Multidimensional Skill Specialization and Mismatch Over the Lifecycle

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Abstract

In this paper, I investigate multidimensional skill mismatch and specialization over the lifecycle. I first present a model of labour choice with heterogeneous worker skills and occupational skill intensities that has 2 key features. Workers accumulate skill over time and frictions inhibit the perfect assignment of workers to occupations. The model yields four implications: (1) some workers will start in occupations for which they are not well suited; (2) due to skill accumulation, some workers who began mismatched will voluntarily continue to use the skill associated with the mismatched occupation, instead of their initial comparative advantage ability; (3) workers who switch occupations that differ in skill intensity hold skill portfolios that are more diversified than those who specialize; (4) there is a larger incidence of workers who switch from mismatched occupations to better matches than vice versa. I then test these implications using U.S. longitudinal data. The data shows the four predictions are statistically valid. For example, workers are likely to specialize within one skill - even when that skill is not a worker's initial comparative advantage. Both the model and data demonstrate the severity of mismatch diminishes over the lifecycle, due to occupation switching and skill accumulation.

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1 Introduction

There exists a significant literature studying worker lifecycles. Researchers have regarded human capital, and especially multiple forms of human capital, as one of the main drivers of wage growth over time (Neal, 1998). In general, this literature has come to some important stylized facts. For example, workers typically see a wage profile that is concave in nature - wages grow rapidly early in life and then grow at a decreasing rate later in life. The reason for this concavity is still up for debate. Menzio, Telyukova, and Visschers (2015) use a life cycle model with search frictions to show the beginning of a worker's labour market experience is characterized by more job transitions until the match is high quality. In a similar vein, Jovanovic (1979) and Gervais et al. (2016) use a Bayesian updating model that allows workers to discover their inherent ability over time. This leads to rapid changes early in life as workers determine their ability and much less change late in life, as workers have already discovered their ability.

A related literature focuses more specifically on the accumulation of human capital itself. Oi (1962) originally found that workers accept wages that fall below their marginal productivity, in essence paying for the ability to improve their human capital to generate higher wages in the future. This leads to relatively slow job mobility, as competing firms will not pay enough to lure workers away from firms since they internalize the cost of training. Lazear (2009) uses a two period model that finds workers only stick to their original occupation if their skill set is more valuable in their incumbent occupations as opposed to any firm making a raiding offer. Kambourov and Manovskii (2009) looks at the hypothesis of occupation-specific human capital. They find that tenure (their proxy for accumulation) only matters for *occupation* tenure, whereas employer or industry tenure had little effect on wages. That is, the only valuable human capital accumulation is at the occupation level. In general, there is a large literature that finds human capital accumulates over time, while there is no specific agreement on why or how. However, there is less research on what workers actually choose to do to deal with this accumulated skill.

In this paper, I look at multidimensional human capital choices made by workers over their lifetime. Specifically, I wish to see if workers diversify the skills required by occupations or choose an occupation that specializes in a single skill. This issue was tackled, in part, by Silos and Smith (2015) who use college credits as a proxy for multidimensional human capital. Their conclusion found that specialization of skills only benefited those that stuck to a single type of job and that, while some fields of study incentivize specialization, most encourage diversification. An additional question I ask is what *type* of skill does a worker specializes in. We might assume a worker would only specialize in the skill they hold a comparative advantage, but this could fail for different reasons. First, it could be an issue of the worker never getting the opportunity to switch into an occupation that uses their preferred skill. Second, if workers can accumulate additional skill over time in an occupation, it may be that an initial mismatch became the worker's optimal choice. If a worker starts a job in which they are using a non-intensive skill, if enough time passes, that skill may become their best. This would lead to the somewhat paradoxical finding of a worker rationally choosing to stay "mismatched". To account for these factors, I write a model of worker behaviour in which workers can be assigned incorrectly (using match frictions) and workers gain skill relative to their occupation's weighting of each skill (skill accumulation).

The model delivers 4 testable predictions. First, some workers will begin their careers in occupations that does not make use of their intensive abilities. This stems from the frictions in the labour market. Second, some of these mismatched workers will voluntarily *continue* using the mismatched skill - even if offered a position using their comparative advantage. This is because of skill accumulation. Workers grow their skills proportional to the intensity they are used in their job, so it is possible a worker's comparative advantage can change if initially mismatched. Third, workers who switch into a different skill intensive occupation hold skill portfolios that are more balanced, as opposed to skill specializers, who end up with much of their skill portfolio's composition in a single skill. Finally, the model predicts the market corrects itself to some extent - the incidence of skill switchers is largely from mismatched workers to good match occupations. These predictions are testable and as such, I take these predictions to the data.

Empirically, I use the NLS79 and O*NET dataset to test the above predictions. I find that nearly 50% of workers begin their career in an occupation that does not match their inherent ability portfolio. As well, inherent ability has little statistical power in explaining workers' first occupation. This is evidence of match frictions being important. Following this, I find workers are *much* more likely to specialize in the skill prevalent early in their career, even when that skill does not match their inherent ability - indicating workers are learning on the job. As well, I find more specialized skill portfolios are negatively associated with the number of job titles a worker holds over their career. Finally, I see the majority of workers who switch skills over their career are switching occupations that *do not* use their inherent ability to one that *does*. In total, the data lends evidence to the conclusions drawn from the model.

Section 2 details the model analyzed through the paper. Section 3 explains the data used to test the implications of the model, while Section 4 presents the different empirical methodolgies used to test the model. Section 5 describes the results of these exercises. Section 6 concludes.

2 Model

2.1 Environment

Consider a set of workers who exist in discrete time and exist for two periods, such that $t = 1, 2$. A unit measure of workers bring a set of skills to the labour market in time period 1 and look for a job. Importantly, workers are aware of their own ability. While empirically I will have access to a set of multiple skills for every occupation, I use 2 skills in the model for ease of exposition. Suppose there exists two types of skills. Let c_i and m_i denotes the *proportion* of cognitive and manual skills a worker i initially holds. In other words, $c_i + m_i = 1$. These skills are drawn from a generic distribution with a CDF $H(c_i)$. Jobs vary in the importance of these skills. Let λ_{cj} and λ_{mj} denote the intensity of cognitive and manual skills in production for job j. To capture the fact that jobs can differ in two different dimensions[1] these intensity weights can be any nonnegative value, in contrast to worker ability[2]. Jobs use worker skills to produce output according to a linear skill aggregation function of form:

$$y_{ij} = \lambda_{cj} c_i + \lambda_{mj} m_i \tag{1}$$

It is sufficient to imagine two types (or submarkets) of jobs. Job 1 is more cognitive intensive (i.e. $\lambda_{c1} > \lambda_{m1}$) while job 2 is more manual intensive (i.e. $\lambda_{c2} < \lambda_{m2}$) where $\lambda_{c1} > \lambda_{c2}$ and $\lambda_{m2} > \lambda_{m1}$. Workers are paid a fixed proportion of job output θ that is fixed across the types of jobs. That is, a worker i's wage can be written as:

$$w_i = \theta(\lambda_{cj} c_i + \lambda_{mj} m_i) \tag{2}$$

[1] This means that jobs can differ in both the composition of the skills they require for production as well as the *total* level of intensity.

[2] This decision comes partially from the data used later in the paper. The skill measures I used can more easily capture both size and composition of jobs compared to my inherent ability measures.

This environment means workers would like to match their skills as closely to job requirements as possible, as this would maximize their wage. However, as noted in Lazear (2009) and others, workers are typically unable to find a perfect match for their ability due to labour frictions. I remain agnostic on the source of these frictions, but these could be due to insufficient vacancies or information coordination frictions.

Unemployed workers draw a job offer randomly that belongs to one of the two types of jobs. Let p_1 be the probability of being offered the type 1 job and p_2 be the probability of being offered the type 2 job. Since the focus of my analysis is on worker skills, I assume $p_1 + p_2 = 1$. In other words, every worker is offered a job, but it may not be the best job for the worker. Given an offer, workers decide to take the job or decline. Employed workers accumulate skill associated with their job. Specifically, workers accumulate skill that matches the intensity their job requires. For example, a worker in a type 1 firm will originally hold c_i cognitive skill and m_i manual skill, but after a period of employment they hold $\gamma_c(1 + \lambda_{c1})c_1$ cognitive skill and $\gamma_m(1 + \lambda_{m1})m_i$ manual skill, where γ and γ_m are scale parameters that inhibit perfect skill accumulation and are positive values between zero and one. In each period, workers are hit with a preference shock with probability ϕ. This shock is match specific. The preference shock can be thought of as a way to model workers learning about themselves[3]. A worker hit with the preference shock will always want to switch occupation types regardless of their ability/occupation combination.

Job offers from the rival type arrive with probability p_{-j} to all employed workers. In other words, some workers are offered the opportunity to switch occupations. If offered, a worker can switch occupations costlessly. Workers who switch occupations still hold the skill portfolio they accumulated at their previous occupation. There is no occupation-specific human capital. Instead, human capital is entirely *skill*-specific.

[3]This parameter can also be thought of as a simplistic analog to Gervais et al. (2016) when there exists only two periods.

2.2 Deriving the Value Functions

Let W_1 and W_2 denote first period values of holding a type 1 or type 2 occupations. Finally, let the set of $\{W_{11}, W_{12}, W_{21}, W_{22}\}$ denote the set of possible paths for each worker. For example, W_{12} denotes the value of a worker whose first occupation was type 1 and then switched into a type 2 occupation in the second period. We write these the six value functions below.

$$W_1 = \theta(\lambda_{c1}c_i + \lambda_{m1}m_i) + \beta[(1-\delta-\phi)W_{11} + \delta U + p_2 \text{max}(W_{12} - W_{11}, 0) + \phi W_{12}] \tag{3}$$

$$W_2 = \theta(\lambda_{c2}c_i + \lambda_{m2}m_i) + \beta[(1-\delta-\phi)W_{22} + \delta U + p_1 \text{max}(W_{21} - W_{22}, 0) + \phi W_{21}] \tag{4}$$

$$W_{11} = \theta(\lambda_{c1}\gamma_c(1+\lambda_{c1})c_i + \lambda_{m1}\gamma_m(1+\lambda_{m1})m_i) \tag{5}$$

$$W_{22} = \theta(\lambda_{c2}\gamma_c(1+\lambda_{c2})c_i + \lambda_{m2}\gamma_m(1+\lambda_{m2})m_i) \tag{6}$$

$$W_{12} = \theta(\lambda_{c2}\gamma_c(1+\lambda_{c1})c_i + \lambda_{m2}\gamma_m(1+\lambda_{m1})m_i) \tag{7}$$

$$W_{21} = \theta(\lambda_{c1}\gamma_c(1+\lambda_{c2})c_i + \lambda_{m1}\gamma_m(1+\lambda_{m2})m_i) \tag{8}$$

For the initial work value functions, the worker is paid their wage and have some additional continuation value. With probability δ, the worker is separated from their job and transitions to unemployment. If they are not separated, they continue working at their occupation. With probability p_{-j}, they are offered the rival job which they can accept or reject. Since there exists only two time periods, the value functions for period 2 have no continuation value. Instead, workers are paid according to their accumulated skills and the weighting of those skills provided by the occupation. My focus is to discuss skill switching and skill specialization. In other words, I want to see under what conditions workers would be willing to switch job types given the opportunity. I determine ability cutoffs by equating the value of switching and staying in both occupations.

2.3 Results

Proposition 1 *There exists a lower ($\bar{c}_L$) and upper ($\bar{c}_H$) bound for the cognitive proportion of a worker's skill that defines if the worker would be willing to switch occupations in the second period if given the opportunity.*

I find these cutoffs by solving the inequality between the staying and switching values of both types of occupations in terms of the ability of the worker. By equating W_{11} and W_{12}, I find workers who are initially in the cognitive intensive occupation who would be willing to switch into the manual intensive occupation. I find that a type 1 worker would be willing to switch into a type 2 occupation given the opportunity if their cognitive proportion is relatively low. Specifically, a worker is willing to switch into the manual intensive occupation if their cognitive ability satisfies

$$c_i < \bar{c}_L = \frac{\gamma_m(\lambda_{m1} + \lambda_{m1}^2 - \lambda_{m2} - \lambda_{m1}\lambda_{m2})}{\gamma_c(\lambda_{c2} + \lambda_{c1}\lambda_{c2} - \lambda_{c1} - \lambda_{c1}^2) + \gamma_m(\lambda_{m1} + \lambda_{m1}^2 - \lambda_{m2} - \lambda_{m1}\lambda_{m2})}. \tag{9}$$

Conversely, a worker beginning in the manual intensive occupation would be willing to switch into the cognitive intensive occupation if their cognitive ability was relatively high. Specifically, if their cognitive ability satisfies

$$c_i > \bar{c}_H = \frac{\gamma_m(\lambda_{m2} + \lambda_{m2}^2 - \lambda_{m1}\lambda_{m2} - \lambda_{m1})}{\gamma_c(\lambda_{c1} + \lambda_{c1}\lambda_{c2} - \lambda_{c2} - \lambda_{c2}^2) + \gamma_m(\lambda_{m2} + \lambda_{m2}^2 - \lambda_{m1}\lambda_{m2} - \lambda_{m1})}. \tag{10}$$

Since the interest is in skill switching, I determine the proportion of the population that switches jobs in the second period. In either mismatched case (i.e. a cognitive worker in a manual job or vice versa), the worker must clear two probabilities. First, they must be mismatched and then they must be offered the other job. Therefore, we can write the expected percent of switchers as:

$$\begin{aligned} switch &= p_1p_2[H(\bar{c}_L)] + p_2p_1[1 - H(\bar{c}_H)] + p_1p_2\phi + p_2p_1\phi] \\ switch &= p_1p_2[H(\bar{c}_L) + (1 - H(\bar{c}_H)) + \phi]. \end{aligned} \tag{11}$$

In words, this equation looks at the tails of the cognitive ability distribution - where workers are willing to switch occupations. Therefore, I use the CDF $H(c_i)$ to determine the percentage of workers willing to switch. I then multiply by the probability of being in the wrong job. As well, only some workers in each occupation get the opportunity to switch. I then multiply by the probability of getting the rival job's offer. Therefore, the entire distribution term is multiplied by both the probability of receiving a type 1 and type 2 offer. As well, a fraction ϕ of workers switch occupations regardless of ability to occupation $-j$. I can write this ϕ as two terms. First, some workers are in job 1 and, due to the preference shock, switch to job 2 ($p_1p_2\phi$). Others are in job 2 and switch to job 1 ($p_2p_1\phi$). Since $p_1 + p_2 = 1$, I can simplify this all to $p_1p_2\phi$. The model also provides some predictions on how workers behave in different scenarios.

2.4 Model Predictions

Prediction 1 *Given two nonzero offer probabilities* p_1, p_2 *and workers who differ in cognitive skill sufficiently, some workers will always be placed in an occupation that* *does not make use of a worker's inherent ability*

As long as some workers would prefer to work in the manual occupation and some would prefer to work in the cognitive occupation, then the matching technology as described above will lead to some workers who are mismatched, in expectation. To be more specific, workers must differ enough across the cognitive ability distribution such that some hold at least 50% of their total ability in cognitive skill and some hold less than 50%. As such, some would want the more cognitive intensive occupation and others would prefer the manual intensive occupation. Since jobs are randomly drawn with differing offer probabilities, we should expect at least some workers to be initially unhappy with their allocation.

Prediction 2 *Given mismatch occurs, some proportion of mismatched workers will voluntarily stay in the occupation, even if offered the job that was more suitable initially.*

Prediction 2 holds due to skill accumulation over time. If a worker is in the mismatched occupation in the first period, they gain skills with the same intensity as their mismatched occupation. If the worker drew a relatively balanced ability portfolio (i.e. c_i is around 0.5), this skill accumulation can change the worker's best skill. For example, imagine a worker who is only *slightly* cognitive intensive in their ability. However, they were allocated into a very manual intensive occupation. After a period of time has occurred, their portfolio may now actually be manual intensive. Now, even though they were initially mismatched, they now optimize their wage by staying in the mismatched occupation. Even if offered their initial better match job, they would decline it.

This can also be shown by demonstrating the cutoff ability values above do not contain the entirety of the mismatched population. As long as some workers become better off after being in the wrong occupation, then Prediction 2 holds. Given cognitive ability is a proportion, this means that as long as $\bar{c}_l \neq \bar{c}_H \neq 0.5$, then some mismatched workers would stay in their mismatched occupations. In other words, some workers who are mismatched would be willing to stay in their mismatched occupation given the model's set-up.

$$\bar{c}_L = \bar{c}_H$$

$$\frac{\gamma_m(\lambda_{m1} + \lambda_{m1}^2 - \lambda_{m2} - \lambda_{m1}\lambda_{m2})}{\gamma_c(\lambda_{c2} + \lambda_{c1}\lambda_{c2} - \lambda_{c1} - \lambda_{c1}^2) + \gamma_m(\lambda_{m1} + \lambda_{m1}^2 - \lambda_{m2} - \lambda_{m1}\lambda_{m2})} = \frac{\gamma_m(\lambda_{m2} + \lambda_{m2}^2 - \lambda_{m1}\lambda_{m2} - \lambda_{m1})}{\gamma_c(\lambda_{c1} + \lambda_{c1}\lambda_{c2} - \lambda_{c2} - \lambda_{c2}^2) + \gamma_m(\lambda_{m2} + \lambda_{m2}^2 - \lambda_{m1}\lambda_{m2} - \lambda_{m1})} \tag{12}$$

Equation (12) can only be true if all of job 1's intensities $(\lambda_{c1}, \lambda_{m1})$ are equivalent to job 2's intensities $(\lambda_{c2}, \lambda_{m2})$. However, we initially assumed that the jobs differ across these intensities in a way that makes it impossible for this to be true. Therefore, with skill accumulation and two distinct jobs who differ in the intensity they use skills in production, there exists a subset of mismatched workers who will voluntarily stay in their initial match.

Prediction 3 *Skill switchers hold skill portfolios that are more diversified compared to skill specializers, regardless of initial skill*

Prediction 3 holds due to the nature of the skill accumulation used. Since I've assumed two jobs that differ in the intensity they use their skills, a worker who stays in a particular job (regardless of whether it is a voluntary or involuntary stay) will always hold a more specialized bundle of skills, since they spend both periods accumulating relatively more of one type of skill. In comparison, one that changes between the two jobs will spend one period accumulating relatively more cognitive skill and the other accumulating relatively more manual skill. This can be seen simply thinking of a single worker with a set c_i, m_i bundle. If they stay in job 1 over two periods (this would also apply if the worker stayed in job 2 for 2 periods), they earn $\lambda_{c1}\theta(1+\lambda_{c1})$ cognitive skill and $\lambda_{m1}\theta(1+\lambda_{m1})$ manual skill. If they switch occupations, they earn $\lambda_{c2}\theta(1+\lambda_{c1})$ cognitive skill, which is strictly smaller. However, they earn $\lambda_{m2}\theta(1+\lambda_{m1})$ manual skill, which is strictly larger. Therefore, workers who switch skills end up with a more diversified skill portfolio while skill stayers end with a specialized skill portfolio.

Prediction 4 *The incidence of workers switching from mismatched occupations to ones that align with their initial ability portfolio is larger than the incidence of workers switching from well matched occupations into mismatched ones.*

Prediction 4 holds because the shock hits all workers in the labour force - even those switching into a better match. As such, we can write the proportion of workers switching from mismatch to a good match and the proportion switching from a good match into a mismatch.

$$switch_{M,G} = p_1 p_2[H(\bar{c}_L) + (1 - H(\bar{c}_H)) + [p_1 H(0.5) + p_2(1 - H(0.5))]\phi$$

$$switch_{G,M} = [p_2 H(0.5) + p_1(1 - H(0.5))]\phi$$

where M, G denotes switches from mismatched occupations to good matches and G, M denotes the opposite. Under fairly standard assumptions[4] the switches from mismatched to good matches is always larger than the opposite.

[4]The distribution is continuous, and both offer probabilities are non zero.

Predictions 1 - 4 can be easily tested using worker level data and reduced form estimation. Since the propositions deal with relative direction and magnitudes, I can use regression analysis to confirm if the predictions from the model hold true in the data. The following section describes the data used for this endeavour.

3 Data

I use two datasets for the analysis. First, I use the National Longitudinal Survey of Youth (NLSY). Specifically I use the 1979 subset (NLSY79). This survey contains information on a set of individuals aged 14-22 when first interviewed in 1979. They are subsequently sampled every year[5] until 2014. The survey collects information on a worker's yearly occupation, yearly wage, demographics, work expectations, and training programs attended. The NLS79 also required all individuals to take the Armed Services Vocational Aptitude Battery (ASVAB) of exams. These exams measure an individual's cognitive, literacy, numeracy, and motor skills in 1980. I take these exam scores as a signal of a worker's aptitude in each of these different types of skills. In particular, I assume that (1) a worker's science score measures their cognitive ability; (2) their math score measures their numeracy ability; (3) their paragraph comprehension score measures their literacy ability; (4) their automotive and shop information score measures their motor ability. As well, individuals in the survey were asked to evaluate themselves using the Rosenberg Self-Esteem scale. This self-evaluation measures the self-esteem an individual feels. These test scores have been scaled using item response theory (IRT) in order to best ensure reliability of the original test scores. These scaled scores are used, as using actual test scores as a measure of an individual's true ability is inherently noisy. We can think of two similarly

[5] In 1994, this changes to biannually.

skilled test takers who only vary in their test speed. The slower test taker may not finish answering all questions and has a lower test score. IRT helps to eliminate this measurement error by weighting questions by their difficulty (as measured by how many test takers got the question correct) to find inherent ability (typically called θ). These transformed scores comes from an item response function, which maps the difficulty as the probability of a certain θ answering a specific question correctly[6]. While all test scores lie on the same scale, I use the percentiles of these test scores in the analysis for ease of interpretability. I exclude workers who are not interviewed or refuse to answer questions regarding these tests, as I need their initial abilities for our estimation.

I also use the O*NET database for information regarding the characteristics of different occupations. These characteristics include the level of sophistication of skills and abilities needs to perform the requirements of each occupation. O*NET reports the average score as reported by a set of occupational experts that, in groups, rate all occupations[7]. In general, these scores have low variance across raters as measured by their standard error, so we take these as appropriate scores for the representative worker of each occupation. Each skill is measured on a 1-7 scale, measuring the level of sophistication required in the occupation for that skill[8]. Using raw O*NET scores to measure skills for a job is inherently problematic. This is because these scores are ordinal - there does not exist equal intervals between scores. As such, arithmetic operations such as averaging can bias results. Figure 1 shows an example of the type of question asked to occupational experts. Each survey question has 3 "anchors" to help raters score each occupation's skill. For the skill *mathematics*, for example, a

[6]See Van der Linden and Hambleton (1997) for a more through discussion of the methodology around item response theory as well as Bock and Moore (1986) for specific details of IRT with respect to the NLSY79 sample.

[7]For more information on the sampling process used by O*NET, see Fleisher and Tsacoumis (2012).

[8]A score of 0 is imputed if the skill is deemed "not important" to the occupation.

rating of 4 means an occupation requires a math skill equivalent to calculating the square footage of a home. An issue develops as we look at more than 1 skill. Each skill has unique anchors, making each skill contain a distribution that is noncomparable across skills. To avoid this problem, I use the methodology proposed by Loree and Stacey (2018). This methodology maps ordinal skill ratings onto one singular scale - log dollars per hour. By doing so, I can now aggregate, compare, and average without the issues inherent to ordinal variables. I follow their proposed naming conventions in that there exists five aggregate skill categories - cognitive, interpersonal, literacy, numeracy, and motor skills. Table 1 gives some examples of skills that lie within the aggregated skill categories. The O*NET only exists from 2003-2016 which does not allow me to fully exploit changes in skill requirements over the time of the NLS79 sample. I can augment this using the Dictionary of Occupational Titles (DOT), the predecessor to O*NET, however there are issues that make this problematic. For one, the skills measured are not equivalent across databases. While I can match some broad categories, I lose many of the components of cognitive and literacy skill. As well, DOT skills do not follow the same scale across skills. While DOT skills are ordinal as well, there still may be bias due to some skills have a smaller scale in general. To avoid these problems I take the skill requirements at the occupation level as constant across the entire time period. This is not an issue since essentially all skill scores across occupations remain unchanged from 2003-2016. This is at least partially because O*NET analysts are reminded of the previous year's score before rating occupations for a given year. As such, analysts only change scores if they believe the skill required in a certain occupation has significantly changed over the previous year. Overall, a rerating is an incredibly rare event in the database.

4 Methodology

I implement several reduced form regression estimations to test the different propositions found in the model regarding initial ability of workers and their skill content in occupations over their lifetime. Before I start, however, I want to determine if the test scores I use as natural ability seem to actually well represent natural ability. I do this by seeing the effect of the test scores on an outcome not perfectly tied to labour market outcomes - education. Specifically, I wish to see if having strong nonmotor test scores lead to workers making higher education decisions differently than those with high motor test scores. Due to sample size issues, I condense education into a dummy variable, which equals 1 if the worker achieved any level of higher education (a bachelor's degree or higher) and 0 otherwise. I then run a logistic regression of form:

$$\log \frac{\text{educ}_i}{1 - \text{educ}_i} = \alpha + \text{A}_i'\beta + \text{X}_i'\gamma + \epsilon_{i,n} \tag{13}$$

where educ is the education dummy variable described above, A is a vector of test score percentiles, and X is a vector of individual covariates including sex, race, immigrant status, and expectations around their future career path. I expect that abilities related to nonmotor skills (cognitive, interpersonal, literacy, and numeracy) to be related with higher levels of higher education consumption. This is because nonmotor skills are typically associated with higher paying jobs[9], and these jobs are also correlated with education level.

I can also look at if workers who are relatively well endowed in certain skills have higher levels of education. I do this with a similar logistic regression specification.

[9] For a more in-depth discussion, see Loree and Stacey (2018)

$$\log \frac{\mathrm{educ}_i}{1-\mathrm{educ}_i} = \alpha + \mathrm{aint}_i'\beta + \mathrm{X}_i'\gamma + \epsilon_{i,n} \tag{14}$$

which is the same specification as equation (13) with additional dummy variables (aint) that indicate if a worker has an "intensive" amount of any ability. Intensity is defined as holding an amount over the median of all workers. For example,

$$\mathrm{aint}_{\mathrm{cognitive}} = \begin{cases} 1 \text{ if cognitive}_i \ > \mathrm{cognitive}_{0.5} \\ 0 \text{ otherwise} \end{cases} \tag{15}$$

where $\mathrm{cognitive}_{0.5}$ is the median value of cognitive test score percentiles. If I see strong correlations, then there is some evidence that the test scores at least somewhat measure a worker's inherent ability.

Given the above estimation demonstrates that test scores reflect inherent ability, I then investigate the effect the test scores have on a worker's initial occupation and corresponding skill portfolio. This is the empirical test of Prediction 1. We first do this by using an OLS regression of specification:

$$\mathrm{s}_{i,n,f} = \alpha + \mathrm{A}_i'\beta + \mathrm{X}_i'\gamma + \epsilon_{i,n} \tag{16}$$

where s is a skill indexed by skill number n for an individual i for their first (f) occupation. However, this regression can only tell us increases in a worker's initial skill portfolio. It is more difficult for it to tell us if a worker is *specializing* within a certain skill. To further cement this idea, we run a logistic regression to determine the odds of being in an intensive initial occupation given their test scores:

$$\log \frac{\mathrm{sint}_{i,n,f}}{1-\mathrm{sint}_{i,n,f}} = \alpha + \mathrm{aint}_i'\beta + \mathrm{X}_i'\gamma + \epsilon_{i,n} \tag{17}$$

which is a logistic transformation of equation (16). The only differences is sint is a dummy variable that is equal to one if the associated skill or ability is above the median value of that skill or ability, much like the ability intensive definition given above. If the regressions indicate that initial test scores do not play a large role in first occupation selection, I take this as evidence of Prediction 1 holding true. If test scores play a large role in first occupation selection, this would be akin to saying that workers tailor their first occupation to their set of abilities. It would also be saying workers have leverage over the type of occupation they start in - violating Prediction 1.

I test Prediction 2 by looking at the relationship between a worker's first and last occupation skill bundle. If skill accumulation is sufficiently important, we should expect a relationship between these two portfolios. In much the same way as discussed above, we test this hypothesis using a linear and logistic regression. Specifically, we run an OLS regression of type:

$$\mathrm{s}_{i,n,l} = \alpha + \mathrm{s}'_{i,f}\delta + \mathrm{A}'_i\beta + \mathrm{X}'_i\gamma + \epsilon_{i,n} \tag{18}$$

where a worker's specific skill at the end of their life (l) is regressed on the worker's education decision, first occupation skill portfolio, and worker characteristics. Again, if we expect learning on the job to be important, we should expect a worker's skill early in their career to grow over time. As such, we should expect the coefficient on the same skill from f to l to be positive and significant. As above, I also determine if a worker's intensive skill early in their life leads to the same intensive skill being used later in life.

$$\log \frac{\mathrm{sint}_{i,n,l}}{1-\mathrm{sint}_{i,n,l}} = \alpha + \mathrm{sint}'_{i,f}\delta + \mathrm{aint}'_i\beta + \mathrm{X}'_i\gamma + \epsilon_{i,n} \tag{19}$$

Since I control for a worker's ability, if a worker's set of first occupation skills significantly impacts their final occupation skill bundle, this would be evidence of Prediction 2. As the data lends credence to Prediction 1, we can see that workers may end up mismatched. If equations (18) and (19) show skill accumulation even after controlling for worker ability, then there is evidence that skill accumulation outweighs natural ability in the decision to specialize or switch skills.

To test Prediction 3, I construct a new variable $skilldif$, which measures the distance between a worker's minimum and maximum skill value in their last occupation skill bundle. For large values of this variable, the workers final skill bundle is relatively specialized. For small values of $skilldif$, the worker's skill portfolio is more diversified. I also create a variable *sameskill*, which equals 1 if a worker uses the same skill intensively in both their first and last occupation. I run a regression of form:

$$skilldif_i = \alpha + \beta sameskill_i + X'\gamma + \epsilon_i \tag{20}$$

If β is positive, it provides evidence for Prediction 3 holds true in the data. After controlling for ability and other job characteristics, with a positive β, workers who specialize will hold a less balanced skill portfolio.

Finally, I test Prediction 4 by simply looking at the proportion of workers who switch into better matched occupations versus those that switch away from good matches based on their initial ability. More specifically, I define workers switching from mismatch to good matches as those that started their career in an occupation that uses a skill intensively that is not a worker's best skill (based on their initial ability) into an occupation that *does* use that skill. Conversely, I define workers moving from a good match to a mismatch as one who started their career in an occupation that uses a skill intensively that the worker holds into an occupation that does not.

In an interesting robustness check, I reduce the reliability of the ASVAB scaled test scores across the different regressions. Schofield (2014) finds that ASVAB test scores, even after the use of item response theory, contain measurement error when discussing worker abilities and will bias results unless this error is modelled. This error persists even after instrumenting ASVAB test scores for other sections of the ASVAB. Unfortunately, to do this, I would require each worker's response to each question on all sections of the ASVAB. Currently, the NLS only provides item level response data for 3 of the 5 aggregate skill proxies used. Instead of estimating this error for a portion of our skills, I decided to reduce the reliability of all scaled test measures to determine the sensitivity of the results. We can think of this issue as an additional error present in each test score. Each test score measures a worker's latent ability in that field, but with noise.

$$\mathrm{a}_{i,n} = \mathrm{a}^*_{i,n} + \eta_{i,n} \tag{21}$$

The additional noise causes the estimated coefficient in each regression to be strictly smaller than the true value. I introduce a regression calibration method in order to adjust for this error. As noted in Carroll and Stefanski (1990) and Hardin, Schmiediche, and Carroll (2003), if I was able to determine the level of measurement error, I can use the variance matrix of the measurement error to correct the bias of the mismeasured estimates. I do this by using the Cronbach α (Cronbach, 1951) in order to determine the reliability of the test measures[10]. The proportion of data that is not reliable must then be mismeasured. As such, I feed in that 1-α% of the data is

[10]This differs from the methodology originally proposed by Gulliksen (1987) for use with ASVAB data, though the reliability scores I compute are very close to those presented there.

mismeasured. The benefits of this method compared to a simulation of extrapolated values comes from the additional generation of standard errors.

I also present a more standard robustness check in which I decrease the total time frame of the data. We may believe that a worker's first occupation when they are 20 years old is too early to appropriately measure a worker's first "real" job. In order to determine if the original specification contains superficial relationships, I count a worker's first occupation as the first one they received in 1990 and beyond - cutting off the first ten years of the data. I do a similar technique at the back end of the data for similar reasons. We might expect some amount of sample selection issues at the end of our data. For example, some workers may require working past their true end of career occupation for budgetary reasons. As such, I check if our results hold after eliminating the final ten years of data.

5 Empirical Results

I first present figures to explain the relationship between variables, before running regressions. Figures 2 - 6 show the density of test score percentiles for each type of test by education choice. Without controls, workers who scored relatively high in any kind of test are more likely to achieve higher education. While the nonmotor skills (cognitive, interpersonal, literacy, and numeracy) show this relationship strongly, the motor test distribution shows a weaker version of this. This would suggest that these test scores are a strong indicator of ability, since they seem to predict the types of workers who go on to post-secondary education. Figures 7 - 11 looks at final job skill measures by test score percentiles and divided into categories. The blue line measures the average last job skill measure if the worker was in an initial skill intensive occupation. The red line measures the same, if the worker was *not* in an initial skill intensive occupation. These figures show a strong shift in end of career skills for any test score if a worker was using the skill intensively early in life. This pattern holds across all skills. Now that I've established at least some correlation between ability, first occupation skills, and last occupation skills, I now present regression results.

Table 2 shows the results from the logistic regression equation (13). Specifically the table shows the percent increase in the probability of achieving higher education by moving a worker from the median of that distribution to one standard deviation above the median of a specific test. As expected, nonmotor skills are strongly tied to positive higher education outcomes. For example, we can compare average workers who only differ in their cognitive test scores and see that the worker who scored a standard deviation higher is 56% more likely to achieve some level of postsecondary education. On the other hand, workers who hold large inherent motor abilities are much less likely to postsecondary education. This table shows that there is a strong and statistically significant relationship between workers' inherent abilities and the education they choose to consume.

Table 3 shows the result of the logistic regression equation (14) and helps to better explain the effect of large inherent ability portfolios. For example, if a worker holds a cognitive ability larger than the median of the sample, they are twice as likely to earn higher education than an observantly identical worker who holds a below-median cognitive ability. Again, this table provides evidence that workers that hold heterogeneous levels of multidimensional ability make different education decisions and that workers are selecting their education decision in a way we would expect - workers who hold a relatively large share of nonmotor ability are much more likely to sort into education. Given test scores seem to reasonably describe worker natural ability, we continue using these scores as a proxy of inherent ability.

Table 4 gives the OLS results for estimation equation (16). Near across the board, initial ability has little effect on a worker's first occupation choice. Even when coefficients are statistically significant, their actual magnitude is extremely small. For example, comparing a worker in the 1$^{\text{st}}$ percentile to the 99$^{\text{th}}$ percentile of the interpersonal test score distribution leads a worker, on average, of holding a first job with \$0.03 log dollars more in interpersonal skill. Given the average amount of interpersonal skill in first jobs is \$0.38 log dollars, this large increase in interpersonal ability has little impact on first occupation behaviour.

I can also look at the composition of first skill portfolios and initial ability portfolios. These results are presented in Table 5 and give the logit regression results of equation (17). These results are slightly more encouraging, but still demonstrate a weak relationship overall. While there is some evidence of a positive relationship between ability and first skill portfolio, compared to the relationship between final and first skill portfolios, it is not particularly strong. Workers who were identified as intensive in a particular ability were more likely to find a first job that also uses that skill intensively. However, some workers still end not using their intensive ability in their first occupation. For example, workers who have a large inherent interpersonal ability are 23% more likely to use interpersonal skills intensively in their first occupation. Still, there is a lot of workers that end up not using that skill intensively. In terms of summary statistics, nearly 50% of the workers sampled start their career mismatched (i.e. their intensive ability does not line up with the intensive skill used in their first occupation). I take the above results as evidence of Prediction 1. At least *some* workers begin their career in an occupation that doesn't use their strongest ability intensively.

Table 6 gives the OLS results for estimation equation (18). Across all skills, an increase in a worker's specific first job skill leads to a large increase in the same skill at the end of their career. For interpretability, if an average worker's first occupation pays an additional log dollar in cognitive skill, that worker will hold a skill portfolio with an additional log 54 cents at the end of their career. More interestingly, is that an increase in most of the first job skills leads to zero or negative changes in end of career skills that *are not* the same. Table 7 shows this more systematically in percent changes for a standard deviation change in initial skill for an average worker. In each case, an increase in a worker's first occupation skill leads to a relatively large increase in the same skill later in life and relatively small or no change in all other skills, even after controlling for initial ability. I take this as evidence of skill specialization. If an average worker is in a relatively cognitive intensive job to begin their career, for example, we would expect them to finish their career with a relatively cognitive focused skill portfolio. This would be the case if learning on the job was an important factor of human capital accumulation. As an individual works in a job, they become better at the skills required for that occupation. As such, they grow specific skills they continue to leverage over their lifetime.

I check the composition effect using a logistic regression. Table 8 shows the odds ratios of workers' final skill portfolio based on their initial skill portfolio. For each skill, there is a significant relationship between initial occupation skill portfolio and last occupation skill portfolio. Specifically, workers seem to tailor their end of career portfolio to focus on the skills most present in their initial skill portfolio. For example, a worker whose initial literacy skill was above the median is more than 7 times more likely to end their career in an above median literacy job. This is strong evidence that workers accumulate skills over their lifetime. Comparatively, earlier steps in this mechanism (initial ability and education) seem to influence worker occupation choice but to a significantly lesser degree. This would indicate that workers start in an occupation, develop the skills used intensively in that occupation and then leverage those upgraded skills through their life. Since this relationship holds strongly even with ability controlled for, we can think of two workers in a single first occupation. For one (Worker A), the job is a perfect fit for their ability. The other (Worker B) is significantly mismatched by being in the same occupation. The results presented in Tables 6 and 8 demonstrates that *both* are very likely to continue specializing in the skill intensive in the first occupation - even though worker B is mismatched. This is empirical evidence of Prediction 2.

Table 9 shows the results of estimating equation (20). The coefficient on *sameskill* (which equals 1 if the worker begins and ends their career using the same skill intensively) is positive. This tells us that workers who specialize in one skill over their career end up with a larger gap between their largest and smallest skill component. In other words, workers who specialize in a skill also end up with a specialized skill portfolio - in which one or a few skills are relatively large, at the expense of other skills. Conversely, workers who switch skills over their life have a smaller gap between their largest and smallest skill - indicating a more diversified skill portfolio. This lends evidence to Prediction 3, in which workers who didn't switch into the other submarket ended up with specialized skill portfolios.

Finally, I provide some empirical evidence for Prediction 4. I do this by investigating the proportion of workers that correct their mismatch compared to workers who *began* in good matches that switch into occupations that are not well aligned with their ability portfolio. In the data, 24% of workers correct their mismatch. Specifically, 24% of workers switch from mismatch to good matches, while 18% of workers switch from good matches to mismatches - which is a statistically significant difference. This provides some evidence that Prediction 4 holds. This is important not only as a prediction of the model, but it also helps to demonstrate that the cost of mismatch declines over time. Not only does mismatch decline because workers accumulate additional skill to neutralize the impact of mismatch, but also, workers correct the market by switching into better matches.

6 Conclusion

Coming soon...

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A Tables and Figures

Figure 1: O*NET math question

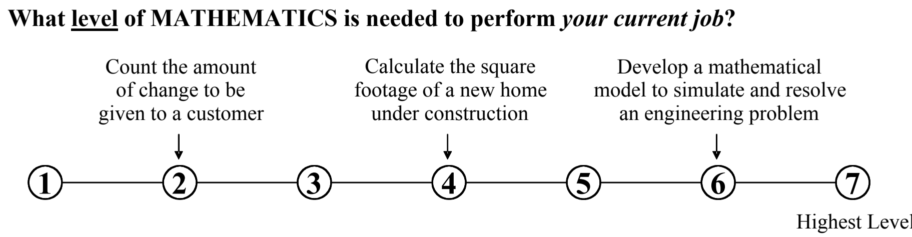

Figure 2: Cognitive test percentile distribution by education

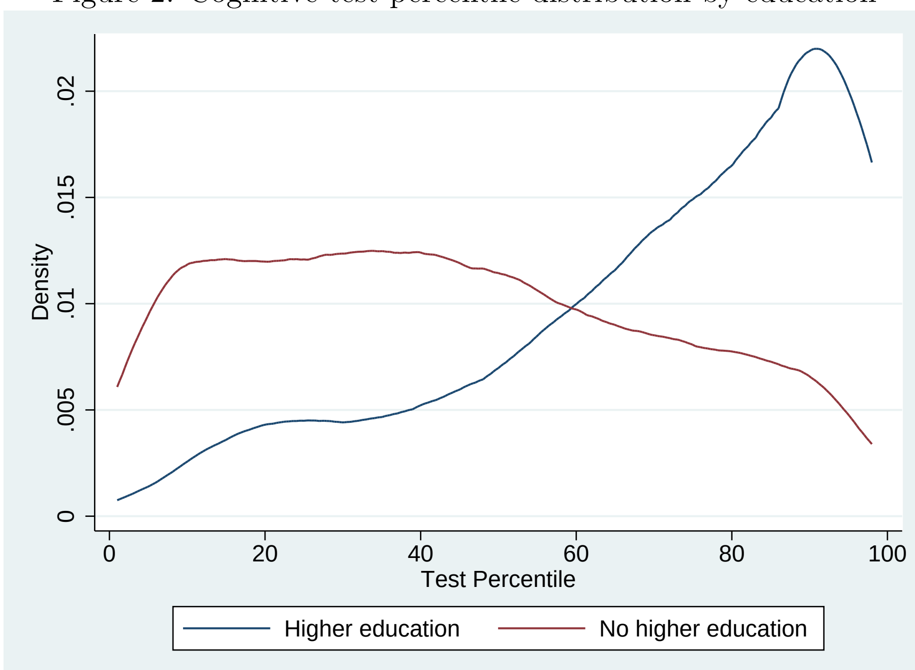

Table 1: Skill examples by skill category

Cognitive	Interpersonal	Literacy	Numeracy	Motor
Complex problem solving	Coordination	Written expression	Mathematics	Manual dexterity
Science	Persuasion	Written comprehension	Information ordering	Multilimb coordination
Critical thinking	Negotiation	Reading comprehension	Inductive reasoning	Dynamic strength

Figure 3: Interpersonal test percentile distribution by education

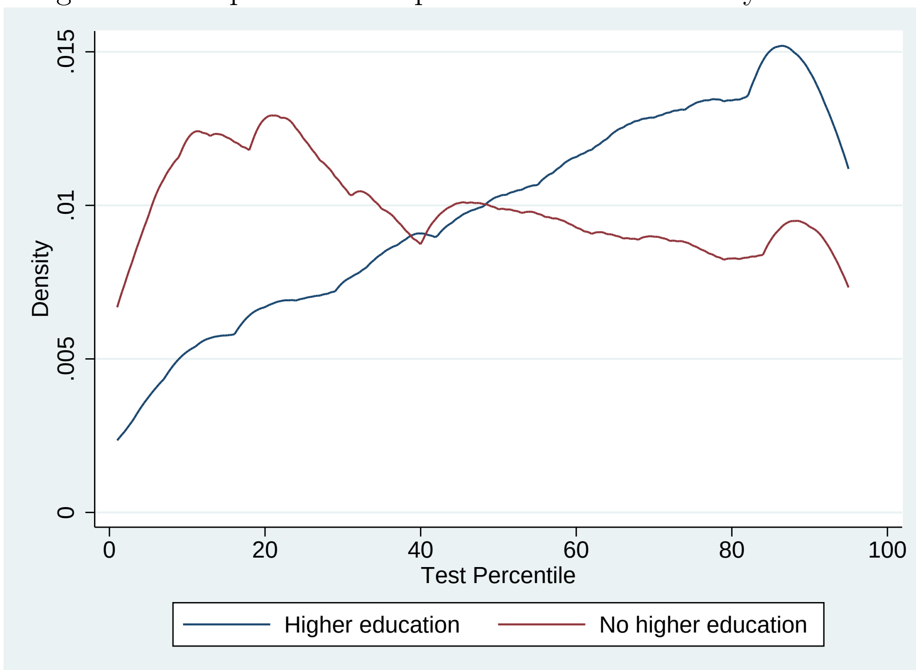

Figure 4: Literacy test percentile distribution by education

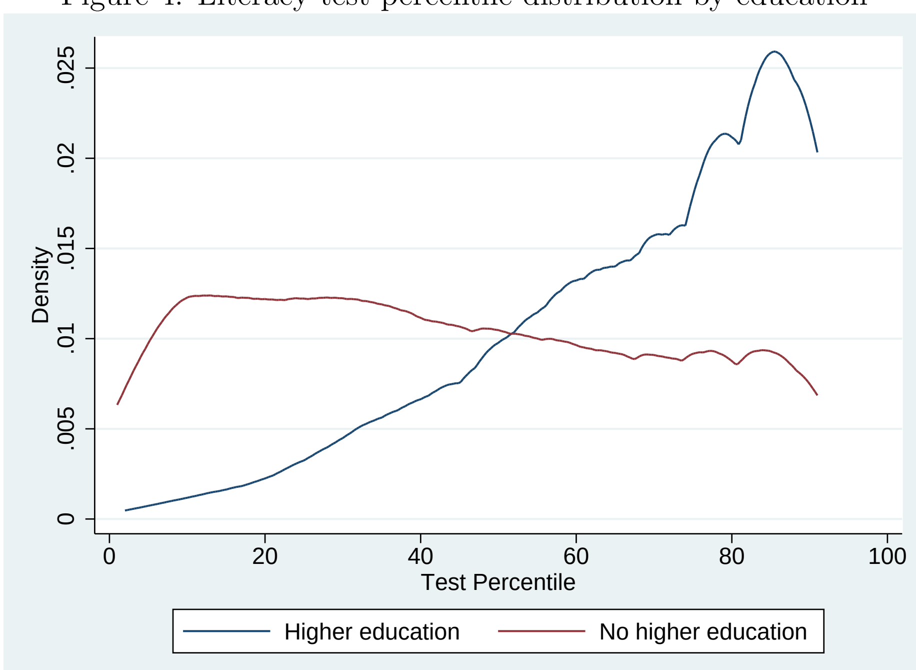

Figure 5: Numeracy test percentile distribution by education

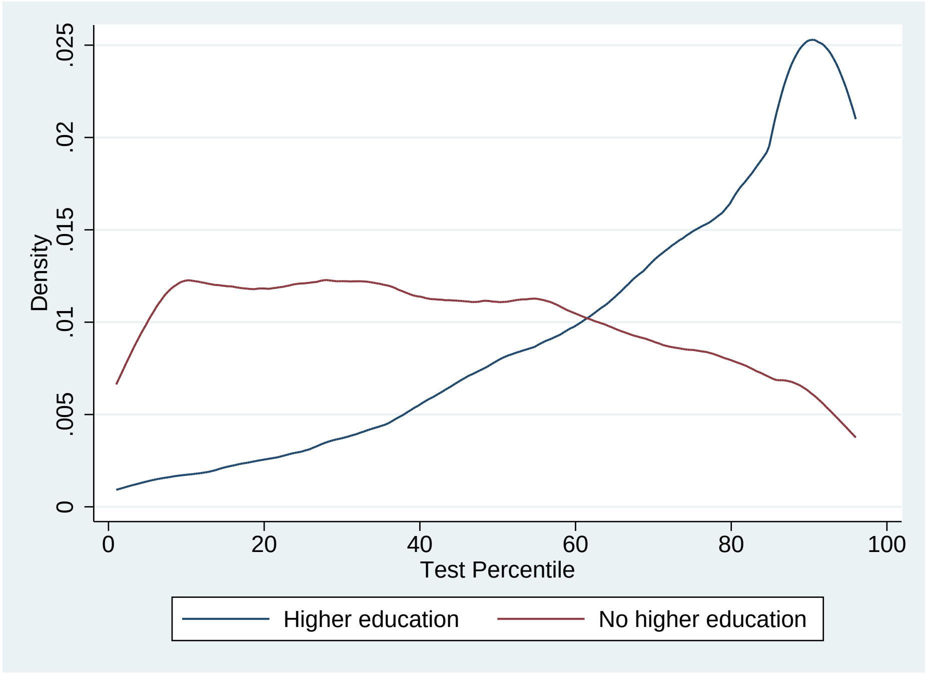

Figure 6: Motor test percentile distribution by education

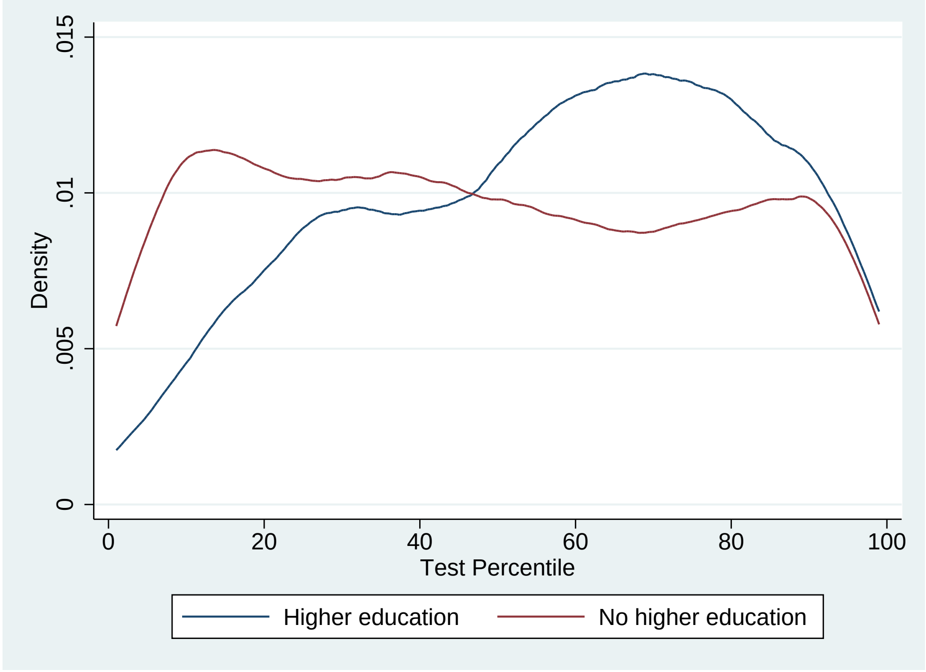

Figure 7: Last cognitive skill by cognitive test score

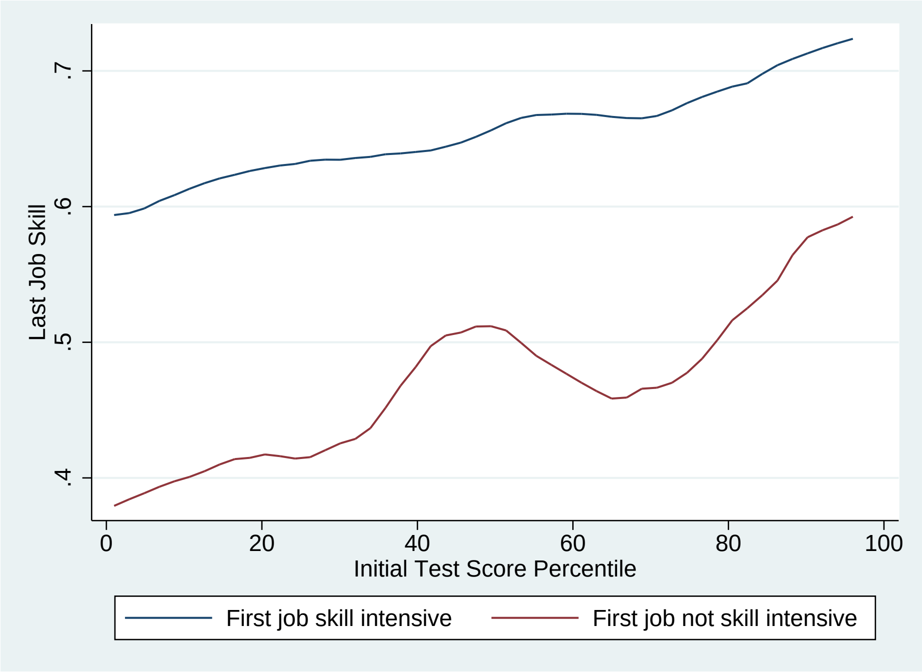

Figure 8: Last interpersonal skill by interpersonal test score

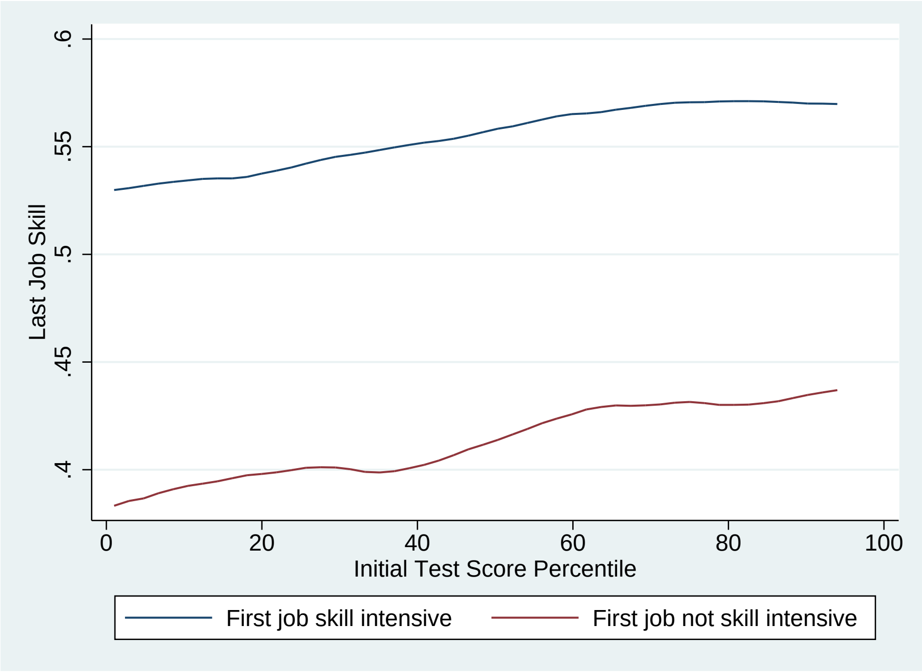

Figure 9: Last literacy skill by literacy test score

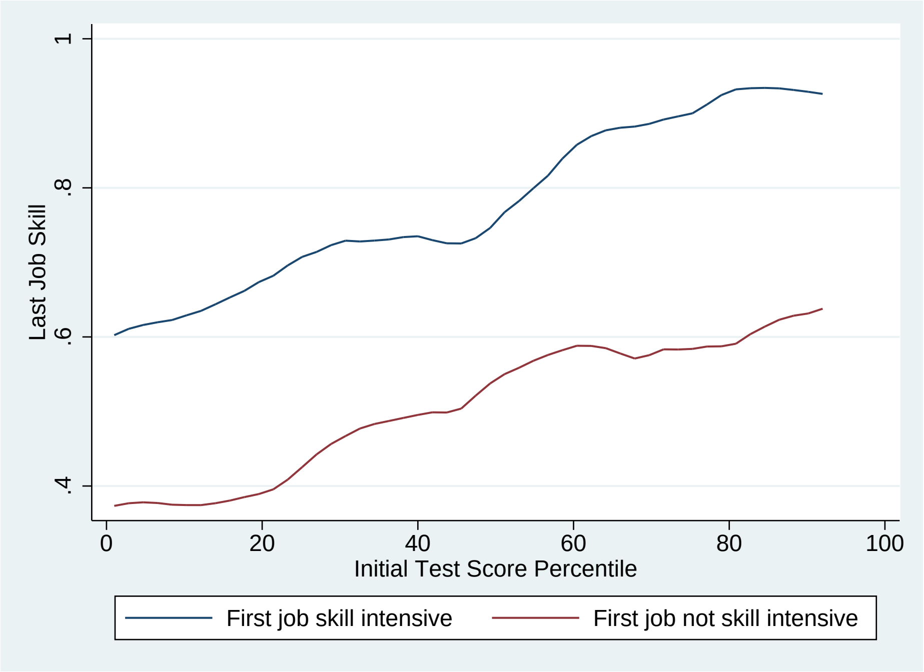

Figure 10: Last numeracy skill by numeracy test score

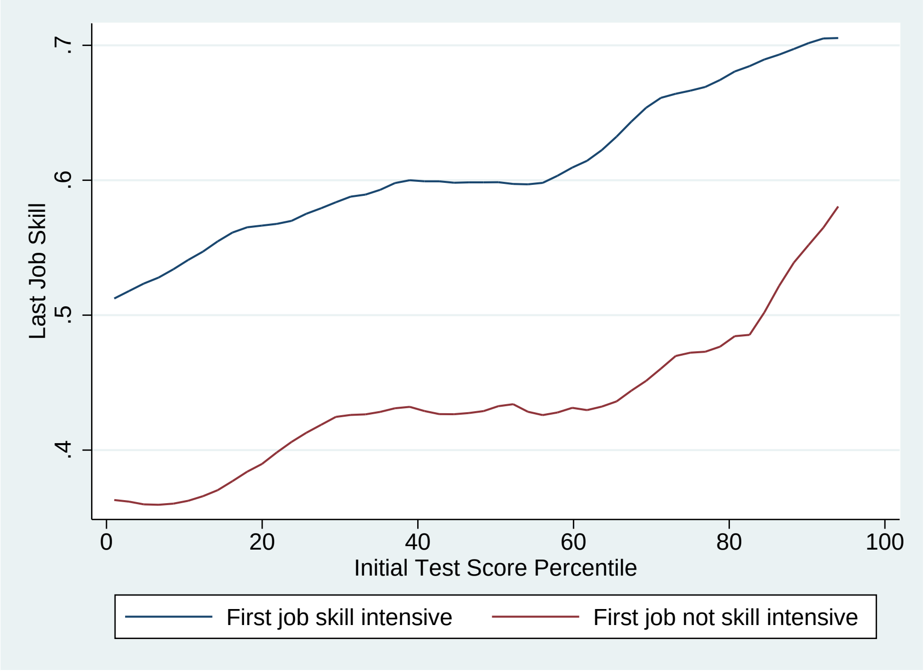

Figure 11: Last motor skill by motor test score

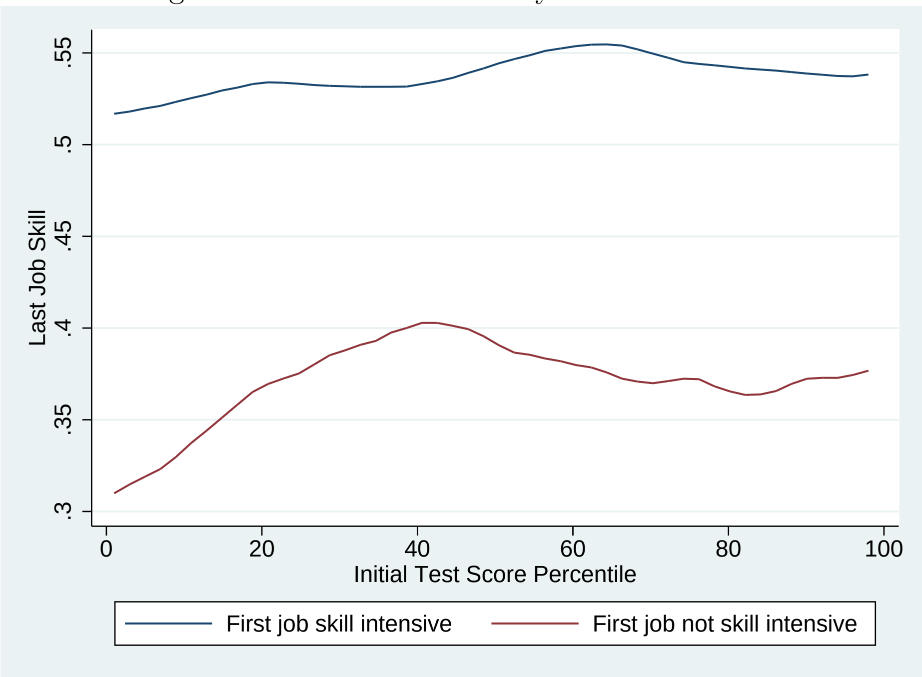

Table 2: Percent changes by test percentile increases on probability of higher education

	(1)	(2)
Cognitive test percentile	58.6%	56.7%
	(0.003)***	(0.003)***
Interpersonal test percentile	19.6%	17.1%
	(0.002)***	(0.002)***
Literacy test percentile	30.0%	33.7%
	(0.002)***	(0.003)***
Numeracy test percentile	72.3%	71.4%
	(0.003)***	(0.003)***
Motor test percentile	-37.0%	-35.2%
	(0.002)***	(0.003)***
Controls?	No	Yes
Pseudo R^2	0.25	0.27

All regressions include a constant. Coefficients reported are percent changes due to a standard deviation increase in the corresponding test score percentile. Controls include sex, race, birthplace, and future occupation expectations. Sample weighted standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Table 3: Education and test score intensive regressions

	(1)	(2)
Cognitive test intensive	2.01	1.98
	(0.20)***	(0.24)***
Interpersonal test intensive	1.65	1.56
	(0.13)***	(0.14)***
Literacy test intensive	2.35	2.82
	(0.23)***	(0.34)***
Numeracy test intensive	3.24	3.41
	(0.33)***	(0.43)***
Motor test intensive	0.75	0.86
	(0.06)***	(0.10)
Controls?	No	Yes
Pseudo R^2	0.17	0.20

All regressions include a constant. Coefficients reported are odds ratios. These are interpreted as the odds of an average worker with a given intensity divided by a worker without that intensity. Controls include sex, race, birthplace, and future occupation expectations. Robust standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Table 4: First skill portfolio OLS regressions

	Cognitive	Interpersonal	Literacy	Numeracy	Motor
Cognitive test percentile	0	-.0002	.0007	-.0001	-.0006
	(0)	(0.0002)	(0.0003)**	(0.0001)	(0.0002)***
Interpersonal test percentile	.0005	.0004	.0008	.0004	.0002
	(0.0001)***	(0.0001)***	(0.0002)***	(0.0001)***	(0.0001)**
Literacy test percentile	.0004	.0004	.0011	.0003	-.0002
	(0.0002)*	(0.0002)**	(0.0003)***	(0.0002)	(0.0002)
Numeracy test percentile	.0014	.0008	.0026	.0014	.0003
	(0.0002)***	(0.0002)***	(0.0003)***	(0.0002)***	(.0002)
Motor test percentile	.0002	0	-.0007	.0001	.0008
	(0.0002)	(0)	(0.0003)***	(0.0002)	(0.0002)***
Controls?	Yes	Yes	Yes	Yes	Yes
R^2	0.09	0.05	0.13	0.09	0.08

All regressions include a constant and several demographic controls. These include sex, race, birthplace, and future occupation expectations. Robust standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Table 5: First skill portfolio logit regressions

	Cognitive	Interpersonal	Literacy	Numeracy	Motor
Cognitive test intensive	1.13	1.08	1.20	1.09	0.94
	(0.108)	(0.102)	(0.118)**	(0.104)	(0.091)
Interpersonal test intensive	1.19	1.23	1.32	1.14	1.14
	(0.087)**	(0.089)***	(0.970)***	(0.084)*	(0.083)*
Literacy test intensive	1.16	1.16	1.48	1.25	0.86
	(0.110)	(0.108)	(0.138)***	(0.118)**	(0.083)
Numeracy test intensive	1.77	1.582	1.75	1.72	1.17
	(0.167)***	(0.150)***	(0.166)***	(0.162)***	(0.113)
Motor test intensive	1.10	1.03	0.94	1.02	1.35
	(0.980)	(0.090)	(0.090)	(0.091)	(0.124)***
Controls?	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.07	0.05	0.08	0.06	0.06

All regressions include a constant. Coefficients reported are odds ratios. These are interpreted as the odds of an average worker with a given intensity divided by a worker without that intensity. Controls include sex, race, education, birthplace, and future occupation expectations. Robust standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Table 6: Last skill portfolio OLS regressions

	Cognitive	Interpersonal	Literacy	Numeracy	Motor
Cognitive first job	**.539**	-.029	-.217	-.098	.073
	(0.065)***	(0.055)	(0.093)**	(0.061)	(0.070)
Interpersonal first job	-.167	**.500**	-.087	-.194	-.211
	(0.050)***	(0.049)***	(0.074)	(0.045)***	(0.047)***
Literacy first job	.030	.025	**.697**	.045	-.030
	(0.028)	(0.025)	(0.043)***	(0.028)	(0.029)
Numeracy first job	0.151	.038	.162	**.788**	.088
	(0.049)***	(0.046)	(0.071)***	(0.047)***	(0.047)*
Motor first job	-.074	-.047	-.140	-.059	**.622**
	(0.036)**	(0.032)	(0.054)***	(0.035)*	(0.038)***
Cognitive test	-.0002	-.0002	0	-.0003	-.0004
	(0.0002)	(0.0001)*	(0)	(0.0002)	(0.0002)**
Interpersonal test	.0004	.0003	.0006	.0003	.0001
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)
Literacy test	0	.0001	0	0	.0001
	(0)	(0.0001)	(0)	(0)	(0.0002)
Numeracy test	.0006	.0005	.0012	.0006	.0002
	(0.0002)***	(0.0001)***	(0.0002)***	(0.0002)***	(0.0002)
Motor test	-.0001	0	-.0001	-.0001	.0001
	(0.0002)	(0)	(0.0002)	(0.0001)	(0.0001)
Controls?	Yes	Yes	Yes	Yes	Yes
R^2	0.48	0.41	0.53	0.49	0.37

All regressions include a constant and several demographic controls. These include sex, race, birthplace, education, unemployment spells, occupation switches, and future occupation expectations. Robust standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Table 7: Percent changes in last job skills

	Cognitive	Interpersonal	Literacy	Numeracy	Motor
First cognitive	**20.00%**	0%	-2.89%	0%	0%
First interpersonal	-6.02%	**20.66%**	0%	-6.75%	-9.59%
First literacy	0%	0%	**33.92%**	0%	0%
First numeracy	5.88%	0%	5.12%	**33.20%**	4.47%
First motor	-2.64%	0%	-4.02%	-2.91%	**28.93%**

Coefficients reported are percent changes in skills over time, given a one standard deviation increase in a first occupation skill (as noted in each row). Elements with 0% mean the original coefficient was not statistically significant at the 10% or lower level, leading to no change in final occupation skill.

Table 8: Last skill portfolio logit regressions

	Cognitive	Interpersonal	Literacy	Numeracy	Motor
Cognitive first job intensive	**2.41**	1.27	1.18	1.14	1.36
	(0.352)***	(0.184)	(0.211)	(0.179)	(0.210)**
Interpersonal first job intensive	1.37	**3.53**	1.14	1.04	1.32
	(0.183)**	(0.440)***	(0.181)	(0.147)	(0.175)**
Literacy first job intensive	2.18	1.67	**7.62**	1.97	0.64
	(0.283)***	(0.202)***	(1.017)***	(0.244)***	(0.087)***
Numeracy first job intensive	1.78	1.69	1.70	**5.17**	1.32
	(0.265)***	(0.245)***	'(0.297)***	(0.785)***	(0.202)*
Motor first job intensive	0.91	0.91	0.38	0.79	**5.24**
	(0.100)	(0.96)	(0.047)***	(0.86)**	(0.490)***
Cognitive test intensive	1.04	0.98	1.25	1.01	0.87
	(0.120)	(0.109)	(0.146)*	(0.113)	(0.965)
Interpersonal test intensive	1.28	1.28	1.29	1.22	1.13
	(0.110)***	(0.107)***	(0.116)***	(0.105)**	(0.911)
Literacy test intensive	0.92	1.10	1.21	1.06	0.81
	(0.106)	(0.119)	(0.139)*	(0.119)	(0.087)*
Numeracy test intensive	1.49	1.35	1.51	1.56	0.96
	(0.170)***	(0.149)***	(0.173)***	(0.175)***	(0.105)
Motor test intensive	1.01	1.07	0.94	1.01	1.19
	(0.107)	(0.109)	(0.107)	(0.104)	(0.120)*
Controls?	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.28	0.25	0.31	0.27	0.19

All regressions include a constant and several demographic controls. These include sex, race, birthplace, education, unemployment spells, occupation switches, and future occupation expectations. Coefficients reported are odds ratios. These are interpreted as the odds of an average worker with a given intensity divided by a worker without that intensity. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Table 9: Skill Specialization on Portfolio Diversification

	(1)	(2)	(3)
Same skill	.168	.163	.129
	(0.008)***	(0.008)***	(0.008)***
Ability controls	No	No	Yes
Demographic controls	No	Yes	Yes
Adjusted R^2	0.10	0.12	0.25

All regressions include a constant and several demographic controls. These include sex, race, birthplace, education, unemployment spells, occupation switches, and future occupation expectations. Robust standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

A Regression Calibrated Results

We present the results from running a regression calibrated model, which takes into account some covariates (in our case test scores) can hold implicit measurement error. We run this methodology on regression (13), as this is our test of the validity of test scores as signals of inherent ability. We run the methodology on this one equation for two reasons. One, if we factor in mismeasurement and the results still hold, it follows that the test score's measurement error is not particularly significant across all equations. Secondly, translating this methodology to the other regressions requires us to take into account we are moving from a binary dependant variable to a continuous one. While doable, we feel the results below (Table 10 demonstrates the quantitative results presented in the main paper hold. In other words, controlling for the measurement error does not seem to impact worker's decision to attend higher education. The point estimates follow the pattern we expected. Those that scored higher on nonmotor tests were more likely to attend post-secondary education, while those that scored high on motor tests were less likely.

B Truncated Time Frame Results

We present the results from running the above specified regressions for a shorter time frame. In the main results, we use data from 1980-2014. For this shortened time frame, we use data from 1990-2008. We do this to help lend credence that our main results are not the result of an empirical quirk. The relationship we estimate is not specific to using a specific year's data, but instead, follows for a smaller time frame as well. Both Tables 11 and 12 show the same qualitative relationship as presented above in Tables 6 and 8.

Table 10: Test score effects on probability of entering higher education with measurement error

	(1)	(2)	(3)
Cognitive test	.021	.048	.046
	(0.002)***	(0.004)***	(0.005)***
Interpersonal test	.009	.009	.009
	(0.001)***	(0.001)***	(0.001)***
Literacy test	.013	.005	.005
	(0.002)***	(0.002)**	(.003)**
Numeracy test	.025	.017	.016
	(0.002)***	(0.003)***	(0.003)***
Motor test	-.019	-.028	-.026
	(0.002)***	(0.002)***	(0.003)***
Controls included?	Yes	No	Yes
Methodology	Logit	Calibrated	Calibrated

Regressions include a constant and several demographic controls. These include sex, race, birthplace, and future occupation expectations. Coefficients reported are marginal probabilities to interpret across methodologies. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Table 11: Last skill portfolio OLS regressions with shortened time frame

	Cognitive	Interpersonal	Literacy	Numeracy	Motor
Cognitive first job	**.380**	-.029	-.198	-.119	.051
	(0.106)* **	(0.095)	(0.143)	(0.102)	(0.128)
Interpersonal first job	-.187	**.342**	-.108	-.233	-.254
	(0.068)***	**(0.066)*** **	(0.108)	(0.058)***	(0.067)***
Literacy first job	.104	.072	**.734**	.080	-.018
	(0.040)***	(0.36)**	**(0.059)*** **	(0.039)**	(0.044)
Numeracy first job	.175	.018	.088	**.740**	.085
	(0.065)***	(0.060)	(0.098)	**(0.059)*** **	(0.067)
Motor first job	-.084	-.050	-.173	-.081	**.558**
	(0.047)*	(0.043)	(0.071)**	(0.045)*	**(0.056)*** **
Cognitive test percentile	-.0001	-.0001	-.0001	-.0002	-.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Interpersonal test percentile	.0003	.0002	.0005	.0003	-.0001
	(0.0001)**	(0.0001)*	(0.0002)***	(0.0001)***	(0.0001)
Literacy test percentile	-.0003	-.0002	-.0003	-.0003	-.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Numeracy test percentile	.0005	.0004	.0011	.0006	.0002
	(0.0002)***	(0.0002)**	(0.0003)***	(0.0002)***	(0.0002)
Motor test percentile	-.0001	.0001	.0001	0	-.0001
	(0.0001)	(0.0002)	(0.0003)	(0.0001)	(0.0002)
Controls?	Yes	Yes	Yes	Yes	Yes
R^2	0.41	0.27	0.52	0.42	0.24

All regressions include a constant and several demographic controls. These include sex, race, birthplace, education, unemployment spells, occupation switches, and future occupation expectations. Robust standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Table 12: Last skill portfolio logit regressions with shortened time frame

	Cognitive	Interpersonal	Literacy	Numeracy	Motor
Cognitive first job intensive	**2.408**	1.238	1.115	1.354	1.250
	(0.327)***	(0.169)	(0.162)	(0.188)**	(0.272)
Interpersonal first job intensive	1.170	**2.572**	1.094	1.069	1.215
	(0.138)	**(0.298)*****	(0.137)	(0.131)	(0.141)*
Literacy first job intensive	0.945	0.762	**2.444**	0.881	0.545
	(0.112)	(0.086)**	**(0.289)*****	(0.105)	(0.063)***
Numeracy first job intensive	1.346	1.142	0.971	**2.692**	0.894
	(0.181)**	(0.152)	(0.135)	**(0.374)*****	(0.115)
Motor first job intensive	0.796	0.798	0.606	0.703	**2.836**
	(0.077)**	(0.076)**	(0.057)***	(0.068)***	**(0.272)*****
Cognitive test intensive	1.053	0.974	0.941	1.002	0.988
	(0.114)	(0.102)	(0.103)	(0.107)	(0.105)
Interpersonal test intensive	1.046	1.123	1.147	1.100	0.986
	(0.087)	(0.090)	(0.096)*	(0.091)	(0.079)
Literacy test intensive	0.784	0.979	1.104	0.837	0.860
	(0.082)**	(0.100)	(0.116)	(0.087)*	(0.089)
Numeracy test intensive	1.232	1.138	1.336	1.364	0.816
	(0.134)*	(0.118)	(0.142)***	(0.148)***	(0.085)**
Motor test intensive	1.229	1.066	0.973	1.086	1.307
	(0.119)**	(0.100)	(0.094)	(0.104)	(0.122)***
Controls?	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.06	0.11	0.09	0.08

All regressions include a constant and several demographic controls. These include sex, race, birthplace, education, unemployment spells, occupation switches, and future occupation expectations. Coefficients reported are odds ratios. These are interpreted as the odds of an average worker with a given intensity divided by a worker without that intensity. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.