New Evidence on Skill Growth and Wages from the Canadian Longitudinal International Study of Adults (LISA)

Preliminary Draft

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1 Introduction-Abstract

The Canadian Longitudinal International Study of Adults (LISA) provides a combination of a skill or ability test measure, an innovative measure of an individual's overall skill growth, and measures of job tasks or skills observed at the level of the individual worker rather than inferred from the worker's occupation. We exploit this unique combination of measures to examine human capital empirical specifications that extend beyond those typically used in the previous literature. We examine the contribution of the skill measures in LISA to human capital explanations of both wage level and wage growth variation across individuals in the LISA panel. Relative to a standard human capital empirical specification that includes only education and job experience measures, the extended specifications result in substantial improvement in explanatory power for both log wage level and log wage growth equations.

The outline of the paper is as follows. Section 2 outlines the human capital framework for the paper, beginning with a standard empirical implementation based on Mincer log wage or log wage growth equations, and extensions within this framework made possible by the skill measures in LISA. The interpretation within the basic human capital framework of skill variables constructed from the LISA skill measures are discussed. Section 3 presents estimates of Mincer log wage equations for standard and extended specifications and discusses the contribution of the measures in the LISA panel to the understanding of wage levels beyond standard specifications. The results show an important role for the new measures. Section 4 repeats Section 3 for log wage growth equations. A major result is that the new skill growth measure substantially improves explanatory power in wage growth equations. In Section 5 the robustness of the basic results to the inclusion of a variety of controls used in analyses that focus on log wage or wage growth determinants that go beyond those used in the standard human capital specification is examined, and some decomposition results are presented. Section 6 concludes with some suggestions for future work based on the LISA panel.

2 Interpretation of the Skill Measures in LISA within the Standard Human Capital Framework

The basic human capital framework has both stocks of human capital at a point in time and flows that either increase (human capital production) or decrease (depreciation) the stocks over time. Wages are generated by renting out some or all of the stock in a period to the market at a competitive rental rate. Wage growth occurs when either the rental rate increases or a larger stock is rented to the market. The predicted life-cycle profile from models of optimal life-cycle human capital investment are most often captured empirically (descriptively) in Mincerian log wage equations that deal with wage levels and differenced log wage equations that capture growth. The original Mincer log wage equation used as "independent variables" years of schooling and years of experience.[1] After entry into the labour market years of schooling are constant, so that schooling mainly plays the role of a measure of human capital stock at the time of labour market entry. Years of experience play the role of capturing the net additions to the stock of human capital rented to the market during the post school period. At a minimum a quadratic specification for experience is specified to allow for a concave shape implied by theories of optimal life-cycle investment, such as Ben Porath (1967).

A disadvantage of the original measures used in the Mincer log wage specification for explaining individual variation in wages (or wage growth) is that individuals are distinguished only by their years of schooling and years of experience. There is strong evidence, however, that there is a large amount of individual variation in both the stock of human capital on labour market entry, and changes in that stock (investment levels) over time within education and experience groups. In addition, there is also evidence for variation in rental rates faced by individuals based on characteristics such as sex, race, immigration status, etc. In response to this, other independent variables have been added to capture this individual variation within schooling and experience category. These include measures of "ability" that capture individual variation in some initial human capital stock or in the ability to produce human capital over the lifecycle. They also include race and sex to address issues of discrimination that may lead to variation in the rental price for human capital across individuals.[2]

The main object of this paper is to examine the contribution of skill measures in the LISA panel to the understanding of individual variation in wage levels and wage growth within schooling and experience groups used in standard specifications. The basic framework of optimal investment in a single type of general human capital over the life-cycle used in Ben Porath (1967) was extended to multiple types of general human capital identified by education level, in part as a response to

[1]See Mincer (1974)

[2]Neal (1996) uses the Armed Forces Qualifying Test (AFQT) as a measure of pre-market skills; Hanushek et al. (2015) uses a Program for the International Assessment of Adult Competencies (PIAAC) score in an international study of returns to skill; Robinson and Poletaev (2008) construct Dictionary of Occupational Titles (DOT) and occupation level skill measures; Gathmann and Schonberg (2010) and Autor and Handel (2013) introduce measures of skills or tasks measured at the individual level. The availability of long panels in the US has also lead to inclusion of measures of firm, industry and occupation tenure to capture types of specific human capital that go beyond the focus on general human capital in the standard framework.

an observed increase in the "college wage premium". This literature includes Heckman, Lochner and Taber (1998) and Bowlus and Robinson (2012), as well as a substantial literature concerned with skill biased technical change, leading to a constant elasticity of substitution (CES) framework with (at least) two types of general human capital, identified by education level, recently called the "canonical model" by Acemoglu and Autor(2011).[3] This framework retains a reasonable level of parsimony in that there are relatively few "types" of human capital, with their associated prices, and optimal life-cycle human capital investment profiles can be derived for each type. To capture this profile in the post-school period, however, some polynomial in experience is still generally used in the absence of more direct measures.

2.1 Skill Measures in LISA

LISA is a rich panel survey that collects information from 34,000 Canadians aged 15+ about their jobs, education, health and family. It spans the years 2012-2020 on a biennial basis and contains monthly labour market histories along with standard wage and worker characteristics. The information on educational achievement in LISA is used to define three "types" of human capital identified with three education levels: (1) high school graduate and below; (2) some college or university beyond high school; (3) BA degree or higher. Measures of experience are derived from the labour market histories in LISA and represent actual rather than "potential" experience. LISA also includes various measures of skills that are used to extend the basic framework beyond the specifications using only education and experience.

2.1.1 PIAAC Scores

The first of the skill measures is the set of Program for the International Assessment of Adult Competencies (PIAAC) scores. A representative subsample (2/3) of respondents aged 16-65 were administered the PIAAC questionnaire in 2012. Each respondent received a numeracy and literacy score. This is a new ability measure for a Canadian data set. There is a roughly analogous measure, the Armed Forces Qualifying Test (AFQT), available in US National Longitudinal Survey of Youth (NLSY79 and NLSY97) that has been widely used in estimating log wage equations for young men. Within the standard human capital framework, the AFQT measure has been interpreted as an ability measure that measures either the "initial" stock of human capital at the time of labour market entry,

[3]See, for example, Murphy and Welch (1990), Katz et al. (1992), Autor et al.(2003), Autor et al.(2008) and Bowlus et al. (2023).

Table 1: Experience Profile of PIAAC Test Scores

	Numeracy		**Literacy**	
	Men	**Women**	**Men**	**Women**
experience	-0.0023	0.0028	-0.0044	-0.0025
	(0.0070)	(0.0058)	(0.0070)	(0.0058)
experience^2	-0.0001	-0.0002	-0.0001	-0.0001
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
mid education	0.6012***	0.4786***	0.5323***	0.5145***
	(0.0609)	(0.0526)	(0.0609)	(0.0533)
high education	1.2277***	1.0943***	1.1494***	1.1267***
	(0.0633)	(0.0529)	(0.0627)	(0.0537)
non-white	-0.5081***	-0.6412***	-0.5621***	-0.7151
	(0.0874)	(0.0665)	(0.0872)	(0.0665)
constant	-0.1770**	-0.4886***	-0.1919**	-0.3505
	(0.0813)	(0.0581)	(0.026)	(0.0574)
N	2600	3200	2600	3200
R^2	0.240	0.253	0.224	0.263

Notes:
[1] Standard errors in parentheses and clustered by individual.
[2] $* \; p < 0.1$, $** \; p < 0.05$, and $*** \; p < 0.01$.

or the ability to produce human capital over the life-cycle, or both.[4] In any case it is measured only once and is treated as a constant at the end of the schooling period.

In the NLSY panels in the US, the AFQT is administered to respondents in a relatively narrow early age range. In LISA the PIAAC tests are taken by all respondents 15-65. To provide some evidence on whether PIAAC scores in LISA could be treated as constants, similar to AFQT scores in the US panels, we examine the pattern of PIAAC scores by experience. The results are presented in Table 1.

The PIAAC scores are regressed on a quadratic in experience with dummy variables for education level and race. They are estimated separately for males and females and show a flat profile in experience for both measures. On this basis we interpret them as measures of the "initial" stock of human capital at the time of labour market entry and/or an ability to produce human capital over the life-cycle. The scores themselves are assumed to have been produced in the period up to entry into the job market and to depend on all the basic determinants of early human capital investment. Thus, they provide individual variation in the level of human capital at the end of the schooling period within education levels. They may also provide variation in the rate of human capital growth

[4] See, for example, Neal and Johnson (1996).

over the life-cycle within education groups.

2.1.2 Job Skill Measures

The second form of skill measure is based on questions regarding the respondent's job. There are two sets of questions in LISA that are asked in alternate waves, both dealing with the nature of an employee's job. Both types of job-based measures were observed for respondents employed during the reference week. The set of questions used in this paper provide new individual skill level measures that focus on the level at which each of 6 skills were performed on the job. The skills are reading, writing, math, communication, manual dexterity and strength. Workers are first asked to pick a number from 1-7 to indicate the "importance" of the skill for their job. If the importance level is at least "somewhat important" workers are then asked to pick a number from 1-7 to indicate the level at which the skill is performed. In answering these questions regarding the level of skill, several "anchor points" are provided to associate a number on the scale - say, 6 - with a description of the level of the skill - say, for the reading skill, reading a journal article. This measure is available for the 2014 and 2018 waves.[5]

There are several issues that arise concerning the interpretation of the job skill measures. In the simplest case they are measures of the level of stocks of heterogeneous human capital within the types defined by education group. The panel aspect provides repeated measures of these levels over time. A major problem with such a wide range of detailed measures is that to treat them all as measures of different stocks would imply as many different prices. This detracts from the parsimony of more simple human capital models, which restrict the problem to a small number of human capital "types" (usually two to four) based on education level.[6] To deal with this problem we reduce the detailed information on job skills to two or three types, which may themselves be interpreted as "subtypes" within the two to four types based on education level as in the previous literature. Using the set of questions that focus on the level of skill, measures of "cognitive", "dexterity" and "strength" skill levels in the post schooling period are created. For the cognitive skill level principle component analysis (PCA) is performed, on the four skills, reading, writing, math and communication. The dexterity and strength skill measures were constructed as standardized measure of scores on the

[5] The second set of questions are PIAAC "frequency of task" questions. These are available for 2012 (PIAAC sample only), 2016 and 2020. These are similar to some task measures used in the previous literature (see, for example, Gathmann and Schönberg (2010)). Since these questions focus on the frequency with which certain tasks are performed, they are less immediately useful for the construction of skill levels in the post school period.

[6] See, for example, Heckman, Lochner and Taber (1998), Bowlus and Robinson (2012) and Bowlus et al. (2023)

original scales for dexterity and strength.

If we have measures of the levels of heterogeneous skills at various points in the life-cycle, these may be able to substitute to some extent for the "black box" of the experience quadratic. Moreover, they can provide individual variation within education and experience groups. Within this human capital interpretation, higher levels of any skill, other things equal, should generate higher wages and larger increases in levels should generate higher wage growth. The optimal life-cycle profile for the heterogeneous skills is more complicated than for a single skill within education group. However, a relatively broad based skill represented by the cognitive composite may be a good candidate for a skill that optimally increases throughout the life-cycle, whereas the dexterity or strength skill levels may decline at some point in an optimal portfolio for some groups of workers to the extent that some careers involve shifts into more emphasis on supervisory or managerial skills as careers advance.

Table 2: Experience Profile of Job Skills

	Cognitive		**Dexterity**		**Strength**	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
experience	0.0232***	0.0284***	0.0261***	0.0152**	0.0165**	0.0007
	(0.0066)	(0.0061)	(0.0070)	(0.0064)	(0.0074)	(0.0054)
experience^2	-0.0003**	-0.0005***	-0.0004***	-0.0002*	-0.0003**	-.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
numeracy	0.2688***	0.2710***	-0.0541*	-0.0674**	-0.1535***	-0.1972***
	(0.0339)	(0.0259)	(0.0301)	(0.0291)	(0.0278)	(0.0252)
mid education	0.3410***	0.2694***	0.0307	0.0935*	-0.0678	0.0596
	(0.0717)	(0.0552)	(0.0626)	(0.0550)	(0.0664)	(0.0543)
high education	0.7965***	0.6546***	0.5197***	-0.0854	-0.7361***	-0.1514***
	(0.0913)	(0.0552)	(0.0802)	(0.0657)	(0.0689)	(0.0584)
non-white	-0.0927***	-0.1517**	-0.1250	0.0416	-0.2192***	-0.0072
	(0.0950)	(0.0614)	(0.0764)	(0.0628)	(0.0637)	(0.0575)
constant	-0.7157***	-0.5949***	-0.0618	-0.2156***	0.3969***	-0.1609***
	(0.0841)	(0.0586)	(0.0775)	(0.0641)	(0.0785)	(0.0560)
N	3700	4100	3700	4100	3700	4100
R^2	0.268	0.229	0.091	0.019	0.158	0.070

Notes:
[1] Standard errors in parentheses and clustered by individual.
[2] $*\ p < 0.1$, $**\ p < 0.05$, and $***\ p < 0.01$.

Within the broad human capital framework, heterogeneous skill levels are assumed to be (potentially) produced throughout the life-cycle in amounts that depend on education level and PIACC ability measure. A descriptive analysis is provided in Table 2. The cognitive, dexterity and strength skill levels are regressed on a quadratic in experience, an ability measure represented by the PIAAC numeracy score, and dummy variables for race and education group separately for males and females. Both cognitive and manual dexterity have the usual Ben Porath concave shape with highly significant coefficients for the experience quadratic for the cognitive skill and for manual dexterity for males. Strength also shows a concave shape for males but not for females.[7] Both education level and the PIAAC ability measure have highly positive and significant effects on the level of cognitive skill for both men and women. In contrast, there is no similar pattern for manual dexterity or strength.

2.1.3 Skill Change Measures

The most novel skill questions in LISA represent a self reported summary measure of the respondent's skill change over time. Once we allow for heterogeneous human capital within a limited number of types of human capital defined by education group, the optimal life-cycle human capital investment problem becomes complicated. Retaining the simplifying assumption that the objective is to maximize the discounted sum of lifetime earnings, the individual now has to solve for an optimal path of a portfolio of stocks with different prices instead of a single stock with a single price. There is no longer the evolution of a single stock that is proportional to earnings via a single price. We assume that the individual "solves" this problem, potentially increasing some stocks while letting others decline via depreciation and that the answers given in the summary skill change questions in LISA are informative about the direction and magnitude of the optimal portfolio.

There are two questions dealing with skill change. First, respondents are asked : "Thinking about the skills you use on your current job, would you say that your skills have changed over the last two years?" If the answer is "yes", respondents are then asked:

"Has your skill level ...?"

1. Decreased (for example, memory is worse so tasks take longer; manual dexterity is not as good as before; I generally find it harder to achieve as much as I did before)
2. Increased somewhat (for example, I do things a little more quickly; I can do things at a higher level than I could before; I can do new things)
3. Increased a lot (for example, I am much better at my job; I have learned a lot more; I can do many more things, or some new things at a higher level)

[7] The PIAAC numeracy and literacy scores are highly correlated. The same pattern of results is obtained if the PIAAC literacy score is used to replace the numeracy score.

These questions are asked in all waves starting in 2014. As noted earlier, in a standard Mincer log wage equation the life-cycle profile of (the value of) an individual's human capital supplied to the market is proxied by a quadratic in experience, so that two respondents with the same experience level (and given, say education level, sex and race) are assumed to have accumulated the same amount of skill since labour market entry. If it was possible to observe the LISA skill change questions since entry into the labour market they could be integrated back to the point of entry into the labour market providing an individual based measure of the skill accumulated post full time schooling up to any given point in the respondent's labour market history, i.e. up to any experience level. In contrast to standard models this would provide a measure of individual heterogeneity in human capital accumulation *within* experience level. This would solve the problem of finding good measures of each of the heterogeneous skills and aggregating them appropriately for use in a log wage equation. Unfortunately, given the panel length to date, this cannot be done in this paper. However, we can use this variable in log wage change equations, where the change in experience is the same for all (continuously working) individuals and thus cannot help explain individual variation in wage growth.

Optimal life-cycle human capital accumulation models generally show a concave life-cycle profile with large early production levels that decline over the life-cycle. To examine the correspondence between the new skill growth measure in LISA and this predicted pattern, we examine the self reported skill change for different experience groups using an ordered probit. The independent variables for this analysis are the PIAAC numeracy score and dummy variables representing five experience groups, the three education levels, sex and race. The omitted categories are the lowest experience (zero to 8 years) and education (high school or less) groups for white males. The results are reported in Table 3. As expected, there is a strong and significant pattern of declining human capital accumulation over the life-cycle and larger skill growth for the higher education groups. In addition, there is a significantly positive effect of an ability measure, as represented by the PIAAC numeracy score, on this measure of skill growth.

Table 3: Experience Profile of the Summary Skill Change Measure

	Summary Skill Increase
experience [8,16) years	-0.1587***
	(0.0516)
experience [16,25) years	-0.3331***
	(0.0537)
experience [25,35) years	-0.5380***
	(0.0519)
experience 35+ years	-0.6674***
	(0.0627)
PIAAC Numeracy	0.0477**
	(0.0217)
mid education	0.1104**
	(0.0495)
high education	0.1393**
	(0.0544)
non-white	-0.0594
	(0.0487)
female	0.0179
	(0.0355)
cutoff 1	-0.3724***
	(0.0525)
cutoff 2	0.4810***
	(0.0527)
N	12400

Notes:
[1] Standard errors in parentheses
[2] $*\ p < 0.1$, $**\ p < 0.05$, and $***\ p < 0.01$.

3 Estimated Log Wage Equations

In this section Mincerian log wage equations are estimated with and without the additional LISA ability and job-based skill variables. The main sample restrictions are as follows. Respondents must be 18-65; they are represented as an observation in the sample whenever they are a full-time employee during the reference week.[8] Observations with weekly wages greater than $5,000 or hourly wages less than the provincial minimum are dropped. The log wages equations are estimated separately for males and females and for each education group. The results are reported in Table 4 for males and Table 5 for females.

[8] This excludes respondents who are unpaid family workers or self-employed.

Table 4: Log Wage Equation for Men

	LOW EDUCATION			**MID EDUCATION**			**HIGH EDUCATION**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
experience	0.0249***	0.0245***	0.0228***	0.0326***	0.0313***	0.0308***	0.0425***	0.0404***	0.0400***
	(0.0092)	(0.0090)	(0.0080)	(0.0070)	(0.0070)	(0.0069)	(0.0095)	(0.0093)	(0.0088)
exper^2	-0.0005**	-0.0004**	-0.0004*	-0.0005***	-0.0005***	-0.0005***	-0.0007***	-0.0006***	-0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
numeracy		0.1203***	0.0645**		0.1525***	0.1228***		0.1705***	0.0997***
		(0.0273)	(0.0267)		(0.0307)	(0.0287)		(0.0295)	(0.0276)
cognitive			0.2118***			0.1371***			0.2142***
			(0.0347)			(0.0234)			(0.0292)
cog x imp			0.0535***			0.0581***			-0.0121
			(0.190)			(0.0188)			(0.0220)
dexterity			-0.0043						
			(0.0382)						
dex x imp			0.0878***						
			(0.0295)						
strength			0.0577						
			(0.0371)						
str x imp			0.0300						
			(0.0282)						
non-white	-0.2273**	-0.1384*	-0.1547**	-0.1199*	-0.0679	-0.0688	-0.1822***	-0.0757	-0.0339
	(0.0931)	(0.0838)	(0.0624)	(0.0621)	(0.0546)	(0.0523)	(0.0587)	(0.0577)	(0.0530)
constant	6.5771***	6.5714***	6.4924***	6.6281***	6.5620***	6.5858***	6.8021***	6.6322***	6.5735***
	(0.0967)	(0.0970)	(0.0926)	(0.0685)	(0.0736)	(0.0736)	(0.0926)	(0.0868)	(0.0854)
N	700	700	700	900	900	900	800	800	800
R^2	0.066	0.126	0.268	0.075	0.149	0.191	0.141	0.219	0.308

Notes:
[1] Standard errors in parentheses, clustered by individual identifiers.
[2] Year dummy is included but not reported.
[3] $*\ p < 0.1$, $**\ p < 0.05$, and $***\ p < 0.01$.

The benchmark (columns 1, 4 and 7) standard Mincer log wage equation has only the quadratic in experience and dummy variables for race and year as independent variables, given the separation by education group and sex. The pattern for experience is as expected, showing a generally highly significant concave shape that shifts up and is steeper for higher education groups. The pattern is the same for men and women.[9] The race dummy is also statistically significant. Non-whites have, in general, substantially lower wages than whites.

The availability of PIAAC test scores makes it possible to augment this benchmark with an ability measure that can capture individual variation within education groups in the initial stock of human capital at the time of labour market entry. The numeracy and literacy PIAAC test scores are highly correlated. Following Hanushek et al. (2015) we use the PIAAC numeracy score as the default ability measure. Columns 2, 5 and 8 report the results after this ability measure is added to the benchmark specification. A higher score has a strong statistically significant effect on wages for all education groups for both males and females. It also captures a substantial amount of the residual variation compared to the benchmark. The R^2 values increase for both men and women across all education groups, close to doubling for the low and mid education groups.

It is also noticeable that the inclusion of the ability measure substantially reduces the wage difference between whites and non-whites. In many cases the non-white dummy variable becomes insignificant. This mirrors results for the US reported in Neal and Johnson (1996) for young men and women entering the labour force in the context of an analysis of employer discrimination, where the AFQT score is used as an ability measure. More generally, AFQT sores have been used in US panels to examine sources of pre-market skills, discrimination and employer learning of a worker's true ability.[10] It is beyond the scope and focus of this paper to examine these issues further in LISA with the PIAAC test measures. However, the patterns in Tables 4 and 5, suggest this would be a good topic for future research.

The final columns (3, 6 and 9) in Tables 4 and 5 add the heterogeneous skill level measures. PCA measures for a "cognitive" skill, together with an interaction with its importance on the job, yields positive and statistically significant effects on log wages for both males and females for all education groups. Preliminary analysis indicated that measures for "dexterity" and "strength" only appear to function as skill measures for the low education group for males. Thus, these are only included in

[9]The only exception is the statistical insignificance for the experience profile for women in the lowest education group.

[10]See, for example, Neal and Johnson (1996), Altonji and Pierret (2001), and Arcidiacono et al. (2010).

Table 5: Log Wage Equation for Women

	LOW EDUCATION			**MID EDUCATION**			**HIGH EDUCATION**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
experience	0.0115	0.0084	0.0092	0.0188***	0.0151**	0.0131**	0.0428***	0.0459***	0.0424***
	(0.0084)	(0.0084)	(0.0084)	(0.0069)	(0.0065)	(0.0064)	(0.0090)	(0.0085)	(0.0069)
$exper^2$	-0.0001	-0.0000	-0.0001	-0.0002	-0.0002	-0.0001	-0.0008***	-0.0008***	-0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
numeracy		0.1178***	0.0687**		0.1294***	0.0903***		0.1886***	0.1507***
		(0.0310)	(0.0320)		(0.0283)	(0.0299)		(0.0238)	(0.0217)
cognitive			0.1697***			0.1745***			0.1865***
			(0.0294)			(0.0195)			(0.0230)
cog x imp			0.0458*			0.0106			0.0150
			(0.0235)			(0.0156)			(0.0192)
non-white	-0.1210*	-0.0073	-0.0019	-0.2371***	-0.1233	-0.0851	-0.2109***	-0.1133**	-0.0743*
	(0.0702)	(0.0763)	(0.0771)	(0.0738)	(0.0787)	(0.0734)	(0.0487)	(0.0449)	(0.0419)
constant	6.3489***	6.4206***	6.4114***	6.4556***	6.4814***	6.4844***	6.6617***	6.5052***	6.4435***
	(0.0904)	(0.0932)	(0.0941)	(0.0701)	(0.0777)	(0.0763)	(0.0641)	(0.0645)	(0.0602)
N	600	600	600	900	900	900	900	900	900
R^2	0.053	0.114	0.208	0.097	0.148	0.272	0.151	0.280	0.342

Notes:
[1] Standard errors in parentheses, clustered by individual identifiers.
[2] Year dummies are included but not reported.
[3] $* \; p < 0.1$, $** \; p < 0.05$, and $*** \; p < 0.01$.

column 3 in table 4. The inclusion of the cognitive skill reduces the effect of the numeracy score, though its effect is still relatively strong and significant. Since the PIAAC test scores are assumed to be determinants of both the cognitive skill level at the time of labour market entry and the growth in the score in the post school period, the PIAAC test scores likely pick up the effect of the cognitive skill level in specifications that omit this skill measure.

The R^2 values increase again for both men and women across all education groups. The combined effect, relative to the benchmark, is to more than double the explanatory power for all groups, and close to triple it for the low education group. Thus, the availability of these measures provides a deeper understanding of the determination of wages and the variation in wages across individuals within a human capital framework implemented using a Mincerian empirical model.

4 Estimated Log Wage Growth Equations

The contribution of the novel skill growth measure in LISA and of changes in the heterogeneous skills level measures to explaining individual variation in wage growth is examined in this section.

4.1 Changes in Detailed Skill Measures

In principle, changes in the measured levels of heterogeneous skills used in the log wage equations of the previous section could be used to explain wage growth. As noted in the previous section, it is difficult to construct good measures of heterogeneous skills, that apply for most groups, except for the cognitive skill measure. However, the overall importance of the cognitive skill measure in explaining wages even in the presence of the PIAAC numeracy test measure suggests some potential for changes in this measure to explain variation in wage growth. The first column for each education group in Table 6 reports the results for the benchmark specification that includes dummy variables for the experience groups defined earlier, and for race and sex.[11] The results show the expected pattern for experience groups with declining human capital production over the life-cycle. Changes in the heterogeneous skill measures are added in the second column for each education group. For the low education group the coefficients on the heterogeneous skill changes are insignificant and there is essentially no change in explanatory power. There is a significant positive effect of the cognitive skill change for the mid education group and an increase in the R^2. For the high education group

[11] Preliminary analysis of the wage growth equation showed no significant difference, using a Chow test when estimating for males and females separately, allowing for pooling in Table 6.

the change in the cognitive skill level is marginally significant, but yields only a small change in explanatory power.

Table 6: Four-year wage growth

	LOW EDUCATION		**MID EDUCATION**		**HIGH EDUCATION**	
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive change		0.0029		0.0073**		0.0065*
		(0.0031)		(0.0030)		(0.0034)
Dexterity change		-0.0011				
		(0.0033)				
Strength change		0.0028				
		(0.0033)				
$8 \leq exp < 16$	-0.0146	-0.0146	-0.0156	-0.0148	-0.0236*	-0.0246*
	(0.0168)	(0.0168)	(0.0123)	(0.0120)	(0.0137)	(0.0130)
$16 \leq exp < 25$	-0.0391**	-0.0386**	-0.0161	-0.0152	-0.0336**	-0.0349***
	(0.0157)	(0.0158)	(0.0114)	(0.0111)	(0.0134)	(0.0127)
$25 \leq exp < 35$	-0.0450***	-0.0439***	-0.0277***	-0.0262**	-0.0448***	-0.0459***
	(0.0154)	(0.0156)	(0.0106)	(0.0103)	(0.0134)	(0.0127)
35+ years exp	-0.0492***	-0.0492***	-0.0300***	-0.0287***	-0.0554***	-0.0569***
	(0.0156)	(0.0156)	(0.0107)	(0.0103)	(0.0139)	(0.0131)
female	-0.0026	-0.0026	0.0011	0.0009	0.0042	0.0041
	(0.0054)	(0.0055)	(0.0045)	(0.0044)	(0.0045)	(0.0044)
non-white	-0.0107*	-0.0107*	0.0057	0.0049	0.0064	0.0057
	(0.0064)	(0.0063)	(0.0087)	(0.0087)	(0.0055)	(0.0054)
constant	0.0614***	0.0613***	0.0391***	0.0378***	0.0559***	0.0575***
	(0.0150)	(0.0150)	(0.0104)	(0.0100)	(0.0134)	(0.0126)
N	600	600	1100	1100	1000	1000
R^2	0.065	0.068	0.018	0.029	0.052	0.058

Notes:
[1] Standard errors in parentheses, clustered by individual identifiers.
[3] $* \; p < 0.1$, $** \; p < 0.05$, and $*** \; p < 0.01$.

Why does there appear to be only a minor role for the change in the level of cognitive skill? One possibility is that in recording levels on the original seven point scales there is likely to be some measurement error. The measurement error relative to the true level may be relatively small, but as is frequently the case, the differencing, in this case over a four year period, greatly increases the measurement error relative to the true change. In any case, the use of changes in measures of heterogenous job-based skills of the type examined here does not appear to be very useful.

4.2 The Summary Skill Change Measure

Given the results of the previous section, changes in the detailed job skills are dropped from the analysis. The new summary skill growth measure in LISA is measured in all waves starting in 2014 so that it is possible to examine wage growth over a much larger sample of pooled 2 year intervals. The descriptive analysis of this measure in Table 3 shows a clear "Ben-Porath" life-cycle shape which lends credibility to the measure as one that can pick up individual variation in skill accumulation within a level of experience.

Table 7: Two-year wage growth

	LOW EDUCATION		**MID EDUCATION**		**HIGH EDUCATION**	
	(1)	(2)	(3)	(4)	(5)	(6)
small skill change		0.0084		0.0086**		0.0118***
		(0.0053)		(0.0038)		(0.0036)
large skill change		0.0180***		0.0279***		0.0295***
		(0.0059)		(0.0046)		(0.0045)
$8 \leq exp < 16$	-0.0457***	-0.0451***	-0.0311***	-0.0285***	-0.0258***	-0.0223***
	(0.0096)	(0.0097)	(0.0089)	(0.0086)	(0.0073)	(0.0071)
$16 \leq exp < 25$	-0.0575***	-0.0547***	-0.0474***	-0.0427***	-0.0458***	-0.0415***
	(0.0089)	(0.0092)	(0.0086)	(0.0085)	(0.0071)	(0.0068)
$25 \leq exp < 35$	-0.0649***	-0.0609***	-0.0516***	-0.0459***	-0.0586***	-0.0527***
	(0.0089)	(0.0092)	(0.0085)	(0.0083)	(0.0072)	(0.0070)
35+ years exp	-0.0807***	-0.0758***	-0.0563***	-0.0494***	-0.0641***	-0.0564***
	(0.0089)	(0.0094)	(0.0086)	(0.0085)	(0.0080)	(0.0078)
female	-0.0110***	-0.0103**	-0.0020	-0.0021	-0.0026	-0.0032
	(0.0042)	(0.0042)	(0.0031)	(0.0030)	(0.0030)	(0.0029)
non-white	0.0059	0.0079	-0.0090	0.0101*	0.0065*	0.0060*
	(0.0068)	(0.0067)	(0.0058)	(0.0057)	(0.0036)	(0.0035)
constant	0.0964***	0.0860***	0.0716***	0.0564***	0.0749***	0.0588***
	(0.0081)	(0.0094)	(0.0085)	(0.0090)	(0.0072)	(0.0071)
N	3600	3600	5600	5600	5100	5100
R^2	0.045	0.049	0.021	0.033	0.038	0.052

Notes:
[1] Standard errors in parentheses, clustered by individual identifiers.
[3] $* \; p < 0.1$, $** \; p < 0.05$, and $*** \; p < 0.01$.

The first column for each education group in Table 7 reports the results for the benchmark specification that includes dummy variables for the experience groups, and for race, sex and year for the larger sample of pooled 2 year intervals.[12] The results for the larger sample show the same expected pattern for experience groups with declining human capital production over the life-cycle. The second column for each of the education groups adds a set of dummy variables for the summary skill change measure. The omitted category is no change. In contrast to using changes in the heterogeneous skill level measures in the previous section, using the summary skill change measure produces highly significant effects, with the largest summary skill increases producing the largest wage increases within each education group. Further, the explanatory power is increased for all

[12] The male and female samples are pooled for each education group based on the results of Chow tests.

education groups. The lowest education group has the least increase in the R^2 of only 9%. This group has the flattest overall life-cycle profile after the schooling period so that the potential for large individual variation in post school investment in human capital is likely to be small. For the higher levels of education there is a much larger increase in the R^2, with a 57% increase for the mid-education group and a 37% increase for the high education group.

These results illustrate the usefulness of the summary skill growth measure as a simple way to increase the explanatory power of standard log wage growth equations. It can pick up variation across individuals within education and experience levels in investment in human capital in the post-schooling period that is not measured in standard specifications. The measure has a low "questionnaire" cost, in that it only requires a few simple questions, thus not adding significantly to the burden of the respondent. As noted in Section 2.1.3, it also has the advantage of offering a simple solution to the problem of "weighting" the changes in the components of a multiple skill portfolio over the life-cycle.

5 Robustness and Decompositions

The analyses in the preceding sections uses a human capital framework, implemented within various forms of Mincer log wage equations, and incorporating new measurement of human capital stocks or changes in those stocks derived from information available in LISA that can be readily interpreted within that framework. In this section we examine the robustness of these results to the inclusion of other measures available in LISA that have been used in the previous literature studying wages that reflect wage determination mechanisms that go beyond a simple human capital framework. We also present some decomposition results regarding the importance of this broader list of variables, relative to the new measures, in explaining wage levels or wage growth in a statistical sense.

Occupation dummy variables have frequently been included in log wage equations in the previous literature. We construct a set of occupation dummy variables to include in the specification for log wages reported in Tables 4 and 5, and examine their effect on the coefficients of the LISA skill measures. Occupation can play various roles in determining wage levels. First, they may capture variation in skill levels of heterogeneous skills in the absence of direct measures and hence could have some interpretation within the human capital framework. Second, they may reflect compensating differentials for variation across occupations in non-wage aspects of the jobs involved. Table 8 reports

Table 8: Occupation and Job Skills

	LOW EDUCATION		**MID EDUCATION**		**HIGH EDUCATION**	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
experience	0.0178**	0.0137**	0.0309***	0.0131**	0.0397**	0.0382***
	(0.0071)	(0.0064)	(0.0062)	(0.0055)	(0.0079)	(0.0062)
experience^2	-0.0003*	-0.0002	-0.0005***	-0.0001	-0.0007***	-.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
numeracy	0.0558**	0.0451	0.1234***	0.0872***	0.0861***	0.1223***
	(0.0236)	(0.0283)	(0.0288)	(0.0291)	(0.0262)	(0.0218)
cognitive	0.2041***	0.1445***	0.1333***	0.1495***	0.1660***	0.1555***
	(0.0316)	(0.0276)	(0.0243)	(0.0190)	(0.0266)	(0.0225)
cog x imp	0.0485***	0.0392	0.0546***	0.0244	-0.0034	0.0228***
	(0.0170)	(0.0272)	(0.0189)	(0.0153)	(0.0203)	(0.0191)
dexterity	-0.0126					
	(0.0336)					
dex x imp	0.0688**					
	(0.0274)					
strength	0.0224					
	(0.0272)					
str x imp	0.0217					
	(0.0245)					
non-white	-0.1210***	-0.0381**	-0.0336	-0.0705	-0.0358***	-0.0473
	(0.0560)	(0.0292)	(0.0524)	(0.0629)	(0.0485)	(0.0405)
Management	0.3368***	0.3236***	0.3349***	0.4208***	0.4548***	0.4603***
	(0.0996)	(0.0912)	(0.0732)	(0.0689)	(0.0974)	(0.0883)
Business	0.1537**	0.2423***	0.0406	0.2127***	0.3529***	0.2096***
	(0.0753)	(0.0481)	(0.0890)	(0.0520)	(0.0960)	(0.0758)
Science	0.3113***	0.3811**	0.2032***	0.3696***	0.2819***	0.4035***
	(0.1054)	(0.1925)	(0.0641)	(0.0691)	(0.0942)	(0.0855)
Health	-0.3888	0.2127***	-0.0049	0.3070***	0.1629	0.4861***
	(0.3286)	(0.0843)	(0.0987)	(0.0576)	(0.1053)	(0.0772)
Education	0.1850	0.1789**	0.3265***	0.1714***	0.1878**	0.3248***
	(0.1187)	(0.0810)	(0.0604)	(0.0551)	(0.0925)	(0.0737)
Art, culture	0.3927***	1.1588**	0.0505	0.1189	-0.0768	0.3307***
	(0.1072)	(0.5140)	(0.1017)	(0.0890)	(0.1169)	(0.1029)
Trades	0.3150***	0.1248	0.3003***	0.2920***	0.0931	0.3544***
	(0.0522)	(0.0980)	(0.0594)	(0.1083)	(0.1041)	(0.1274)
Agriculture	0.5404***	0.2607	0.5249***	0.1843	0.0067	0.0810
	(0.1836)	(0.2188)	(0.1240)	(0.1377)	(0.1620)	(0.2363)
Manufacturing	0.2130***	0.1561*	0.1257*	0.1204	0.0485	-0.0702
	(0.0651)	(0.0823)	(0.0673)	(0.0846)	(0.1153)	(0.1018)
constant	6.3548***	6.2286***	6.3410***	6.2681***	6.3778***	6.1886***
	(0.0835)	(0.0699)	(0.0804)	(0.0658)	(0.1052)	(0.0866)
N	700	600	900	900	800	900
R^2	0.351	0.324	0.294	0.350	0.400	0.414

Notes:
[1] Standard errors in parentheses and clustered by individual.
[2] $*\ p < 0.1$, $**\ p < 0.05$, and $***\ p < 0.01$.
[3] Year dummies are included but not reported.

Table 9: R^2 Decomposition: Relative Contribution of Occupations and Skills

	Percentage of R^2			
	Experience	**Occupation**	**Job Skills**	**Job Skills + Ability**
Low education: men	9.2%	35.0%	45.4%	55.3%
Low education: women	11.2%	47.9%	30.3%	40.9
Mid education: men	21.2%	35.1%	25.1%	43.7%
Mid education: women	14.4%	34.6%	37.5%	51.0
High education: men	25.1%	34.9%	27.7%	40.0%
High education: women	23.3%	31.1%	27.9%	45.6%

Notes:

the results. A consistent effect across all groups is that the results regarding the LISA skill measures reported in Tables 4 and 5 are robust to the inclusion of occupation dummy variables. There are some small reductions in point estimates for the job skill coefficients but they remain highly significant in all cases. The same is true for the ability measure, except that it is no longer significant for women with low levels of education.

The occupations themselves frequently have significant effects on wages. The occupations "Management" and "Natural and applied sciences and related occupations" have a highly significant positive effect for all groups, relative to the omitted occupation, "Sales and Services occupations". The same is true for "Business, finance and administration occupations", except for men with a mid level of education.[13] The explanatory power is increased substantially for all groups when occupation is included. It is beyond the scope of this paper to investigate in more detail the role of occupation in wage determination. One possibility is that the occupation dummy variables are capturing primarily compensating differentials, given the inclusion of the LISA job skill measures that are themselves highly significant. However, they could also be capturing other components of a heterogeneous skill portfolio not captured by the LISA measures.

Table 9 reports results of a Shapley-Shorrocks decomposition of the R^2 for each of the columns in Table 8 to provide an assessment of the relative contributions of the LISA skill measures and occupations to explaining log wage levels in a statistical sense.[14] The LISA skill measures in the last

[13] The full titles for the occupation groupings are as follows: the omitted group is Sales and service occupations ; the included dummy variables represent, respectively, Management occupations, Business, finance and administration occupations, Natural and applied sciences and related, Health occupations, Occupations in education, law and social, community and government services, Occupations in art, culture, recreation and sport, Trades, transport and equipment operators and related occupations, Natural resources, agriculture and related occupations, Occupations in manufacturing and utilities.

[14] See Shorrocks (2013)

column account for a substantially larger part of the variation in log wages than occupations for all groups except women with a low education.[15]

Table 10: Two-year Wage Growth with Employer and Occupation Switching

	LOW EDUCATION	**MID EDUCATION**	**HIGH EDUCATION**
small skill change	0.0088*	0.0086	0.0119***
	(0.0053)	(0.0038)	(0.0036)
large skill change	0.0189***	0.0268***	0.0281***
	(0.0058)	(0.0045)	(0.0044)
occupation switch	-0.0071	0.0039	0.0106**
	(0.0056)	(0.0043)	(0.0044)
employer switch	-0.0042	0.0166**	0.0263***
	(0.0089)	(0.0067)	(0.0064)
$8 \leq exp < 16$	-0.0456***	-0.0264***	-0.0199***
	(0.0098)	(0.0084)	(0.0068)
$16 \leq exp < 25$	-0.0557***	-0.0397***	-0.0389***
	(0.0093)	(0.0084)	(0.0065)
$25 \leq exp < 35$	-0.0621***	-0.0427***	-0.0492***
	(0.0095)	(0.0081)	(0.0067)
35+ years exp	-0.0769***	-0.0485***	-0.0529***
	(0.0097)	(0.0084)	(0.0075)
female	-0.0107**	-0.0012	-0.0019
	(0.0042)	(0.0030)	(0.0028)
non-white	0.0077	0.0099*	0.0051
	(0.0067)	(0.0056)	(0.0034)
constant	0.0890***	0.0509***	0.0509***
	(0.0100)	(0.0089)	(0.0067)
N	3600	5600	5100
R^2	0.050	0.036	0.062

Notes:
[1] Standard errors in parentheses, clustered by individual identifiers.
[3] $*\ p < 0.1$, $**\ p < 0.05$, and $***\ p < 0.01$.

The broad literature on wage growth examines a wide variety of channels through which wage growth may occur, going beyond the human capital framework used in this paper. In particular, switching employers or occupations have frequently been included in log wage change specifications. Table 10 reports the results when dummy variables capturing employer and occupation switches are included in the specification of the log wage growth equations with the summary skill change measure reported in Table 7 in Section 6. The inclusion of both employer and occupation switch dummy variables has virtually no effect on the coefficient estimates for the summary skill change variable for any of the education groups. For the switch variables themselves, occupation switches

[15] This group is an outlier in the contribution of occupation across all groups, which presents an interesting question for future research.

Table 11: R^2 Decomposition: Relative Contribution of Summary Skill Change and Employer and Occupation Switches

	Percentage of R^2			
	Experience	**Firm Switch**	**Occ Switch**	**Skill Change**
Low education: men	78.7%	2.3%	2.7%	16.3%
Mid education: men	44.9%	13.0%	3.7%	38.4%
High education: men	51.3%	16.7%	5.1%	26.9%

Notes:

have a significantly positive coefficient only for the high education group, while employer switches have significant positive coefficients for both the mid and high education groups.

Table 11 reports results of a Shapley-Shorrocks decomposition of the R^2 for each education group in Table 10 to provide an assessment of the relative contributions of the LISA skill change measure and employer and occupation switches to explaining log wage change in a statistical sense. The LISA summary skill change measure in the last column accounts for a substantially larger part of the variation in log wage change than either employer or occupation switches, or the sum of the switch variables.

6 Conclusions and Future Work

The Canadian LISA panel provides a combination of ability test measures, job skill levels and an innovative measure of an individual's overall skill growth, all measured at the level of the individual. The empirical analysis in this paper exploits this unique combination of measures to examine human capital empirical specifications that extend beyond those typically used in the previous literature. The results provide strong evidence that the availability of the PIAAC test scores in LISA provides an ability measure that can play a direct role in increasing the explanatory power of human capital models implemented in the form of Mincer log wage equations. The analysis also provides evidence that some components of a heterogeneous skill portfolio constructed from detailed job skill information in LISA, most particularly the cognitive skill measure, is very useful in explaining individual variation in wage levels, though is not very useful in explaining wage growth, which may be due to the problem of large measurement error resulting from differencing noisy level measures. What *is* useful in explaining wage growth is the most innovative skill related measure in LISA - the self-reported skill change measure. The evidence shows that it can capture individual variation in skill growth within education and experience groups, and hence increase the explanatory power of wage growth equations. Moreover, it can be obtained with very little questionnaire burden. These basic results are robust to the introduction of a range of other variables used in the previous literature dealing with wage levels and wage growth at the individual level.

The inclusion of the PIAAC test scores as an ability measure, similar to the AFQT measure in the US NLSY panels, raises some interesting questions beyond the main focus of the paper. As noted in Section 3, the AFQT measure in the US NLSY panels has been used to examine both discrimination and employer learning of a worker's true ability. Results from Neal and Johnson (1996), for example, show that the inclusion of the AFQT ability measure in log wage equations largely removes any evidence of wage discrimination by employers towards young black employees, i.e. the negative coefficient on the black race dummy becomes insignificant when the ability measure is included. The results in Section 3 show a similar pattern in a Canadian sample that covers a full age range of employees, suggesting a promising topic for future work based on the LISA panel. In Neal and Johnson (1996) the ability measure is assumed to be produced "pre-market" so that the source of black-white wage differences is pushed back to the schooling period. An additional feature of the results in Section 3 for a sample covering all age ranges is that both the PIAAC ability measure and the job skills based cognitive skill measure interact in affecting the wage differential by race, suggesting that the post-schooling period may be relevant as well. The post-schooling period is examined in the context of employer learning of true ability of different groups in the US data which also may be examined in LISA.

Finally, LISA contains a great deal of job skill related questions that may provide better measures of the components of a heterogeneous skill portfolio than those used in this paper. While the cognitive skill measure performed well in the wage level equations, the repeated panel observations were of limited use in explaining wage growth. Our experiments to construct other heterogeneous skill measures were not very successful. Further examination of the detailed information in LISA may lead to better measures.

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