship is a specific case of a general relationship between abilities and *performance*. Finally, the theoretical parsimony of the abilities-intelligence approach could also lead to empirical parsimony. If GMA is indeed the variable that underlies performance in general and wage in particular, then surveys that rely on direct measures of GMA rather than various measures of skills may require shorter interview time, which translates to considerable savings in large surveys.

The skills approach, in contrast to the abilities-intelligence approach, calls for developing theoretical postulates about individual abilities, an endeavor that cannot lend itself to empirical verification because of the high correlations between the ability measures. In fact, different abilities are seldom, if ever, used in wage models. Rather than including different abilities in each of their models, researchers usually examine models that include only one ability, verifying that the results are the same for the other abilities. For example Nieto and Ramos (in press) report results that rely only on literacy, but emphasize that "Given the high correlation between literacy and numeracy.., we only perform the next analysis using literacy skills. However, we repeat the whole analysis using numeracy skills instead of literacy skills as a robustness check" (p. 5 of the paper). Indeed in reviewing the PIAAC literature we could not find any paper that estimated models in which differences between skills were examined. A case in point is a paper by Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) the most cited paper based on the PIAAC data. The authors inform the reader that "All three scales are intended to measure different dimensions of a respondent's skill set. The IALS, the predecessor of PIAAC, suffered from pairwise correlations of individual skill domains that exceeded 0.9, making it virtually impossible to distinguish between different skills" (p. 108). They then suggest that "The score domains in PIAAC are less strongly correlated with an individual-level correlation between numeracy and literacy (TSP) of 0.85 (0.76)". Yet they state "we will focus on numeracy skills, but we show that our results do not depend on the choice of a particular measure of cognitive skills." The confused reader asks herself why emphasize the effort to construct measures that are not highly correlated if the focus is only on one of these measures when in fact the results are independent of whichever measure is used.

Finally, we emphasize that although the current analyses highlight the central role of General Mental Ability in understanding wage differentials, it does not suggest that studying and understanding individual abilities is unimportant. Our results do show that specific abilities – those portions of individual abilities that do not depend on GMA – are meaningful constructs by documenting their relationship with sex and age. But our analyses also suggest that despite these indications for their construct validity, specific abilities play a trivial role in predicting wages. The effects of age and sex on wages cannot be explained by differences in the specific abilities of males and females or by the difference in the abilities of older and younger workers, but by remuneration policies that are unrelated to measured abilities. The ability construct that is relevant to predicting wages is GMA, and not specific abilities.

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