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COGNITIVE AND NONCOGNITIVE SKILLS AND THE SELECTION AND SORTING OF MIGRANTS

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ABSTRACT

There is growing evidence that cognitive and noncognitive skills are strong predictors of the economic and social outcomes of individuals. In this paper, we analyze how they affect the migration decisions of individuals over their lifecycles. We use data that combine military enlistment and administrative records for the male population born in 1932 and 1933 in Norway. Records of interviews with a psychologist at age 20 allow us to construct an index of `sociability' and `adaptability' for each individual, as well as an index of cognitive ability, the intelligence quotient. We find that adaptability and cognitive ability have significant and positive impacts on the probability of an individual migrating out of his area, whether this involves rural-urban, long distance, or international migration. Adaptability has a particularly strong impact on migration for individuals with low cognitive skills, implying a strong positive selection of less educated migrants with respect to the (previously unobserved) adaptability skill. We also show that cognitive skills have a strong positive effect on sorting of migrants across destinations, whereas adaptability has no significant effect on sorting. This evidence suggests that adaptability reduces the psychological cost of migrating, whereas cognitive skills increase the monetary returns associated with migration.

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1 Introduction

Recent economic research has found that noncognitive skills, often referred to as 'soft skills', including the degree of sociability or adaptability to new people and situations, are important predictors of economic outcomes such as earnings and employment. Although the traditional theory of human capital has emphasized the role of schooling and mainly focused on cognitive abilities, we are beginning to understand the role of other noncognitive abilities in labor productivity. These abilities may affect the marginal productivity of individuals (see Lindqvist and Vestman, 2011; Lundborg, Nystedt, and Rooth, 2014; Gensowski, 2014, among others), enhance their accumulation of human capital (Segal, 2013), or affect their occupational choice (see, e.g., Bacolod, Blum, and Strange, 2009). They may also affect other social outcomes with important economic consequences, such as the probability of becoming an entrepreneur, the probability of criminal activity, or an individual's health outcomes.[1] In the context of this literature, the present paper analyzes how noncognitive skills affect individuals' probability of migrating and their sorting across destinations. We also compare the role of noncognitive skills to that of cognitive skills (measured as the intelligence quotient, IQ) in the selection and sorting of migrants.

International, interregional, and rural–urban migration are crucial ways of enhancing the labor market outcomes of individuals. The literature (e.g., Malamud and Wozniak, 2012; Grogger and Hanson, 2011) has long recognized the positive role of schooling in predicting the propensity to migrate internally and internationally. This is known as 'positive selection' of migrants in terms of skills. What part of this selection is due to cognitive and what part to noncognitive skills remains little known. To our knowledge, this is the first paper to analyze how cognitive and noncognitive skills, measured at age 20 years, help predicting the probability of migration and the sorting of migrants across locations for individuals over their lifetime.

Answering this question advances a line of research that has been central in the migration literature. As already mentioned, this paper improves our understanding of migrant selection and sorting across destinations. If having certain skills makes individual more likely to migrate, then the migrant population will have a higher intensity of that skill relative to the nonmigrant population. This is known as 'positive selection' of migrants along that skill dimension. Second, and equally important, if migrants move in response to opportunities which increase their compensation for that skill, then also the sorting of migrants across locations will depend on their skills and the geographic compensation of those. However, if a skill simply decreases the cost of migrating, then selection of migrants, but not their sorting will be affected by the skill and the monetary return to migration may also not be correlated with that skill. A positive selection and/or sorting of migrants on noncognitive characteristics, such as adaptability and sociability, affects their subsequent outcomes

[1] Noncognitive abilities appear to differ between men and women more than cognitive ones and, hence, they may contribute to explaining the gender wage gap and its secular decline (Beaudry and Lewis, 2014)

as a group.[2]

This paper contributes also to another branch of the literature, which studies the channels through which cognitive and noncognitive skills affect an individual's economic success. Migration is an important investment and a mechanism through which people increase their permanent income. Migrants pay a cost to move to locations where the income for their skills is higher and, hence, brings higher returns to their abilities. The connection between abilities and labor market success can be mediated by geographical mobility. Skills that reduce the cost of or increase the economic returns to moving may, in the long run, facilitate better employer–employee matches and encourage more efficient allocation of productive resources, with gains for workers and firms.

The correlations between schooling and migration and the selection of migrants along the educational dimension have been studied extensively (see, e.g., Borjas, 1987; Borjas, Bronars, and Trejo, 1992; Dahl, 2002; Grogger and Hanson, 2013). However, to our knowledge, fewer studies have analyzed how cognitive and noncognitive abilities affect the selection and sorting of migrants (Jaeger, Dohmen, Falk, Huffman, Sunde, and Bonin, 2010; Jokela, Elovainio, Kivimäki, and Keltikangas-Järvinen, 2008; Jokela, 2009). The main contribution of this paper is to analyze whether two types of noncognitive skills, which we define as 'adaptability' and 'sociability', and one cognitive skill, 'IQ', all measured at age 20 years, affect the probability of individuals migrating and their sorting across destinations during their working life. We investigate these effects by using detailed population registry data from Norway from 1960 until 2010, which include annual information on the municipality of residence and labor market outcomes of all individuals. These data can be linked to those on military enlistment for men. Military enlistment was mandatory for Norwegian men during the considered period. The military enlistment data include an abundance of individual and family background characteristics and, more interestingly, several scores assessing the cognitive ability of individuals and their psychological suitability for military service, evaluated at the time of enlistment. The psychological suitability for military service, evaluated by military psychologists in personal interviews, assesses two interesting traits of the recruits: adaptability and sociability, which we will define precisely below.[3] The data on psychological characteristics are available only for individuals who enlisted in 1952 and 1953 (birth cohorts 1932 and 1933). Hence this paper analyzes these two cohorts, that we can follow over their working life, starting in 1960, when they were 27 to 28 years old, until their retirement.

Our main goal is to analyze whether IQ, adaptability, and sociability scores at military enlistment predict the probability of migrating and where individuals will move over their lifecycle. We

[2]For instance high selectivity of migrants may help explain why some studies find that migrants have higher entrepreneurial rates (Robb and Fairlie, 2009), lower incarceration rates (Butcher and Piehl, 2007), and better health outcomes (Center for Disease Control and Prevention, 2015) than U.S. natives with similar observable characteristics. In general, if cognitive and noncognitive abilities that increase the probability to migrate also contribute to their economic and social success, this bodes well for their assimilation into the receiving economy.

[3]We follow previous work by Lindqvist and Vestman (2011) in considering that assessments by military psychologists offer a reasonable and objective measure of noncognitive abilities. We discuss the details below.

also analyze whether the cognitive and noncognitive attributes of an individual interact with one another in determining the propensity to migrate. Besides establishing a link between skills and the probability of moving out of one's local labor market, we ask a second important question: through what channels do adaptability, sociability, and cognitive ability affect migration? In particular, with a focus on noncognitive skills, did these factors mainly affect the potential economic return to migration or rather did they reduce the psychological cost of migration.

We develop a simple variation of the Roy (1951) model of migration and selection, where a rational individual decides to emigrate if the expected returns from migration are larger than the (monetary plus psychological) costs of moving. We allow for different skills and we derive different predictions of the model in regard to the migration probability, the sorting between destinations and the pre- and post-migration earnings differential, depending on whether a skill affect productivity (and hence returns) or psychological costs of migration. This model generates the prediction that, under assumptions that are satisfied in our data, a person with high level of a productivity-enhancing skill should be more likely to migrate and more likely to choose a destination with high returns to that skill. Moreover, such a person should have positive and significant pre-post migration earnings differential. Instead, a skill that affects the psychological cost of migration still has a positive predictive power on the migration probability, but it will not be correlated with the sorting into destinations with high returns to those abilities and should show a null (or negative) pre-post migration average earnings differential.

We find that IQ has a significant and positive predictive power on the probability of migrating (across regions or moving from rural to urban locations) within the first decades of working life. Sociability does not exhibit any correlation with the propensity to migrate. Adaptability, instead has a strong predictive power on the probability of migration and this is particularly strong for individuals outside the top quintile of cognitive ability. Adaptability is an attribute significantly increasing the probability of migration, except for people with very high cognitive skills, whose probability of migrating is high in any case. This suggests a strong and positive selection of migrants along the adaptability dimension, especially for those with lower cognitive abilities.

In several extensions and checks, we show that adaptability has a strong predictive power on the probability of migrating, even when we control for all unobserved family-specific effects by using within-family variation between male siblings. Moreover this association is not due to migration during childhood or relocation during military service, or because of marriage, as controlling for those does not change the impact of adaptability. This higher propensity to migrate of highly 'adaptable' individuals is stronger earlier in life and also applies to international mobility. Moving to sorting across destinations, our empirical analysis shows that higher individual adaptability does not increase the probability of sorting into destination with high returns to adaptability. This is in contrast with the role of cognitive skills. Individuals with high levels of cognitive skills have higher probability of migrating as well as of locating in places with high returns to cognitive skills. Finally we show that pre-post migration earnings differential are positive and positively correlated with the IQ, while the pre-post migration earnings differential are not correlated with the individual level of adaptability. Taken together, these findings are consistent with adaptability reducing the psychological costs of migration while IQ increase the economic returns of migration.

The rest of the paper proceeds as follows. Section 2 summarizes the previous literature that analyzes the effect of noncognitive abilities on labor market characteristics. Section 3 presents the theoretical model. We discuss the data and provide descriptive statistics in Section 4. We describe our empirical strategy in Section 5. We discuss our results and the robustness analysis in Section 6 and Section 7. Section 8 provides concluding remarks.

2 Previous Literature

The existing literature on the selection of migrants is abundant. Part of this literature is based on variations of the model introduced by Roy (1951), and then adapted by Borjas (1987) and Grogger and Hanson (2013), to analyze the skill selection of international migrants. Those models emphasize different types of selection across skills depending on the skill returns in the sending and receiving economies. In the context of internal migration, Borjas, Bronars, and Trejo (1992) finds that workers are more likely to leave their state of origin if their skills are mismatched with the reward structure offered by their current state, and Dahl (2002) shows that differences in the returns to education and amenities across states are important determinants of the relative state-to-state migration flows of individuals with university versus high school educations. Another strand of the literature focuses on documenting the higher geographic mobility of university-educated relative to less educated individuals, both internally (e.g. Malamud and Wozniak, 2012; Molloy, Smith, and Wozniak, 2011) and internationally (e.g. Marfouk, 2007). Some studies analyze the selection of migrants on observable and unobservable characteristics (e.g. Fernández-Huertas Moraga, 2011; Ambrosini and Peri, 2012), mainly relying on wages before migration to capture the unobserved human capital characteristics of migrants. Hence, these papers characterize the migrant selection as positive or negative depending on the premigration wage of migrants relative to that of nonmigrants. Much less common are investigations of the connection between cognitive and noncognitive skills and migration behavior. One reason for this is the extremely limited availability of measures of cognitive and noncognitive skills at the individual level, in data that track individuals across locations. In many cases, the skill content of individuals is derived from their occupational choice (e.g. Beaudry and Lewis, 2014), which is clearly the result of a choice (often made jointly with geographical mobility) and hence is ill suited to predict propensity to migrate.

One of the few papers analyzing the impact of noncognitive skills of individuals on migration is a study by Jaeger, Dohmen, Falk, Huffman, Sunde, and Bonin (2010), which looks at the relationship between self-assessed risk attitudes and migration using data on risk aversion from the German Socioeconomic Panel (GSOEP). The authors find that individuals who are more willing to take risks are also more likely to migrate, confirming the theory that migration is a risky investment in human capital.[4] Differently from our paper, Jaeger, Dohmen, Falk, Huffman, Sunde, and Bonin (2010) do not analyze sorting of migrants, nor are they able to use early-life measures of cognitive and noncognitive skills to predict migration over the whole lifecycle. We are also able to control for many more family and individual background characteristics to isolate more carefully the role of noncognitive and cognitive skills in selection and sorting of migrants. Finally, relative to Jaeger, Dohmen, Falk, Huffman, Sunde, and Bonin (2010) we consider broader measures of skills, spanning cognitive and non-cognitive characteristics of individuals and assessed by experts rather than just one specific attitude, self-assessed as in the GSOEP sample.

A few studies in the psychological literature have investigated the relationship between self-assessed personality traits and migration. Examples include Jokela, Elovainio, Kivimäki, and Keltikangas-Järvinen (2008), who examine whether sociability and emotionality predict migration propensity, selective urban to rural migration, and migration distance in a 9-year prospective study in Finland. The authors find that high sociability predicts migration to urban areas and longer migration distances. In addition, Jokela (2009) examines the role of personality in predicting the propensity to migrate within and between states in the U.S. He shows that high openness and low agreeableness increase within- and between-state migration, whereas high extroversion increases within- but not between-state migration. Other mental traits were not related to migration probability. Therefore, our study is the first to use individual panel data from administrative sources fully covering a two-year birth-cohorts of males in a country (Norway) and a measure of noncognitive soft skills based on personal interviews (not self-assessed or occupation-inferred) and analyze whether they predict propensity to migrate and selection into destinations. As these abilities are measured at age 20 years and the individuals are followed over their whole working life, we can assess the long-term predictive ability of different cognitive and noncognitive abilities on migration outcomes.

Although few studies have analyzed noncognitive skills in relation to migration choices, the literature on the impact of noncognitive skills on the labor market outcomes of individuals is growing. The majority of these papers, however, measure noncognitive abilities based on self-reported questionnaires (Duncan and Morgan, 1981; Murnane, Willett, Braatz, and Duhaldeborde, 2001; Goldsmith, Veum, and Jr., 1997; Mueller and Plug, 2006; Borghans, Meijers, and ter Weel, 2008) or infer noncognitive ability from observed behavior (Heckman and Rubinstein, 2001; Heckman, Stixrud, and Urzua, 2006; Kuhn and Weinberger, 2005). More recently, noncognitive ability has been measured using teacher evaluations (Segal, 2013) or personal interviews with a psychologist (Lindqvist and Vestman, 2011). In particular, Segal (2013) finds that eighth-grade misbehavior, as assessed by a teacher, is negatively correlated with earnings and is associated with lower educational

[4]Bauernschuster, Falck, Heblich, Suedekum, Lameli (2014) study the mechanisms behind the higher mobility of risk-loving individuals and find that these people are more mobile over longer distances because they are more willing to cross cultural boundaries and move to regions that are culturally different from their homes.

attainment, even after controlling for test scores and family background characteristics. Lindqvist and Vestman (2011) use Swedish data from military enlistment, similar to the data that we use in this paper, and find that a low level of labor market attachment and low annual earnings are closely associated with a lack of noncognitive, rather than cognitive skills, in Swedish men. On the other hand, they present empirical evidence showing that cognitive ability is a stronger predictor of earnings for highly skilled workers. Several other papers use the same Swedish military enlistment data as Lindqvist and Vestman (2011). For example, (Grönqvist and Vlachos, 2016) analyze the effects of teachers' social abilities on student achievement and show that an increase in teachers' social abilities reduces the achievement gap between high- and low-aptitude students. Moreover, Black, Grönqvist, and Öckert (2017) study the effect of birth order on noncognitive abilities and find that earlier-born men are more emotionally stable, persistent, socially outgoing, willing to assume responsibility, and able to take the initiative than later-born men. Edin, Fredriksson, Nybom, and Öckert (2017) examine the changes in the relative rewards to cognitive and noncognitive skills from 1992 to 2013. In addition, Huttunen, Møen, and Salvanes (2018) and Løken, Lommerud, and Lundberg (2013) show that noneconomic factors such as family ties are very important for migration behavior in Norway. Our study uses data with quality comparable to that of Lindqvist and Vestman (2011). To our knowledge, this is the first study using individual data over individuals' lifecycle to analyze the selection into migration and the sorting of migrants as affected by cognitive and noncognitive skills. We do this within the simple framework of a Roy model.

Let us emphasize that most of this literature, and our paper too, considers the cognitive and noncognitive abilities of individuals as determined early in life (in part possibly as innate) and then analyze how these traits help to predict outcomes during people working and social life. This literature cannot be considered as genuinely identifying 'causal' effects, because it is impossible to randomly assign or change these skills. However, it is still very important to identify skills that have a strong and stable predictive power for labor market and economic outcomes.[5] In terms of migration, our analysis will help characterize what are the specific traits of migrants, how they differ from those of the general population, and how these traits predict probability of migrating and sorting. This is the sense in which, sometimes, we will say that noncognitive skills 'affect' migration. As in all this literature such a statement is not so much about causality (as random assignment of noncognitive skills is impossible) as about prediction and robust association.

3 Framework

We consider a framework that extends the typical model by Roy (1951) to two skills, cognitive and non-cognitive, and we discuss the selection of migrants. In this framework, individuals differ in terms of two observable characteristics $\underline{s}$ (consider cognitive skills as s_1, and noncognitive skills

[5] In recent OECD report, Kautz, Heckman, Diris, ter Weel, Borghans (2015) discuss that individual skills are stable at a point in time, but can be shaped in the early years of life.

as s_2), and one residual unobservable characteristic ε, the distribution of which, conditional on the other characteristics, is a random normal with a 0 average and a standard deviation of one.[6] These individuals live in location H, maximize their wage income, and are considering whether to migrate to location F. Location F has higher return to cognitive skills relative to H, as well as higher return to noncognitive skills. This captures the fact that in the Norwegian regions that we analyze, the return to cognitive and noncognitive skills are strongly positively correlated across regions (see scatterplot in Figure A1 in the appendix); Individuals compare the alternative location to their current one. The wage that individual i would receive if he remains in H and works in that location is:

$$w_i^H = \mu^H + \underline{\beta}^H * \underline{s}_i + \beta_\varepsilon^H \varepsilon_i, \tag{1}$$

where $*$ indicates a vector product, μ^H is the average productivity of an individual in location H, $\underline{\beta}^H = (\beta_1^H, \beta_2^H,)$ is the vector of linear returns to units of cognitive and noncognitive skill s_i in location H and $\underline{s}_i = (s_{1i}, s_{2i},)$ is the endowment of each skill for individual i. In expression (1), we assume that skills affect productivity linearly and independently of each other. This is a simplification that can be removed to analyze interactions across skills (as we do in the empirical analysis). Similarly, we assume that the parameter $\beta_\varepsilon^H \geq 0$ represents the return to one unit of the unobservable skill and ε_i is individual i's endowment of that skill. The wage that individual i receives if he were to move to F is:

$$w_i^F = \mu^F + \underline{\beta}^F * \underline{s}_i + \beta_\varepsilon^F \varepsilon_i, \tag{2}$$

where μ_F is the average productivity of location F and $\underline{\beta}^F = (\beta_1^F, \beta_2^F)$, with $\beta_1^F > \beta_1^H \geq 0$ and $\beta_2^F > \beta_2^H \geq 0$ are the returns to individual cognitive and noncognitive skills, respectively, in location F. Consider the case where region F has also larger return for the unobservable skill ($\beta_\varepsilon^F > \beta_\varepsilon^H$). This case presumes that locations in Norway with large returns to cognitive and noncognitive skills have also higher returns to unobservable skills. As we think of our indicator of cognitive and noncognitive skills as imperfect measures of the latent skills of an individual the unobserved part likely captures skills that are valued similarly to the observed ones.[7] We also assume that the cost of moving to any location for individual i is equal to C_i. C_i has two components: C_M, representing monetary costs, which is expressed in units of labor income and is common to all migrants; and $c(\underline{s}_i)$, representing psychological costs that may depend also on the cognitive and noncognitive individual skills $\underline{s}_i$. In particular, it is plausible to assume that $\partial c/\partial s_i \leq 0$ for $i's = 1, 2$, so

[6] Skills may be correlated in their distribution across individuals. The term ε is the residual skill and, conditional on observable skill endowments, is randomly distributed across individuals with a mean of zero.

[7] Dustmann, Fadlon, and Weiss (2011) consider a model in which different locations have different rates of returns for two separate skills. They consider all possible cases, including one in which a location grants higher returns to one skill and lower returns to the other and they also include different learning in each skill dimension. Their goal is to explain potential migration and return.

that higher endowments of cognitive, or noncognitive skills may reduce (or have no effect on) the psychological costs of migration.

Given this very simple setup, the decision of an income maximizing agent on whether to migrate is driven by a comparison of the wage income at home (H) with the wage income at the destination (F), net of migration costs. Hence, individual i migrates from H to F if:

$$w_i^F - w_i^H - C_M - c(\underline{s_i}) > 0. \tag{3}$$

Substituting (1) and (2) into (3) and solving for the variable ε_i, we find that individual i migrates if his unobservable skills ε_i satisfy the following condition:

$$\varepsilon_i > \varepsilon^T(\underline{s_i}) = \frac{C_M + c(\underline{s_i}) - (\mu^F - \mu^H) - (\underline{\beta}^F - \underline{\beta}^H) * \underline{s_i}}{(\beta_\varepsilon^F - \beta_\varepsilon^H)}. \tag{4}$$

The above expression implies that, given the assumptions on the parameters and on function $c(.)$, the threshold ε^T for the nonobservable skill such that individual i will migrate is decreasing in each component of the vector $\underline{s_i}$ so that $\partial\varepsilon^T/\partial s_1 \leq 0$ and $\partial\varepsilon^T/\partial s_2 \leq 0$. An individual with higher cognitive and noncognitive ability will (possibly) gain more from migration and (possibly) have lower costs of migrating. Hence, the unobserved productive component will have a lower threshold above which the individual will migrate. This structure implies also that the selection on the unobserved skill, ε^i, is positive, just as the selection on observed skills s_i.

Consider now individuals organized into groups that have a certain vector of observable characteristics $\underline{s_G} = (s_{G1}, s_{G2})$. Within each group, there are individuals with different unobservable characteristics ε_i, and these characteristics are normally distributed with a mean of zero and a standard deviation 1, independent of the other characteristics. Then, the probability of migration for an individual in group G (i.e., with observable characteristics s_G) is:

$$prob_i^{MIG}(\underline{s_G}) = \Pr(\varepsilon_i > \varepsilon^T(\underline{s_G})) = 1 - \Phi(\varepsilon^T(\underline{s_G})), \tag{5}$$

where $\Phi(.)$ is the cumulative density function of a standard normal distribution, the first derivative of which is strictly positive. Expression (5) implies that the probability of migrating $prob_i^{MIG}$ for individual i in group G is larger when any of the observable skill components s_{G1} or s_{G2} is larger. Interestingly, this simple model implies that, looking at the probability of individuals migrating as a function of their (cognitive and noncognitive) abilities that may have a productivity or migration cost-reducing effect, one obtains a similar positive relation with migration probability.

There are two channels through which higher skills affect the probability of migrating, both of which imply a nonnegative effect under the assumptions of the model. One is through the term $-(\underline{\beta}^F - \underline{\beta}^H) * \underline{s_i}$ in expression (4), which implies a higher return to migration for individuals with a higher value of any of the skill components $\underline{s_i}$ that have a positive productivity effect. This term also reduces the unobserved skill threshold, increasing the probability of migrating. The other effect works through the term $c(\underline{s}_i)$ in expression (4), which implies a lower psychological cost of migration, associated with higher skills, a reduction of the migration threshold, and an increase in migration probability.

While the qualitative implication of cost-reducing and productivity-enhancing skills on probability to migrate may be similar there is a crucial difference. The intensity of the effect of skill on migration probability increases with the return to the skill in the receiving country for productivity-enhancing skills, while it does not for cost-reducing skills. In this sense, productivity-enhancing skills affects the intensity of 'sorting' of migrants in destination countries and not just their selection into migration.

Think of a country F where the returns to a skill (say cognitive) increase (β^F increases), then the probability of emigration to that country increases (the threshold $\varepsilon^T(\underline{s_G})$ decreases) and proportionately more for individuals with larger values of s_1 because of the interaction effect. Hence across countries with different returns to productivity-enhancing skills migrants will sort according to their level of productivity enhancing skills. To the contrary for cost-reducing skills which have no productivity effects (which implies $\beta_i^H = \beta_i^F = 0$ for that skill), higher values of that skill will still imply higher probability of migrating, but they will have no implication on sorting.

A second difference between skills affecting returns and skill affecting costs is on the average migration premium for people who migrate. The migration premium is the difference in wages between migrating and staying for individual i in group G. For individual i in group G, that premium can be expressed as:

$$w_G^F - w_G^H = (\mu^F - \mu^H) + (\underline{\beta}^F - \underline{\beta}^H) * \underline{s}_G + (\beta_\varepsilon^F - \beta_\varepsilon^H) \int_{\varepsilon^T(\underline{s_G})}^{\infty} x dx. \tag{6}$$

This expression allows us to characterize the impact that an increase in a specific skill s_i for the group will have on the expected return to migration for people who migrate. First, let us consider a skill s_i, which has no impact on productivity, $\beta_m^F = \beta_m^H = 0$, but does have an impact on migration through reducing the costs of migration $\partial c/\partial s_i < 0$. In this case, an increase in that skill will imply a larger probability of migrating in (5), as $\partial \varepsilon^T/\partial s_i < 0$. Moreover, the only effect on the migration premium is through the factor $\varepsilon^T(\underline{s_G})$ in the last term of (6). As that average of the normally distributed variable x, conditional on $x > \varepsilon^T(\underline{s_G})$, is an increasing function of $\varepsilon^T(\underline{s_G})$, an increase in the skill s_i will reduce this term. Hence, if skill s_m only affects the cost of migrating, by decreasing these costs, without any impact on the returns to migration, the effect of an increase in such a skill on the expected return for people who migrate is negative.

Consider instead a skill, $s_{i'}$, that only affects productivity, and hence the return to migration, so that $\beta_{i'}^F - \beta_{i'}^H > 0$ and $\partial c/\partial s_{i'} = 0$. In this case, the first effect of an increase in $s_{i'}$ will be an increase in the term $(\underline{\beta}^F - \underline{\beta}^H) * \underline{s}_G$ in expression (6). This term increases the expected returns to migration. However, the same increase will also have an effect on reducing $\varepsilon^T(\underline{s_i})$ and hence, the last term of expression (6) would decrease. However, for a sufficiently large value of $(\underline{\beta}^F - \underline{\beta}^H)$—that is, if the effect on returns to migration is sufficiently large—the first term will prevail and an increase in the productivity-enhancing skill $s_{i'}$ will have a positive impact on the average premium of migrants. On the other hand, this skill will also have a positive impact on the probability of migrating $s_{i'}$.

Overall, the effect on expected returns to migration will depend on the relative strength of the two effects on productivity and costs. A larger impact of such a skill on the cost of migrating will reduce the expected returns to migration. A larger impact on productivity will imply a positive effect on expected returns. At the same time, the increase in that type of skill will increase the probability of migration through both channels.

Hence, we can summarize the implications of the model above into the following stylized predictions:

1. **Productivity-enhancing skill:** Consider two groups, G and G', of workers with different levels of skill m so that $s_m^G < s_m^{G'}$. If this skill *mainly affects productivity* (positively):
   - We should observe a higher emigration probability of group G', namely $prob_i^{MIG}(\underline{s_{G'}}) > prob_i^{MIG}(\underline{s_G})$ (*Selection*).
   - Considering two destination countries 1 and 2, such that $\beta_1^F > \beta_2^F$, we should observe higher probability of group G' to migrate to country 1 relative to group G (*Sorting*).
   - Finally, we should observe higher average wage differential from pre to post-migration for group G' relative to G: $w_{G'}^F - w_{G'}^H > w_G^F - w_G^H$. (*Returns*)
2. **Cost-reducing skills:** Consider two groups G and G' of workers with different levels of skill n so that $s_n^G < s_n^{G'}$. If this skill *mainly affects migration costs* (negatively):
   - We should observe a higher migration probability of group G', namely: $prob_i^{MIG}(\underline{s_{G'}}) > prob_i^{MIG}(\underline{s_G})$ (*Selection*).
   - We should observe no sorting of these groups across foreign countries.
   - Finally we should observe a lower or equal average wage differential pre- and post-migration for G' relative to G: $w_{G'}^F - w_{G'}^H \leq w_G^F - w_G^H$. (*returns*)

These three predictions relating different types of skills to selection, sorting and income-differentials of migrants are tested in our empirical analysis. This allows us a consistent interpretation of the role played by cognitive and noncognitive skills in increasing returns or reducing the cost of migration.

4 Data and Descriptive Statistics

The data used are compiled from various sources. Our primary data source is the Norwegian Registry Data, a linked administrative dataset that covers the whole resident population in Norway up to 2010. These data combine different administrative registers, including the central population register, the family register, the education register, and the tax and earnings register. The data follow individuals over time in a longitudinal design and provide information about place of birth, place of residence, educational attainment, labor market status, earnings, and demographic variables, as well as information on family background. This information is collected for each individual every year. To obtain information on individual cognitive and noncognitive skills, we linked the registry data with detailed military enlistment data for two full cohorts of men, born in 1932 and 1933, for whom these data are available. These two cohorts include all male individuals born in Norway between 1932 and 1933 who were subject to mandatory military enlistment in 1952 and 1953. They constitute our sample. We describe the variables and summary statistics for our sample and some of the average characteristics in the following sections.

4.1 Registry Data: Migration and Demographics

The central population register contains the municipality of birth and the municipality of residence of each individual from 1960 onwards. In addition, the central population register includes an indicator identifying individuals who emigrated permanently to a foreign country after 1960. Moreover, the enlistment data include the place of residence at enlistment, which represents the location where an individual lived at about age 20 years. Hence, from 1960 (when individuals in the sample were 27 or 28 years old), we know their residence and, in particular, whether they moved from the municipality of residence at military enlistment. Educational attainment is obtained from the educational database provided by Statistics Norway and enlistment records.[8] The earnings measure is not top-coded and includes labor earnings (expressed in constant 2014 NOK), taxable sick-leave benefits, unemployment benefits, parental leave payments, and pensions.

Table 1 contains the summary statistics for various migration outcomes used as dependent variables in our analysis and summary statistics for demographic characteristics and skills for male Norwegian individuals born in 1932 and 1933. Examining the years of schooling completed at enlistment, we clearly see that the majority of individuals had already completed their schooling at enlistment: the average years of schooling were 8.4 at enlistment, compared with an average completed years of education of 9.5 years for the same sample of individuals. This reflects the fact that in the two considered cohorts, only a few individuals continued to university education.

[8]Since 1974, educational attainment has been reported directly on an annual basis to Statistics Norway, thereby minimizing any measurement error. For individuals who completed their education before 1974 (most of our sample), we use self-reported information from the 1970 Census, which is considered to be very accurate (see, e.g., Black, Devereux, and Salvanes, 2005).

The average earnings in 1980 were 325,442 NOK (in 2014 values); in 1967, the first year for which income data is available, the average earnings were 239,388 NOK (in 2014 values), reflecting the real growth in earnings for this group over time and over their lifecycle.

We use several different indicators of mobility: the first captures mobility by ages 27–28 years and is a dummy equal to one if an individual resides in a labor market in 1960 different from the one where he resided at enlistment. Labor market areas are an aggregation of municipalities (the smallest political entity in Norway) based on commuting patterns between municipalities, subject to the constraint that regions should be sufficiently large for empirical analysis (see Bhuller, 2009).[9] There are a total of 46 local labor market areas in Norway (see Figure A2).[10] These local labor market areas have no administrative or political purposes. We use an alternative mobility indicator, equal to a dummy for living in a different local labor market as of year 1980, that captures overall mobility by ages 47–48 years. The average of these two variables (0.39 and 0.45, respectively) implies that 39 percent of the Norwegian male population born in 1932–33 moved out of the local labor market where they resided at age 20 years by age 28 years. By age 48 years, 45 percent had moved. These statistics confirm that most migration out of local labor markets took place when individuals were young, and that Norwegian male individuals were quite mobile during this period. Interestingly, 31 percent moved permanently. That is, they moved out of the local labor market where they had resided at age 20 years and never moved back (as of 2010 or the year of death). The data also show that, among those who moved out of their labor market region of origin, 74 percent had only moved once as of 1980. Only 5 percent of the movers moved three times or more. The average distance that individuals moved between age 20 years and year 1980 was 470 km, which is comparable to the distance between Paris and London or Milan and Munich. The median distance was 225 km, which implies that a large proportion of the moves were more local.

To capture mobility between more distant locations specifically, we consider an additional indicator, which is equal to one when an individual had moved to a different 'macroregion' (in Norwegian, a landsdeler) as of 1980. Norway is commonly divided into five geographical macroregions (see Figure A3), which are geographical characterizations only and have no administrative purposes. As shown in Table 1, by 1980, 19 percent of the Norwegian male population born in 1932–33 had moved out of the macroregion where they resided at age 20 years.

Finally, in terms of migration outcomes, we consider a dummy variable that captures rural–urban migration and a dummy for having moved abroad. Statistics Norway divides municipalities into four different levels (on a scale from 0–3) in terms of centrality (see, e.g., SSB, 1994). We define municipalities as urban areas if they have the highest level of centrality and as rural if they have lower values. The highest level of centrality includes urban settlements with a population of

[9] We focus on migration across local labor markets rather than across counties (Norwegian: fylke). Some large cities in Norway encompass more than one county and, therefore, cross-county movement may not reveal genuine changes in work locations and environments.

[10] The archipelagos in the Arctic Ocean, Svalbard and Jan Mayen, are not included in the labor market regions.

at least 50,000, as well as municipalities located within 75 minutes travelling time from the center of an urban settlement with a population of at least 50,000. By ages 27–28 years, about 19 percent of individuals had moved from a rural to an urban location, and by ages 47–48 years, about 23 percent had moved from a rural to an urban location. Even more than overall mobility, rural–urban mobility takes place early in the working life of an individual. These features are consistent with male migration in the age range between 20–48 years being mainly job driven: it is easier to change jobs when one is young because the urban environment provides greater opportunities for jobs and people usually move once or at most twice for a job opportunity.

4.2 Military Enlistment Data

Military enlistment and military service was mandatory for men in Norway in 1952 and 1953. Hence, our enlistment data include all male individual born in 1932 and 1933 (20 years old in 1952 and 1953). Before these young men could join the military, their medical and psychological suitability was assessed. Note that we focus on these two birth cohorts as we can only link these two cohorts' measures of noncognitive skills from military enlistment to the population register. In the 1950s, about 20 men per day were examined in military enlistment centers. Each conscript was interviewed individually by an officer and a psychologist, in addition to receiving an examination by a doctor. In addition to the interviews and medical tests, the enlistment procedure included physical fitness and cognitive ability tests and a questionnaire that aimed to reveal noncognitive skills and personality traits. However, a low score on a cognitive or noncognitive ability test did not mean that a conscript could avoid military service. Only serious health issues such as tuberculosis or physical disabilities such as severe hearing problems were reasons for being exempted from military service. Of those who received sufficient health ratings, almost all served in the military. The test scores defined the type of service that conscripts were selected for, ranging from the King's Guard to support troops.

Although medical tests had been performed since enlistment was instituted, tests of conscripts' cognitive and noncognitive ability were introduced in the 1950s. These tests have changed substantially since their introduction. However, the tests are identical for each cohort. As we focus on two subsequent cohorts only, the major test components are highly comparable. The tests introduced in the 1950s for military sessions in Norway were developed by Erik Adrian Lundgren at the Department for Psychology within the military (Thrane, 1977). Including instructions, breaks, and time to answer the questionnaire items on personality and noncognitive traits, the tests take about 2 hours and 30 minutes to complete.

4.2.1 Cognitive and Noncognitive Skills

The tests administered to determine cognitive skills consist of four different components. The first two components aim to assess general cognitive ability by testing logical and mathematical skills (in a procedure similar to the Army Alpha test used to evaluate U.S. military recruits during World War I) and spatial visualization skills (based on J.C. Ravens' 'Progressive Matrices', which were used to classify military recruits in Britain during World War II). The third component assesses the technical knowledge of mechanics, which was important for military practices.[11] The last component is a test measuring processing speed (Thrane, 1977). As the first two tests measure math and analytical skills as opposed to knowledge, we used them to measure cognitive ability in an index that mirrors IQ measures.

Our data include the scores of these two subtests, which range from 0–26 for the logical, mathematical skills test and from 0–24 for the spatial visualization ability test. We add the two scores to construct our index of cognitive ability. The total score is then percentile rank-transformed and converted by taking the inverse of the standard normal distribution (see also Lindqvist and Vestman, 2011). The conscripts were also interviewed by a psychologist. The goal of the interview was to analyze whether a conscript met the psychological requirements of military service. The psychologists assigned each conscript a score for sociability on a scale from 0–10. The variable follows a Stantine scale that approximates a normal distribution. Characteristics such as willingness to take on responsibility, an outgoing personality, independence, persistence, and emotional stability increase the score. Motivation for military service does not affect the score (see, e.g., Cronbach, 1964). Psychologists found that high sociability was linked to professional success. In the context of military service, sociability was valued because it increased a leader's ability to interact with his subordinates (see, e.g., Goleman, 2011). In addition, the psychologist assessed a conscript's ability to adjust to a new environment. Generally, an individual is classified as being adaptable if they can modify their behavior to meet the demands of a new situation (Pulakos, Arad, Donovan, and Plamondon, 2000). Hence, if the situation or environment changes, an individual must deal with the change in an effective manner. For the military, adaptability was relevant to assessing a conscript's ability to complete tasks and his interest in learning new tasks.[12] Similar to sociability, adaptability may have a broad value as a skill. Adaptability is important in a working environment where innovation and changes are paramount. An individual's adaptability is valuable to firms (Griffin and Hesketh, 2003) and may be an asset when one is exposed to new environments. Adaptability is reported on a scale from 0–10 in the military psychologist tests. We use these two measures of noncognitive ability (sociability and adaptability) based on the psychologists' interviews and normalize both 0–10 scores to distributions with a mean of zero and a unit variance.

Table 2 contains correlation coefficients for cognitive ability, sociability, adaptability, processing speed, and technical knowledge of mechanics all standardized to have a mean of zero and a standard deviation equal to one. The table also includes the years of education at age 20 years. These raw

[11] This test was based on the mechanical comprehension test introduced by G.K. Bennett to U.S. military sessions during World War II (see Anastasi, 1968, page 362).

[12] In recent studies, self-efficacy, openness to new experiences, and interest in learning new tasks have been found to be good predictors of adaptive performance (Griffin and Hesketh, 2003; Pulakos, Schmitt, Dorsey, Arad, Borman, and Hedge, 2002).

correlations are interesting as they show three important facts. First, the two indices of noncognitive abilities have a relatively low correlation (0.2 or lower) with cognitive skills at the individual level.[13] The very low correlations suggest that sociability and adaptability genuinely capture different type of skills relative to the cognitive tests. Second, those two measures have a low correlation with each other (–0.056). The skill that we call adaptability measures a trait not captured by the other indices. While such a skill is not available in most data, it seems that being able to adjust to new environments and cope with changing tasks can be particularly useful when moving to a new region. The third interesting fact is that the correlation between cognitive skills, processing speed, technical knowledge of mechanics, and schooling is the highest. This reveals that education is mainly an indicator (or a result) of cognitive skills and specific knowledge, but it does not proxy noncognitive skills very well. As processing speed and technical knowledge of mechanics are strongly correlated with cognitive ability (0.72 and 0.74) and education (0.49 and 0.48), we focus on cognitive, sociability, adaptability indices below.

As final summary statistics, in Table 3, we report the average values for the cognitive, sociability, and adaptability indices separately for movers and nonmovers (as of 1960) either across labor markets (columns 1–4) or from rural to urban areas (columns 5–8). For each of the measures, we see a significant positive difference in average values for movers relative to nonmovers (the p-values for the difference are significant at the 1 percent level, with the exception of sociability for rural to urban movers relative to nonmovers). Once we standardize the difference for the standard deviations of the skill variable, we can see that average cognitive ability is 0.37 standard deviations higher for movers than for nonmovers, sociability is 0.10 standard deviations higher for movers, and adaptability is 0.11 standard deviations higher for movers. In general, it seems that there is a positive selection of migrants according to each of these skills. This is compatible with our model of positive selection on all skills and with the assumption that those skills increase the returns to migration or decrease costs.

4.2.2 Parental Background

Migration propensity might also be affected by socioeconomic background. The military enlistment data contains information on the conscripts' parents. As proxy variables for parental background, we use a dummy indicating whether both of the conscript's parents were present in the household where the conscript grew up. Furthermore, we include the father's work status and profession. We divide professions into high, medium, and low socioeconomic status. We classify engineers, academics, and highly ranked professionals in public administration as high status. The skilled labor professions, such as mechanics or carpenters, are classified as medium status. Low status

[13] The correlation of the cognitive and noncognitive measures is smaller compared to the correlation found by Lindqvist and Vestman (2011), who focus on more recent cohorts of Swedish men born in 1965 or later. In a 2006 working paper, Heckman, Stixrud, and Urzua (2006) report correlation coefficients between 0.07 and 0.21 for a different set of cognitive and noncognitive measures for men.

professions include those related to agriculture, fishing, forestry, mining, and factory work. About 12.4 percent of fathers have a high status profession and 41.2 percent a medium status profession. About 96.3 percent of fathers were present in the household. We include these parental background variables as controls in our regressions.

5 Empirical Strategy and Identification

Following the empirical predictions of the model in Section 3, we estimate the following basic specification:

$$M_{i,t} = \beta_C C_{i,t0} + \beta_S S_{Si,t0} + \beta_A A_{i,t0} + \gamma X_{i,t0} + \varepsilon_i, \tag{7}$$

where $M_{i,t}$ represents a migration outcome at time t (which could be 1960 or 1980) for individual i, who was 20 years of age at time t_0. The migration outcome can be a dummy either for living in a different local labor market at t relative to t_0, for living in a different macroregion, or for having moved from a rural to an urban location between t_0 and t. The three linear terms reported above, $\beta_C C_{i,t0}, \beta_S S_{Si,t0}, \beta_A A_{i,t0}$, capture the linear association of cognitive skills, $C_{i,t0}$, sociability, $S_{i,t0}$, and adaptability, $A_{i,t0}$ on the outcome. The skills are measured by the military recruitment test and standardized to have a mean of zero and a standard deviation equal to one. Cognitive and noncognitive skills, as well as control variables, are measured at time t_0, which represents the year of enlistment when the individual was 20 years old. In the basic specification, we consider cognitive and noncognitive skills as affecting the probability of migration via a linear term $\beta_C C_{i,t0} + \beta_S S_{Si,t0} + \beta_A A_{i,t0}$, which is consistent with the simple structure of the theoretical model. In addition, we will consider nonlinear forms and specifications with interactions. $X_{i,t0}$ is a vector of controls for the individual i at time t_0, which includes the region of residence at age 20 years, the occupation of the father, an indicator for the death of the father, the mother, or both parents, the parent's civil status, the individual's height in cm at age 20 years (as a health indicator), and his year of birth. Hence, all control variables are predetermined at the time of military enlistment. ε_i is a mean zero nonobservable idiosyncratic characteristic of individual i. The predictions of our model on the signs of the coefficients are as follows: if skills have a positive effect on the productivity of an individual, or a negative effect on the nonmonetary costs of migrating, then the estimates of β_C, β_S, and β_A will be positive. A zero estimate will reveal no impact of that skill on productivity or on migration costs. We also estimate a specification identical to (7), but with the variable $P_{i,t,t_o} = \ln w_{i,t} - \ln w_{i,t_0}$ as a dependent variable. This variable captures the logarithmic change in wage from pre- to post-migration, but only for individuals who have migrated. This is a proxy for the 'migration premium'. The model predicts that the coefficient will be positive if the effect of a specific ability mainly works by affecting productivity. However, if a specific ability mainly affect costs, the coefficient will be negative or zero as there will only be an effect through selection of migrants on the basis of unobserved skills.

The estimated coefficients β_C, β_S, and β_A in (7) should capture the impact on migration probability of increasing a specific skill, keeping the other skill fixed. A concern affecting our interpretation is that measurements of cognitive ability and adaptability or sociability could be positively correlated (see Table 2). In our sample, the correlation between cognitive ability and sociability was 0.21, and that between cognitive ability and adaptability was 0.12. On the one hand, it is possible that the military psychologists, knowing the cognitive test scores of the conscript prior to the psychologist assessment, would be influenced in evaluating his noncognitive skills. Then, the positive correlation would only derive from measurement error, which could result in measurement error bias and underestimation of the effects of noncognitive skills. On the other hand, higher noncognitive ability can result in better performance in cognitive tests, and hence, by controlling for cognitive performance, one could underestimate the effect of noncognitive ability. Borghans, Meijers, and ter Weel (2008), for example, show that individual performance at cognitive tests depends on noncognitive skills. To see whether the potential bias affected our results, we estimated specifications that include one skill at a time and specifications that are included together. Given their relatively low correlations, it is unlikely that the two specifications would produce very different estimates.

6 Estimates of Migration Probability and Sorting

6.1 Cognitive and Noncognitive Ability and Probability of Migration

In this section, we illustrate and discuss the basic association of cognitive and noncognitive abilities with different measures of migration. We consider seven different outcomes as dependent variables, corresponding to the seven columns of Table 4. The first two variables capture mobility at two time points: when young and during prime working age. The first variable is a dummy indicating whether an individual changed location (between local labor markets) between ages 20–28 years (by year 1960). The second is a dummy equal to one if the individual changed locations between ages 20–48 years (by year 1980). The third outcome is a dummy variable indicating whether an individual moved permanently after age 20. The fourth is the number of moves across local labor markets after age 20 years. Then, we focus on longer distance migration by including a dummy variable indicating whether an individual moved to a different macroregion after enlistment. Finally, in specifications 6 and 7, we consider dummies indicating whether an individual migrated from a rural to an urban area by age 28 years (in 1960) or by age 48 years (1980), respectively.

The coefficients of interest for Regression 7 are presented in Table 4, where each column shows the results from a regression with different dependent variables, as described above. The main results, show consistently across all columns (i.e., for all migration outcomes), that cognitive ability and adaptability have a strong and positive association with the probability of migrating, whereas sociability is usually uncorrelated with that outcome. Column 1 shows that an increase in cognitive ability by one standard deviation predicts an increase in the probability of moving across local labor markets before 1960 by 5.1 percentage points. This is an increase of about 15 percent relative to the unconditional migration probability of 39 percent between ages 20–28 years (recall that these individuals were born in 1932 and 1933). Similarly, an increase in cognitive ability by one standard deviation predicts an increase in the probability of moving across counties before year 1980 by 5.7 percentage points, or 13 percent relative to the unconditional migration probability over this time range (45 percent). Overall, sociability has no significant impact on mobility across local labor markets. However, adaptability has a robust and statistically significant correlation with mobility. A one standard deviation increase in the adaptability index increases the probability that an individual migrates before 1960 by 3.8 percentage points and before 1980 by 4.2 percentage points. Relative to the corresponding unconditional migration probabilities of 39 percent (column 1) and 47 percent (column 2), this indicates a 10 and a 9 percent increase, respectively. When entered linearly, the measure of adaptability at age 20 years has an effect on the probability of migration after enlistment that is approximately two-thirds the impact of cognitive skills.

In column 3, we find similar results when investigating the probability of migrating permanently to a different labor market area. An increase in cognitive skills by one standard deviation predicts an increase in the probability of moving permanently, before 1980, by 5 percentage points. In the case of an increase in adaptability by one standard deviation, the corresponding increase is 3.5 percentage points. Similarly, in column 4, we find that the number of moves across labor market regions increases by about 0.06 when cognitive ability is increased by one standard deviation and by 0.02 when adaptability is increased by one standard deviation. Column 5 focuses on moving to a different macroregion within Norway, which represents a longer distance move. We find that this increases by about 4.4 percentage points when cognitive ability is increased by one standard deviation, and by 2.8 percentage points when adaptability is increased by one standard deviation.

Columns 6 and 7 in Table 4 present the results for Regression 7 with indicators of migration from rural to urban areas as outcomes. The sample here is different as it only included individuals who were first observed in rural areas. For this group of individuals, economic success was likely to be strongly correlated with ability to move to a more productive urban environment. Hence, migration to a city may be a particularly important determinant of their economic success. We find that adaptability had a significant and positive effect on migration into an urban area: an increase in adaptability by one standard deviation predicts an increase in the probability of moving into an urban area before 1980 by about 2.7 percentage points. This is an increase of about 10 percent relative to the unconditional migration probability. The same change in cognitive ability predicts an increase in the probability of moving into an urban area before 1980 by 5.8 percentage points, or 21 percent relative to the unconditional migration probability. Even for this type of migration, sociability is not a significant predictor of migration propensity.

Overall, the linear regressions including cognitive and noncognitive skills confirm some of the findings from the previous literature. As there is a strong correlation between cognitive skills and schooling, the significant positive effect of this index on migration probability implies a positive selection of migrants along the standard measures of human capital (see, e.g., Malamud and Wozniak, 2012). The new finding of our analysis, however, is that adaptability measured at age 20 years is an important additional predictor of the probability of migrating: a one standard deviation increase in adaptability results in a 4 percent higher probability of migrating across labor market areas, compared with a 5–6 percent increase for the same change in cognitive skills.[14]

One concern in interpreting the coefficients estimated in Table 4 is that there may be a very strong correlation between adaptability and cognitive ability. In fact, one may say that adaptability could simply be a by-product of higher IQ, or that smarter people receive a higher adaptability score. In that case, part of the cognitive effect works through higher adaptability and, by controlling for this, we underestimate the total effect of cognitive skills. Alternatively, if these two skills are not related to each other, and each contributes independently to important aspects of migration outcomes, do the partial effects estimated in Table 4 fully capture the total effect of each skill? As we saw above, cognitive ability and adaptability are only weakly correlated (0.123). The correlation between sociability and adaptability is even smaller, and negative (–0.056). These covariances may affect our interpretation of the results discussed above. To capture the 'total' effect of each skill, we estimate Regression 7 separately for each measure. Table 5 presents the estimated effects when cognitive skills (panel A), sociability (panel B), and adaptability (panel C) are each included separately in the regression. The estimated coefficients on cognitive ability and their significance level do not change much. For adaptability, the coefficients become marginally larger, but not statistically different from their values when estimated jointly. The association between sociability and migration propensity is somewhat higher and significant when cognitive ability and adaptability are not included. However, the point estimate is much smaller than for the other two. Overall, the estimates are very similar when the three skills are measured together or separately. This indicates that the three measures capture three sufficiently different types of ability. Cognitive ability and adaptability turn out to have the larger and more significant effects on the propensity to migrate.

The basic set of control variables included in Tables 4 and 5 do not include the schooling level at the time of enlistment. Schooling may have an important role in the formation and measurement of skills (see, e.g., Lindqvist and Vestman, 2011). For the cohorts born in 1932 and 1933, the mandatory schooling requirement was only 7 years. Hence, the conscripts who only obtained mandatory schooling completed their education 3 years before the enlistment date. Conscripts who were still in school at enlistment received substantially more schooling than those with only mandatory schooling. Conscripts with only mandatory schooling had a cognitive ability score that was 1.1 standard deviations lower compared with those with more than mandatory schooling. Men with more than mandatory education also had a higher average level of noncognitive ability.

[14]Note that when including processing speed or technical knowledge of mechanics in Equation 7 the estimated coefficients for both measures are not statistically different from zero for all outcomes.

The difference equals 0.04 standard deviations for sociability and 0.42 standard deviations for adaptability. The significant correlation between cognitive test scores and years of schooling can proceed from two factors. First, high ability men sort into higher education but years of schooling do not affect the cognitive ability of people. In this case, controlling for schooling biases the total effect of cognitive ability on migration downward. Second, schooling might increase cognitive skills, and different schooling levels may be correlated with skills, so not controlling for schooling may generate an upper bias of the effects of cognitive skills. In short, if the differences in cognitive test scores are mostly driven by sorting, controlling for education at the time of enlistment could create a downward bias in determining the partial effect of cognitive ability on migration. If schooling increases cognitive skills, not controlling for the education level at age 20 years may create an upward bias in measuring the coefficient of interest. Therefore, we estimate Equation 7, where we either include a dummy variable for whether an individual has education above mandatory schooling at enlistment[15] or the number of years of schooling at enlistment. Table 6 presents the estimates, when including progressively more comprehensive measures of schooling, on the probability of migration by age 48 years (columns 1–4) or on the probability of migration from rural to urban labor markets (columns 5–8). Introducing a dummy variable for whether an individual has education above mandatory schooling at enlistment did not greatly alter the results (see columns 2 and 6). When controlling for the number of years of education at enlistment, the association between cognitive ability and migration became somewhat weaker (see columns 3 and 7), but remained significant and quantitatively relevant. These findings suggest a significant correlation between cognitive skills and schooling. If one believes that schooling is mainly a mechanism to 'sort' individuals according to their endowment of cognitive skills, and that those are the only relevant skills determining returns to and costs of migration, then we should consider that the total effect of pure cognitive skills on migration is 0.058 (column 1), and that adding schooling 'over-controls' the results, producing a partial effect. If, instead, we believe that schooling itself increases the productivity or reduces the costs of migration, then the pure impact of cognitive skills on migration probability is 0.035 (column 3), and the remaining part is an effect of schooling (which in turn is related to cognitive ability). Similarly, for rural–urban migration, the impact of cognitive skills can be as high as 0.058 (column 5) when not controlling for schooling, or 0.03 when controlling for schooling (column 7). More interestingly, however, we see that the relationship between adaptability and migration is not altered at all when controlling for different measures of schooling. Adaptability does not seem to be related to the level of schooling at age 20 years (or later), and its impact on the propensity to migrate is about 0.042 (for migration to another labor market) or 0.027 (rural to urban migration) for each one standard deviation increase of the measure. This result also suggests that, although schooling can be used as a good indicator of cognitive skills and their effect on migration, it does not proxy at all for sociability and its impact on migration.

[15] This specification reflects the main specification used by Lindqvist and Vestman (2011).

In columns 1–3 and 5–8 of Table 5, all included controls are predetermined at the time of enlistment. However, selection into higher education (for a relatively small group in this period, as only 5 percent of people in our sample graduated university) might be an important mechanism that increases migration probabilities and is affected by cognitive and noncognitive skills. In columns 4 and 8 of Table 6, we include completed education as a control variable. If the only way in which skills affected mobility was by determining total schooling, such a variable would absorb most of the skill impact. This is close to being true for cognitive skills. When controlling for the completed years of education, the effect of cognitive ability becomes small, though still significant, at 0.016. Completed years of schooling seems to be almost sufficient to capture the impact of cognitive abilities on the probability of moving: by controlling for completed years of schooling, the coefficient on cognitive skills declines by more than 70 percent. However, this is not true for adaptability. The association between adaptability and migration is equally strong regardless of whether completed years of education are included. Hence, selection into higher education and into a job market for highly qualified workers might be a fundamental channel by which cognitive ability affects the migration decision, but it is not likely to be the mechanism through which adaptability affects the migration decision.

6.2 Nonlinear Predictions and the Interaction between Skills

The effect of cognitive ability and adaptability on the probability of migration may not be linear. As we have detected significant and robust linear effects for those two skills only, we focus on these in the remainder of the analysis. The existing literature has found positive selection of internal migrants, and has pointed out that there could be a stronger effect for very high levels of schooling (or IQ).[16] Hence, we consider nonlinear forms for function $f(\cdot)$ in Regression 7. To impose the least amount of structure, we allow for skill intensity at different quintiles of the skills distribution. We estimate a specification in which we split the cognitive ability measure and the adaptability measure into quintiles, and then estimate a separate coefficient for (dummies relative to) each quintile, omitting the lowest one. The results, presented in Table 7, focus on four migration outcomes. The first two columns show the probability of migration across labor market areas (before 1960 and before 1980 in columns 1 and 2, respectively). The third and the fourth columns focus on migration from rural to urban locations. Interestingly, the effect seems to be monotonic and not too far from linear in the quintiles for cognitive ability. Migration probability across labor market areas (columns 1 and 2) seems to increase only after the second quintile of cognitive abilities, and after that, it increases by 2–3 percent for each quintile. Rural to urban migration seems to increase more gradually, by 3–4 percent for each quintile of the cognitive distribution (columns 3 and 4). While some convexity of mobility in IQ may exist, given that the largest increase in the probability of migration is between the fourth and fifth quintiles, the overall shape of the function is not too far from linear. The effects

[16] For example, Glaeser and Mare (2001) discuss the selectivity of migrants in the context of rural–urban migration.

of adaptability look different. While there is some positive effect on migration from being in the second to fourth quintiles of the adaptability distribution (relative to the first and lowest quintiles), these effects are similar to each other. One cannot rule out the possibility that the probability of moving (across labor markets and from rural to urban areas) is the same for individuals at the second or fourth quartile of the adaptability distribution. By contrast, individuals in the fifth (top) quintile of adaptability exhibit a much larger probability of migrating. The increase in mobility from being in this group (relative to the lowest adaptability group) is almost as large as the increase from being in the top relative to the lowest cognitive skill group, and is very precisely estimated. Adaptability measures a skill that makes a real difference in the probability of migration, but only at high levels. People can really possess entrepreneurial or 'pioneer' spirits and this makes them more likely to move. Although they may not necessarily possess the highest intellectual abilities, they have genuine abilities that make them better at dealing with new environments and more attracted to new opportunities.

So far, we have considered cognitive skills and adaptability as independently (i.e., additively) affecting migration probability. However, it is plausible that these two skills may interact with each other. In particular, it may be the case that individuals with high cognitive ability are likely to migrate regardless of their adaptability level. Given their very high intellectual abilities, they may have large gains to migrating that push them to move, independent of their level of adaptability. By contrast, individuals with lower cognitive ability and smaller monetary gains from migration may be much more affected by their degree of adaptability in deciding whether to migrate. Adaptability may reduce their psychological discomfort in moving and may imply that they more proactively consider alternative locations. It is plausible that higher adaptability may be a crucial factor in the decision to migrate when people do not have extremely high cognitive ability and the associated large gains from migration.

In order to explore this hypothesis, we have partitioned the cognitive and adaptability skill continuum into three groups, comprising the bottom quintile, the (three) intermediate quintiles, and the top quintile. Then, we estimate a regression in which we include dummies for all the possible interactions between the three groups of each ability (hence, there are nine separate effects). We report the coefficients in Figure 1 after standardizing the coefficient on the dummy for the interaction between the two lowest skill quintiles to zero. The estimated effects for each dummy are presented in the Appendix Table A1. Figure 1 visualizes these results by showing the estimated coefficient for the three different cognitive skill groups in the bottom, intermediate, or top quintile of adaptability, arranged in the figure from left to right, respectively. We connect the estimates for those individuals in the bottom cognitive ability quintile (dashed line), in the intermediate cognitive ability quintiles (dotted line), and in the top cognitive ability quintile (solid line). The left panel of Figure 1 shows the estimated effect on migration across local labor markets, and the right panel shows the impact on the probability of rural–urban migration. Three clear patterns emerge. First, both cognitive ability and adaptability increase migration propensity as the reported coefficients increase from left to right, and when moving from the dashed to the dotted to the solid line. Second, increases in adaptability are much more relevant for individuals with low and intermediate cognitive ability (dotted line and light grey lines, respectively) and much less relevant for individuals with high cognitive ability (dark dotted line). For the first two groups, going from the bottom quintile of the adaptability distribution to the top quintile increases the probability of migration across local labor markets before 1980 by 20 percentage points. This is a sizable effect compared to the average probability of migrating of 47 percent. By contrast, for individuals with cognitive ability in the top quintile, the level of adaptability does not seem to make any significant difference to their probability of migrating. The third important fact emerging from the estimates is that individuals with cognitive ability in the top quintile are highly likely to migrate, independent of their adaptability levels. These results imply that, although there is a positive selection overall of migrants with cognitive and adaptability skills, there is an even stronger selection of migrants with low to intermediate cognitive abilities on the basis of adaptability. Our results show that people with low cognitive skills are much more likely to be migrants if they have high levels of adaptability. If they do have high adaptability, they are almost as likely to migrate as individuals with high cognitive skills. As cognitive skills have a very high correlation with schooling, but adaptability does not, this implies that selection on one (previously) unobserved characteristic, the adaptability of individuals, is much more important for low skill than for high skill migrants. If this characteristic helps individuals adjust, integrate, and assimilate into the receiving economy and to succeed in any way, then migrants with low cognitive skills have a much better chance than comparable nonmigrants to achieve economic success. Moreover, this result shows that individuals select themselves into migration following a criterion that the receiving economy would use, if such skill could be observed, to select migrants who can assimilate well to new circumstances and new working situations. Furthermore, this results compares well with the findings of Lindqvist and Vestman (2011), who show that noncognitive skills are a stronger predictor of labor force participation and the wages of unskilled than of skilled workers.

6.3 Role of Early Mobility and Family

Our data measure individual skills at age 20 years. Although they certainly reflect some innate abilities, the measures we use are also affected by the experiences of the individual as a child, and as a student. Our regression controls for some characteristics of the family, and of the parents in particular, and we discussed the effects of including schooling as a control to capture the effect of upbringing on the probability of migration. In this section, we analyze whether moving as child, presumably with one's family, between birth and military enlistment affects a person's cognitive and adaptability skills. It is important to analyze whether this increases the propensity of an individual to migrate later in life. Through a process of positive feedback, experiencing a move with the family could make individuals more adaptable, and may affect the likelihood of mobility as an adult. On the other hand, if mobility disrupts the learning process, it may affect cognitive ability. Moreover, if higher adaptability is associated with early moves in life, then this skill may be transmitted to the children of migrants via their early childhood experience. To address this question, we perform two regressions. First, we analyze whether cognitive ability, sociability, and adaptability are significantly associated with a dummy variable equal to one if an individual moves across local labor markets between birth and the date of enlistment. Then, we analyze whether the inclusion of such a dummy affects the coefficients on the effects of sociability, adaptability, or cognitive ability on the probability of migrating. The results, displayed in the Appendix Table A2, show a significant positive association between cognitive ability and the probability of moving during childhood. Sociability and adaptability, however, are not significantly affected by moving during childhood. Noncognitive abilities do not seem to be affected by the experience of migrating as a child. Then, the regression reported in Appendix Table A3 analyzes whether controlling for childhood mobility affects the impact of adaptability on the probability of migrating as an adult. In Table A3, we include a dummy for having moved as a child in Regression 7. We find that moving during childhood is positively and significantly associated with all of the migration measures considered. The coefficients on cognitive ability, sociability, and adaptability were not significantly changed by the inclusion of the dummy variable for moving during childhood. Hence, adaptability at age 20 years is neither a simple consequence of previous mobility nor a less important determinant of migration when controlling for childhood mobility.

6.4 Sorting Across Destinations

Do migrants sort into labor markets with higher monetary returns to their skills? Wozniak (2010) shows that, in the U.S., college-educated workers are disproportionately attracted to regions with better entry-level labor market conditions for the college educated. In a similar way, we test whether individuals with high cognitive ability or high adaptability are likely to move to labor markets where they receive a high return for their skills.

In this test, we consider the specific location choice of an individual in terms of labor markets, rather than simply the probability of migrating. The probability that an individual will choose to move to a specific local labor market $m*$ depends on the conditions in $m*$, as well as conditions in all other local labor markets, $m \neq m*$. This is a standard choice problem and we analyze it using McFadden's conditional logit representation (McFadden, 1974). To estimate whether individuals choose to locate in labor markets where their skills have a higher return, we first estimate the linear returns to both cognitive ability and adaptability separately in each local labor market (with a Mincerian regression) and standardize these measures with a mean of zero and a standard deviation of one. The conditional logit specification includes the following controls: returns to cognitive ability in the local area, returns to adaptability in the local area, an interaction term of both the returns to cognitive ability and adaptability with an indicator variable that is equal to one if the individual's skill is in the second tercile of the distribution for that skill (cognitive ability or adaptability), and an interaction term of both the returns to cognitive ability and adaptability with an indicator variable that is equal to one if the individual's skill is in the top tercile of the distribution for that skill (cognitive ability or adaptability). We also include an indicator for birth region and dummy variables for each potential choice region.

The results from the conditional logit estimation are presented in Table 8. The top numbers in each cell are odds ratios, implied by the estimated coefficients (unreported). Z-statistics are presented in parentheses. The odds ratios in the two top rows of Table 8 show that the returns to both cognitive ability and adaptability have no detectable effects on the choice of a person with a cognitive ability score or an adaptability score in the lowest tercile (reference group). The coefficients are not different from one, which implies that persons with low ability and adaptability are not more likely to move to regions with high return. However, individuals with higher cognitive abilities have significant responses to local returns to cognitive abilities. The odds ratios on the interactions of the returns to cognitive ability with dummies for IQ scores in the second and third terciles of the IQ score distribution are significantly greater than one in both specifications. These results show that individuals with higher cognitive abilities are more responsive in their migration choices to returns to cognitive ability in a local labor market than are individuals with low cognitive ability. High IQ individuals sort themselves into areas with high monetary returns for cognitive abilities. For an individual with an IQ score in the second tercile, a standard deviation increase in the return to cognitive ability increases the odds of choosing that labor market by 10–11 percent. For an individual with an IQ score in the top tercile of the IQ score distribution, the increase is 14–16 percent. These coefficients are consistent with migration being directed by increasing returns to skills.

On the other hand, individuals with an adaptability score in the second or top tercile of the adaptability distribution are not more likely to choose a local labor market with large monetary returns to adaptability. Migration of highly adaptable people is not directed by high return regions, in contrast to the migration of high IQ individuals. These results can be interpreted within the framework presented in section 3. They are consistent with cognitive ability being an attribute increasing mobility by directing people to locations with higher monetary returns to that skill, whereas individuals with high adaptability may be more mobile as a result of the lower psychological costs of migration.

6.5 Extensions and Robustness Analysis

In the past, a man's birth order within his household influenced his probability of inheriting farmland in Norway and thereby his probability of migrating to another local labor market or city (see Abramitzky, Boustan, and Eriksson, 2012, for a discussion of this issue in the context of international migration). If birth order also affects personality traits such as adaptability, this could create a correlation between the two. Interestingly, the probability of migrating to a different area differs between the firstborn son, for whom it is 43 percent, and other, later born sons, for whom it is 46 percent. The difference is significant at the 5 percent significance level (p-value = 0.0499). By contrast, the probabilities for rural to urban migration are not significantly different for firstborn or later born sons. To test whether different skills have different effects on the migration decisions of firstborn and later born sons, we estimate Regression 7 separately for the two groups. The results, displayed in Appendix Table A4 (Panel A), show that the association of cognitive ability, sociability, and adaptability with cross-area migration (columns 1 and 3) and rural to urban migration (columns 2 and 4) are not significantly different between the two groups. Hence, birth order does not seem to affect the role of abilities in affecting migration.

In Panel B of Appendix Table A4, we analyze whether different socioeconomic backgrounds may be related to the impact of skills on migration. Although we controlled for the parents' socioeconomic backgrounds in our regressions, in this table, we analyze whether partitioning individuals into high and low socioeconomic backgrounds generates any difference in the impact of cognitive skills and adaptability on the probability of migrating. We find that cognitive ability is somewhat more important for the migration decisions of individuals from a high socioeconomic background. For both groups, however, the cognitive variable is very significant. On the other hand, the association of adaptability and migration probability across local labor market regions and, to a lesser extent, from rural to urban, is significantly higher for individuals with low socioeconomic backgrounds. Together, these results imply that adaptability skills are very strongly related to migration probability for individuals with low socioeconomic backgrounds, who are less likely to be highly educated. In the case of cross-area migration, adaptability is as important as cognitive skills for these individuals with low socioeconomic backgrounds. By contrast, for individuals with high socioeconomic backgrounds, cognitive ability is the more relevant characteristic affecting migration.

Finally, in Appendix Table A4, we analyze whether skills affect the probability of migration from the most remote parts of Norway, where the cost of moving may be larger owing to isolation from the rest of the country. The area comprising the local labor markets in the very north of Norway is larger than in the south of Norway and distances to other populated regions are on average much longer in the north of Norway. Therefore, we determine whether the association between cognitive and noncognitive abilities and migration outcomes differs for individuals born in northern Norway compared to the rest of the country. Panel C of Table A4 shows that the point estimates are similar for individuals born in northern Norway and those born in the other macroeconomic regions.

One possible determinant of the relation between different individual abilities and migration propensity is unobserved family of origin characteristics. Rather than individuals varying in their adaptability or IQ, and this affecting the costs and benefits from migrating, different families may provide better or worse environments for the development of some skills as well as different incentives or perceptions of migration. Although we control for parental and family characteristics, many unobservable variations remain. Our data include individuals from only two consecutive cohorts (1932 and 1933). We are, however, able to identify 104 brother couples in our dataset, based on parents' personal identification number. These data allow us to perform a very demanding specification and estimate Regression 7 based on siblings only, including family-fixed effects.[17] Such a specification will only identify the effect of skills on migration based on within-family variation between brothers, who must be born less than 2 years apart to be included in the data. The results are reported in columns 1 and 2 in Table A5. The variance and number of observations is drastically reduced, making the power to identify effects much more limited. Nevertheless, whereas differences in cognitive ability between brothers are not associated with differences in migration propensity, their differences in adaptability predict differential mobility outcomes among brothers. The point estimates for adaptability in the brothers' fixed effects regressions are even slightly higher than our baseline results in Table 4, although they do not differ significantly. Moreover, we note that they are much less precisely estimated. These two very demanding regressions suggest that adaptability is a skill that may vary even more significantly than IQ within a family between brothers, and that its impact on migration does not seem to be simply a reflection of the family attitude.

One channel through which the different abilities may affect migration is family life dynamics, which may have a more direct impact than the costs and benefits of economic migration discussed above. If some characteristics (e.g., IQ, sociability, and adaptability) make men more likely to marry at an earlier age, this may negatively affect subsequent mobility, because moving as a couple or family may be more costly than moving as an individual. We test this channel by regressing a 'married' dummy in 1960 (when men were either 27 or 28 years old) on cognitive ability, sociability, and adaptability. Being married at these ages could be a reason why people are less likely to move and may explain some of the effects of the skills. The results are presented in column 3 of Appendix Table A5. Cognitive ability and adaptability were positively and significantly correlated with the probability of being married in 1960, whereas sociability was not. The coefficients on IQ and adaptability were around 0.01, which is much smaller than those on the probability of migrating. Moreover, even if marriage decreases mobility, these results reveal that IQ and adaptability enhance it, even if these individuals marry younger. An interesting result is that sociability does not seem to affect marriage probability. The knowledge of this skill (or at least the measure of this skill obtained by the test) does not provide much insight into the family and migration decisions of individuals.

A further channel thought which cognitive ability, sociability, or adaptability may affect migration is directly though thetype and location of military service. If the cognitive or noncognitive

[17] Note that fathers' occupation, county of origin, height, cognitive ability, sociability and adaptability do not differ significantly between the main sample and families with two sons. However, parents with two sons in the sample are significantly more likely to both be alive at military enlistment and married.

assessment in the enlistment test affected the type and location of military service, especially increasing the probabliity of a person being sent farther, that may be the reason for larger subsequent mobility. We cannot control for the main military base an individual was assigned to. However, men assigned to the King's Guard are almnost certainly stationed in Oslo (the capital and main residency of the royal family). Hence, we can test whether among members of the King's Guard cognitive ability and adaptability are equally good predictors of mobility for men who grew up in Oslo and for men who grew up outside the capital. Moreover, we can control for the assignment to the King's Guards in the regressions focusing on rural to urban migration and test whether the inclusio of this variable reduces the role of adaptabililty in predicting migration. Column (3) in Appendix Table A3 shows estimates only considering Men assigned to the King's guard. For them the basic effects of cognitive ability and adaptability are similar to those estimated on the general population and the association between mobility their skills is not significantly different for men already residing in Oslo before military service and men who resided elsewhere. This can be seen by the interaction of "Oslo" with the level of each skill in regression (3). The coefficient is quite imprecisely esitmated but not significant. Column (4) in Table A3 focuses on men residing in a rural area at time of enlistment and suggests that controlling for assignment to the King's guard (and thereby for service in the capital city) did not alter the importance of cognitive ability and adaptability in explaining rural to urban migration. Hence, the available data suggests that relocation during the military service was not the main driver of our results.

A final extension of our results is to determine whether the most substantial form of mobility, namely the probability of international migration, is affected by the three skills considered. As mentioned in Section 4, the central population register includes an indicator identifying individuals who emigrated permanently to a foreign country after 1960. In total, 372 individuals, or about 1.2 percent of our sample, emigrated during the observation period. Thus, this was quite a low probability event for the cohort analyzed. To test whether cognitive and noncognitive skills are relevant for the probability of emigrating abroad, we estimate Regression 7 using a dummy variable indicating whether an individual emigrated to a foreign country as an outcome variable. The results are presented in column 4 of Table A5. They show that an increase in cognitive ability by one standard deviation predicts an increase in the probability of emigrating by 0.6 percentage points, and that an increase in adaptability by one standard deviation predicts an increase in the probability of emigrating by 0.3 percentage points. Although the estimated coefficients are small, they indicate a 50 and a 25 percent increase, respectively, relative to the unconditional emigration probability of 1.2 percent. Sociability has no significant association with the probability of emigrating. Hence, the importance of skills in determining the decision to emigrate abroad is similar to the importance of skills determining geographic mobility within Norway. The implied selection of international migrants from Norway was also strongly positive in terms of cognitive skills and significantly positive in terms of adaptability skills. Taken together, these estimates reveal a significant and robust effect of adaptability in increasing the probability of migration of any kind, whether local, rural to urban, long distance, or international.

7 Migration Earning Premium

The empirical evidence presented so far establishes that both cognitive skills and adaptability have a significant, robust, and quantitatively relevant effect on the migration probability of individuals in our sample. We also found that individuals with medium to low cognitive skills are strongly selected into immigration if they have very high levels of adaptability. Moreover, we show that individuals with a high cogtnitive ability score are more likley to choose a local labor market with large monetary returns to cognitive ability while individuals with a high adaptability score are not more likely to choose a local labor market with large monetary returns to adaptability. Building on the implications of the model developed in Section 3, we perform and additional test. In particular, we analyze whether cognitive ability and adaptability increase the monetary returns to migration, measured as the difference in (log) earnings between 1 year (or 3 years) before and 1 year (or 3 years) after migration to a different labor market area or from a rural to an urban location. The model in Section 3 predicts that if the skill under consideration mainly affects productivity, and hence the monetary returns to migration, then one would find a positive correlation between such a skill and the average pre- and post-migration wage differential. However, if the skill mainly affects the psychological (nonmonetary) costs of migration, one should find a negative or null correlation between the skill and the average pre- and post-migration wage differential, but a positive effect on migration probability. Figure 2 (a) presents the earnings differences between individuals in the highest and lowest IQ terciles, and Figure 2 (b) presents the earnings differences between individuals in the highest and lowest adaptability terciles, relative to the year of moving across labor markets.[18] The earnings differences between individuals with high and low cognitive abilities increase quite soon after the migration event and are substantial in size 10 years after moving. On the other hand, the earnings differences between highly adjustable individuals and low adjustability individuals increases more slowly and are very small even 10 years after moving. Table 9 shows the coefficients from a specification similar to Regression 7, where the dependent variable is the pre- and post-migration earnings difference for the individual.[19] In columns 1 and 2, the dependent variable is the difference in log earnings between the year before and the year after migration for migration across local labor markets or rural–urban migration). In columns 3 and 4, the dependent variable is the earnings differential between 3 years before and 3 years after migration. The 3-year differential avoids the possible effects of negative conditions occurring right before the migration decision that

[18] Figure A4 in the Appendix plots the same relationship for individuals moving from a rural to an urban area and shows the same pattern.

[19] Note that when estimating Regression 7 with log earnings as an outcome variable, all three skills, cognitive ability, sociability, and adaptability, are significantly and positively correlated with earnings.

could push people away and, at the same time, negatively affect their premigration earnings.[20] The results are clear: cognitive ability significantly and positively affects the post-migration earnings premium, conditional on individuals moving and having positive earnings prior to moving. This implies that individuals with higher cognitive skills have higher monetary returns from moving to a new local labor market. The earnings difference is between 0.2 and 0.4 logarithmic points (between 22 and 41 percent) and is highly significant. This is consistent with cognitive ability mainly affecting productivity and, through that channel, increasing the pre- and post-migration earnings differential. The average migrant will earn 22 to 41 percent more after migrating, if he has a one standard deviation higher IQ. On the other hand, the measure of adaptability does not affect the pre-post-migration earnings difference. People who are more adaptable are more likely to migrate, but conditional on migrating and having positive earnings prior to moving, higher adaptability does not provide a higher earnings premium. This is consistent with adaptability mainly affecting the nonmonetary cost of migration so that, for a given monetary return, people who are more adaptable are more likely to move. The effect is zero rather than negative, confirming that there is not a strong negative selection of migrants on nonobservable productive characteristics (associated with higher adaptability), but that adaptability per se does not affect the pre- and post-migration earnings premium. This indicates that adaptability must affect migration through nonmonetary costs.

8 Conclusion

In this paper, we combined measures of the cognitive and noncognitive abilities of individuals, measured at 20 years of age, and data on their subsequent working life. Characteristics that have been considered as unobservable but that are potentially important to predict labor market outcomes and career choices, such as sociability and adaptability, can be observed and measured in our data. The data also include details of the working career and the migration behavior of individuals. Our sample, based on the Norwegian male population born in 1932 and 1933, for which we have information on cognitive and noncognitive skills, allows us to analyze how those predict migration behavior. This allows us to infer how migrants are selected and sort themselves on the basis of their cognitive and (unobserved thus far) noncognitive skills. Our results suggest that cognitive skills, which are highly correlated with schooling, have a strong positive predictive power on the probability of migrating and induce sorting of migrants in locales with high returns for those skills. This is a known fact in the literature on internal and international migration: migrants are positively selected based on schooling and cognitive skills. However, this is the first study to find a second important result, namely that people with high adaptability, as measured

[20] If individuals migrate after having experienced some idiosyncratic shock, we would expect a premigration wage dip similar to Ashenfelter's dip, which shows that the mean earnings of participants in training programs generally decline just prior to participation (Ashenfelter, 1978).

by tests assessing their ability to cope with new environments and situations, also have a much higher probability of migrating. In particular, among individuals with low levels of education and low cognitive abilities, those with high adaptability are much more likely to migrate than the rest of the population. To understand whether cognitive skills and adaptability affect the monetary returns or the psychological costs of migration, we developed a simple variation of the Roy model. This model predicts that a skill increasing labor productivity would increase both the probability of migration, will induce sorting across location with different return to that skill and, conditional on migrating, will be positively associated with the pre-post-migration earnings differential. By contrast, a skill decreasing the (nonmonetary) psychological costs of migration increases the probability of migration, but, does not induce specific sorting and, conditional on migrating, would not be associated with larger pre- and post-migration earnings differences.

We found that both cognitive ability and adaptability have a significant and positive impact on the probability of migration across labor areas, from rural to urban areas, as well as on long distance and international migration. In addition, we presented empirical evidence that cognitive skills are positively correlated with the sorting of immigrants across locations with different return to those skills and have a significant positive effect on the pre-post migration earnings differential. Adaptability, on the other hand, predicts migration probability but it is not associated with sorting nor with pre-post migration wage differential. This evidence is consistent with adaptability being a skill that mainly reduces nonmonetary migration costs. Interestingly, we also found that the effect of high adaptability on increasing the migration probability is stronger for individuals with low cognitive skills and low socioeconomic backgrounds.

These results have interesting implications. First, adaptability, an unobserved skill thus far, can be measured at age 20 years, and it has an important effect in that it increases mobility. Moving to a different region or country requires the ability to deal with new situations and people; therefore, better adaptability skills can decrease adjustment costs and increase the propensity to migrate. As mobility within a country improves the functioning of the labor markets, enhances the efficiency of firm–worker matches, and reduces the impact of local economic shocks, better measurement of this skill may have important implications for our understanding of the labor market consequences of local shocks. Second, the importance of adaptability raises the question of whether such a skill can be increased in the population. The possibility of improving the adaptability of individuals through schooling, or by exposing students to a varied and changing environment and to individuals with diverse and heterogeneous backgrounds, suggests an important additional role for diversity and flexibility in the learning environment. These are interesting issues that we leave to future research.

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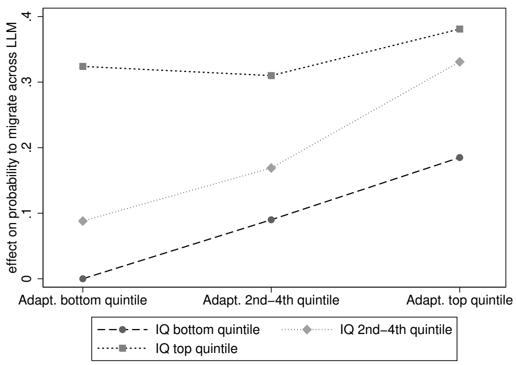
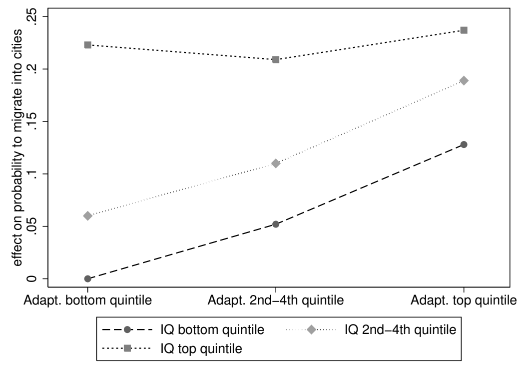
9 Tables and Figures

Figure 1: Interactions of Cognitive Ability and Adjustability



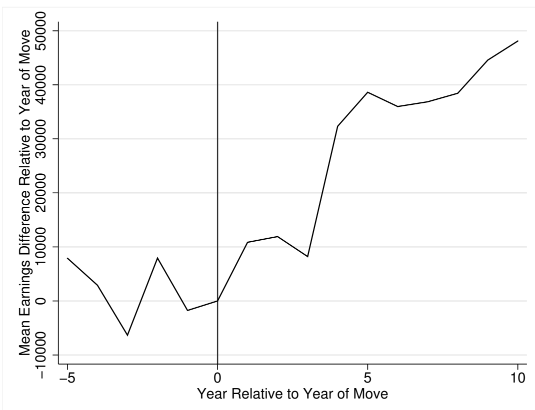
(a) Mobility across local labor markets



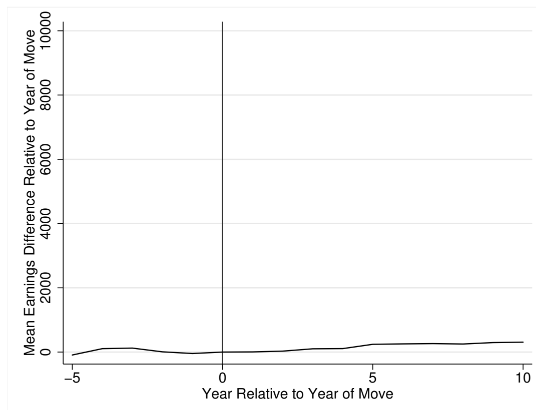
(b) Rural to urban migration

Notes: The figures reflect the estimated associations of cognitive ability (IQ) and adaptability on the probability of moving across local labor markets or into cities, as reported in Table A1. The left figure shows how the probability of moving across local labor markets changes with adaptability for different levels of cognitive ability. The right figure shows how the probability of moving from a rural to an urban area changes with adaptability for different levels of cognitive ability.

Figure 2: Average Earnings Difference Relative to the Year of Moving across Local Labor Markets



(a) Highest IQ vs. Lowest IQ Tercile



(b) Highest Adaptability vs. Lowest Adaptability Tercile

Notes: Figure (a) displays the average earnings differences between individuals in the highest IQ tercile and individuals in the lowest IQ tercile in 1998 NOK, relative to the year of moving across local labor markets. Figure (b) displays the average earnings differences between individuals in the highest adaptability tercile and individuals in the lowest adaptability tercile in 1998 NOK, relative to the year of moving across local labor markets.

Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation
Percent of local labor market movers as of 1960	0.394	0.497
Percent of local labor market movers as of 1980	0.446	0.489
Percent of permanent movers	0.310	0.463
Number of cross-local labor market moves	0.188	0.562
Percent of region movers as of 1980	0.191	0.393
Percent of rural-to-urban movers as of 1960	0.192	0.394
Percent of rural-to-urban movers as of 1980	0.232	0.422
Percent emigrated as of 1980	0.012	0.091
Earnings in 1960 (in 2014 NOK)	239,388	99,685
Earnings in 1980 (in 2014 NOK)	325,4412	174,308
Completed years of education	9.5	2.8
Years of education at age 20 years	8.4	1.6
Cognitive ability (ranging from 0 to 50)[a]	20.3	9.42
Sociability (psychologists' evaluation, ranging from 0 to 10)[a]	4.95	1.42
Adaptability (psychologists' evaluation, ranging from 0 to 10)[a]	4.86	1.71
Processing speed	41.7	17.6
Technical knowledge of mechanics	5.30	1.85
Number of observations	30387	

Notes: [a]In the regressions, the scores are normalized to have a mean of zero and a unit variance.

Table 2: Correlation Coefficients

	Cognitive ability	Sociability	Adaptability	Processing speed	Mechanics	Education age 20
Cognitive ability	1.000					
Sociability	0.209	1.000				
Adaptability	0.123	-0.056	1.000			
Processing speed	0.721	0.150	0.118	1.000		
Mechanics	0.736	0.172	0.118	0.586	1.000	
Education (age 20)	0.680	0.250	0.131	0.486	0.483	1.000

Notes: Entries represent correlation coefficients for cognitive ability, sociability, adaptability, processing speed, and technical knowledge of mechanics, all standardized to have a mean of zero and a unit variance. Years of education are measured at enlistment at age 20 years.

Table 3: Differences between Movers and Stayers

	Across LLM movers				Into city movers			
	Stayers	Movers	Difference	p-value	Stayers	Movers	Difference	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cognitive ability	-0.09	0.28	-0.37	0.00	-0.17	0.15	-0.32	0.00
Sociability	-0.03	0.07	-0.10	0.00	-0.05	0.04	-0.09	0.02
Adaptability	-0.03	0.08	-0.11	0.00	-0.07	0.07	-0.14	0.00

Notes: Columns 1 and 5 display the average standardized values of cognitive ability, sociability, and adaptability for stayers, columns 2 and 6 show the average standardized values for movers, and columns 3 and 7 show the differences between the average values for movers and stayers. Columns 4 and 8 contain the p-values indicating whether the difference is significant. Movers are defined as individuals who moved across the border of their local labor market of origin before 1960 (columns 1–4) or those who moved from a rural to an urban area before 1960 (columns 5–8). The sample includes birth cohorts for 1932 and 1933. In columns 5–8, the sample only includes individuals who lived in a rural municipality at the time of enlistment.

Table 4: Cognitive and Noncognitive Abilities and the Probability of Moving

	Moved across LLM			Number of moves	Moved across	Moved into cities	
	before 1960	before 1980	before 1980 permanently	before 1980 across LLM	region before 1980	before 1960	before 1980
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cognitive ability	0.051***	0.057***	0.053***	0.058***	0.044***	0.046***	0.058***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)
Sociability	0.003	0.001	0.003	-0.011**	0.000	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)
Adaptability	0.038***	0.042***	0.035***	0.022***	0.028***	0.016***	0.027***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Mean of dep. variable	0.39	0.45	0.31	0.19	0.19	0.19	0.23
R-squared	0.122	0.123	0.080	0.037	0.080	0.170	0.133
N	23829	23829	23829	18220	23829	16221	16221

Notes: Entries represent the estimated coefficients with standard errors in parentheses from the OLS regression of the effects of cognitive ability, sociability, and adaptability on different mobility indicators. Columns 1–4 examine migration across local labor markets, column 5 migration across macroregions, and columns 6 and 7 rural–urban migration. The sample includes birth cohorts from 1932 and 1933. In columns 6 and 7, the sample only includes individuals who lived in a rural municipality at the time of enlistment. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Cognitive and Noncognitive Abilities and the Probability of Moving: Separate Regressions

	Moved across LLM			Number of moves	Moved across	Moved into cities	
	before 1960	before 1980	before 1980 permanently	before 1980 across LLM	region before 1980	before 1960	before 1980
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A: Cognitive Ability			
Cognitive ability	0.056***	0.062***	0.057***	0.058***	0.044***	0.048***	0.061***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
				Panel B: Sociability			
Sociability	0.009***	0.007**	0.009***	-0.003	0.006*	0.005	0.008**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
				Panel C: Adaptability			
Adaptability	0.042***	0.046***	0.039***	0.026***	0.031***	0.021***	0.032***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
N	23829	23829	23829	22683	22683	16221	16221

Notes: Entries represent the estimated coefficients, with standard errors shown in parentheses, from the OLS regressions of the effects of cognitive ability, sociability, or adaptability on different mobility indicators. Columns 1–4 examine migration across local labor markets, column 5 examines migration across macroregions, and columns 6 and 7 examine rural–urban migration. The sample includes birth cohorts from 1932 and 1933. In columns 6 and 7, the sample only includes individuals who lived in a rural municipality at the time of enlistment. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Controlling for Different Education Measures

	Moving across LLM				Moving into cities			
	No education controls	Some secondary education at session (0/1)	Years of education at session	Completed years of education	No education controls	Some secondary education at session (0/1)	Years of education at session	Completed years of education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cognitive ability	0.057***	0.058***	0.035***	0.016***	0.058***	0.058***	0.030***	0.018***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Sociability	0.001	-0.002	0.001	-0.002	-0.001	-0.001	-0.006*	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Adaptability	0.042***	0.045***	0.042***	0.042***	0.027***	0.027***	0.024***	0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R-squared	0.123	0.124	0.123	0.129	0.133	0.133	0.139	0.159
N	23829	23829	23825	23278	16221	16221	16218	15801

Notes: Entries represent the estimated coefficients, with standard errors in parentheses, from the OLS regressions of the effects of cognitive ability, sociability, and adaptability on different mobility indicators. Columns 1–4 examine migration across local labor market, and columns 5 and 6 examine rural–urban migration. Columns 1 and 5 do not include control variables for education and reflect the main specification of Table 4. In columns 2 and 6, a dummy variable indicating whether an individual has some secondary education at the time of enlistment (at age 20 years) is included in the regression. This specification reflects the main specification used by Lindqvist and Vestman (2011). In columns 3 and 7, the number of years of schooling at the time of enlistment is included in the regression, and in columns 4 and 8, the completed years of education. The sample includes birth cohorts from 1932 and 1933. In columns 5–8, the sample only includes individuals who lived in a rural municipality at the time of enlistment. Further control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth.

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Nonparametric Functional Form

	Moved across LLM		Move into cities	
	before 1960	before 1980	before 1960	before 1980
	(1)	(2)	(3)	(4)
Cognitive ability in 2nd quintile	0.005	-0.000	0.033***	0.029***
	(0.009)	(0.009)	(0.010)	(0.010)
Cognitive ability in 3rd quintile	0.055***	0.054***	0.036***	0.054***
	(0.009)	(0.009)	(0.010)	(0.010)
Cognitive ability in 4th quintile	0.080***	0.087***	0.062***	0.074***
	(0.009)	(0.009)	(0.010)	(0.010)
Cognitive ability in 5th quintile	0.118***	0.125***	0.114***	0.131***
	(0.009)	(0.009)	(0.010)	(0.010)
Adaptability in 2nd quintile	0.031***	0.032***	0.017*	0.025**
	(0.009)	(0.009)	(0.009)	(0.010)
Adaptability in 3rd quintile	0.052***	0.054***	0.013	0.016*
	(0.008)	(0.008)	(0.009)	(0.009)
Adaptability in 4th quintile	0.041***	0.045***	0.023**	0.027**
	(0.011)	(0.011)	(0.012)	(0.012)
Adaptability in 5th quintile	0.104***	0.122***	0.070***	0.093***
	(0.009)	(0.008)	(0.009)	(0.010)
R-squared	0.162	0.167	0.168	0.129
N	25367	25367	17299	17299

Notes: Entries represent the estimated coefficients, with standard errors shown in parentheses, from the OLS regressions of the effects of different cognitive ability quintiles and adaptability quintiles on different mobility indicators. Columns 1 and 2 examine migration across local labor markets, and columns 3 and 4 examine rural–urban migration. The sample includes birth cohorts from 1932 and 1933. In columns 3 and 4, the sample only includes individuals who lived in a rural municipality at the time of enlistment. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Sorting across destinations: Cognitive Abilities and Adaptability

	Moved by 1960	Moved by 1980
Returns to cognitive ability	0.92	0.90
	(-1.12)	(-0.92)
Returns to adaptability	0.87	0.89
	(-1.02)	(-0.92)
Cognitive ability in second tercile	1.11**	1.10**
× returns to cognitive ability	(2.16)	(2.02)
Cognitive ability in top tercile	1.16***	1.14***
× returns to cognitive ability	(4.10)	(3.92)
Adaptability in second tercile	1.07	1.04
× returns to adaptability	(1.11)	(0.89)
Adaptability in top tercile	1.08	1.00
× returns to adaptability	(1.04)	(0.92)

Notes: The top numbers in each cell are odds ratios, implied by the estimated coefficients (unreported). Z-statistics are shown in parentheses. The conditional logit specification includes the following controls: returns to cognitive ability, returns to adaptability, an interaction term of both the returns to cognitive ability and adaptability with an indicator variable that is equal to one if an individual's IQ score is in the second tercile of the IQ distribution, an interaction term of both the returns to cognitive ability and adaptability with an indicator variable that is equal to one if an individual's IQ score is in the third tercile of the IQ distribution, an indicator for birth region, and dummy variables for each potential choice region.

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

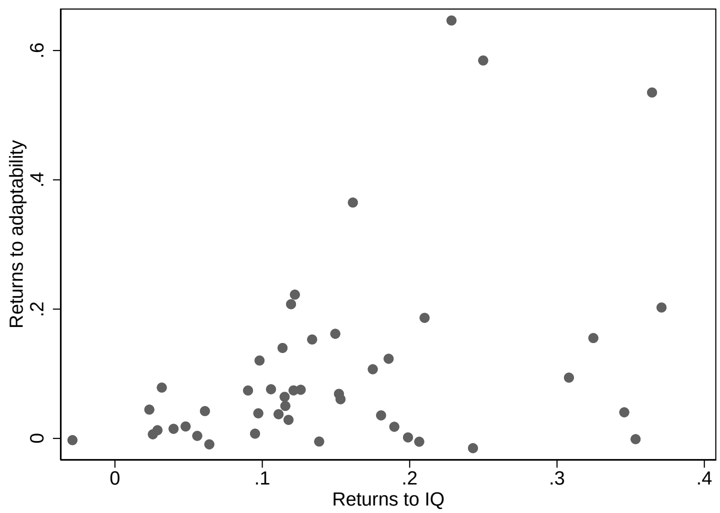
Table 9: Log Earnings Difference before and after Moving

	Differences in log earnings 1 year before and after moving		Differences in log earnings 3 years before and after moving	
	Moved across LLM	Moved into cities	Moved across LLM	Moved into cities
	(1)	(2)	(3)	(4)
Cognitive ability	0.227**	0.223**	0.418***	0.212**
	(0.099)	(0.090)	(0.130)	(0.101)
Sociability	-0.036	0.047	0.028	0.187*
	(0.092)	(0.087)	(0.087)	(0.104)
Adaptability	0.021	0.032	0.026	0.065
	(0.088)	(0.084)	(0.116)	(0.101)
R-squared	0.841	0.855	0.784	0.797
N	8674	7356	8651	7288

Notes: Entries represent the estimated coefficients, with standard errors shown in parentheses, from the OLS regressions of the effects of cognitive ability, sociability, and adaptability on log earnings differences 1 year prior compared with 1 year after migration (columns 1 and 2) and log earnings differences 3 years prior compared with 3 years after migration (columns 3 and 4). The sample includes movers with positive earnings before moving from the 1932 and 1933 birth cohorts. Columns 1 and 3 focus on individuals who moved across counties. Columns 2 and 4 focus on individuals who lived in a rural municipality at the time of enlistment and later moved to urban areas. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Online Appendix

Figure A1: Correlation between Returns to Cognitive and Non-Cognitive Skills

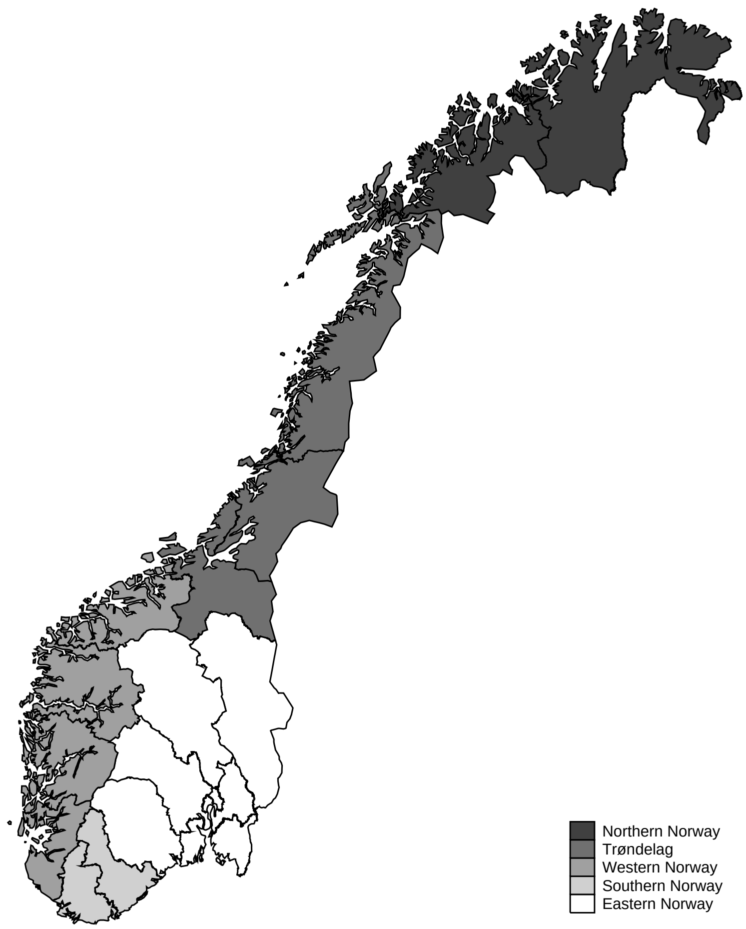


Notes: The y-axis displays the returns to adaptability in each local labor market. The x-axis plots the returns to cognitive skills in each local labor market. The returns are estimated using average yearly earnings between age 35 and 40.

Figure A2: Local Labor Markets

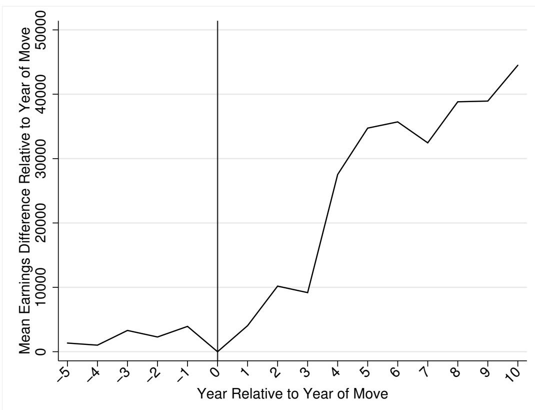
Notes: The map displays the 46 local labor markets in Norway. Labor market regions are an aggregation of municipalities (the smallest political entity in Norway), based on commuting patterns between municipalities, subject to the constraint that regions should be sufficiently large for empirical analysis (see Bhuller, 2009). The archipelagos in the Arctic Ocean, Svalbard and Jan Mayen, are not included in the labor market regions.

Figure A3: Macro-regions

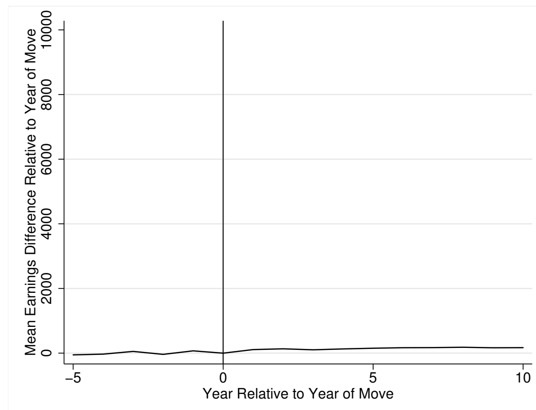


Notes: The map displays the five different macroregions (Norwegian: landsdeler): Northern Norway, Trøndelag, Western Norway, Southern Norway, and Eastern Norway. In addition, the map shows the 19 administrative areas called counties (Norwegian: fylke). The archipelagos in the Arctic Ocean, Svalbard and Jan Mayen, are outside the county division and are ruled directly at the national level.

Figure A4: Average Earnings Difference Relative to Year of Rural-to-Urban Move



(a) Highest IQ vs. Lowest IQ Tercile



(b) Highest Adaptability vs. Lowest Adaptability Tercile

Notes: Figure (a) displays the average earnings differences between individuals in the highest and those in the lowest IQ tercile in 1998 NOK, relative to the year of moving from a rural to an urban area. Figure (b) displays the average earnings differences between individuals in the highest and those in the lowest adaptability tercile in 1998 NOK, relative to the year of moving from a rural to an urban area.

Table A1: Interactions between Cognitive and Noncognitive Skills

	Moved across LLM		Move into cities	
	before 1960	before 1980	before 1960	before 1980
	(1)	(2)	(3)	(4)
Medium cognitive ability	0.078***	0.088***	0.052***	0.060***
	(0.015)	(0.014)	(0.015)	(0.016)
High cognitive ability	0.296***	0.324***	0.176***	0.223***
	(0.018)	(0.017)	(0.019)	(0.020)
Medium adaptability	0.067***	0.090***	0.032**	0.052***
	(0.015)	(0.015)	(0.015)	(0.016)
High adaptability	0.171***	0.185***	0.093***	0.128***
	(0.022)	(0.022)	(0.023)	(0.024)
Medium cognitive ability ×	-0.007	-0.009	-0.009	-0.002
Medium adaptability	(0.018)	(0.017)	(0.018)	(0.019)
Medium cognitive ability ×	0.056**	0.058**	0.002	0.001
High adaptability	(0.027)	(0.028)	(0.026)	(0.027)
High cognitive ability ×	-0.104***	-0.102***	-0.062***	-0.066***
Medium adaptability	(0.021)	(0.021)	(0.023)	(0.024)
High cognitive ability ×	-0.115***	-0.128***	-0.089***	-0.114***
High adaptability	(0.028)	(0.027)	(0.030)	(0.031)
R-squared	0.143	0.146	0.168	0.130
N	25367	25367	17299	17299

Notes: Entries represent the estimated coefficients, with standard errors shown in parentheses, from the OLS regressions of the effects of different cognitive ability quintiles and adaptability quintiles, as well as the interactions of these, on different mobility indicators. Columns 1 and 2 examine migration across local labor markets, and columns 3 and 4 examine rural–urban migration. The sample includes birth cohorts from 1932 and 1933. In column 2, the sample only includes individuals who lived in a rural municipality at the time of enlistment. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth.

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Reverse Causality: Association between Moving during Childhood and Cognitive and Noncognitive Abilities

	Cognitive ability	Sociability	Adjustability
Moving during childhood	0.096****	-0.002	0.007
	(0.013)	(0.012)	(0.013)
R-squared	0.138	0.026	0.016
N	24161	24668	24899

Notes: Entries represent the estimated coefficients, with standard errors shown in parentheses, from the OLS regressions of the effects of a variable indicating whether an individual moved during childhood on cognitive ability (column 1), sociability (column 2), and adaptability (column 3). The sample includes birth cohorts from 1932 and 1933. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Controlling for Childhood and Military Service Mobility

	Moved across LLM before 1980 (1)	Moved into cities before 1980 (2)	Moved across LLM before 1980 (3)	Moved into cities before 1980 (4)
Cognitive ability	0.053***	0.057***	0.061***	0.059***
	(0.003)	(0.004)	(0.015)	(0.004)
Sociability	0.001	-0.001	0.004	-0.001
	(0.003)	(0.004)	(0.014)	(0.004)
Adaptability	0.040***	0.025***	0.050***	0.027***
	(0.002)	(0.003)	(0.012)	(0.003)
Childhood mobility	0.506***	0.084***		
	(0.005)	(0.007)		
Cognitive ability × Oslo			0.104	
			(0.110)	
Sociability × Oslo			-0.094	
			(0.111)	
Adaptability × Oslo			-0.080	
			(0.151)	
Oslo			-0.238**	
			(0.118)	
King's Guard				-0.019
				(0.012)
R-squared	0.189	0.141	0.134	0.133
N	23829	16221	1358	16221

Notes: Entries in Columns 1 and 2 represent the estimated coefficients, with standard errors shown in parentheses, from the OLS regressions of the effects of cognitive ability, sociability, adaptability, and childhood mobility on different mobility indicators. The sample includes birth cohorts from 1932 and 1933 and in column 2, the sample only includes individuals who lived in a rural municipality at the time of enlistment. Entries in column 3 only include member of the King's Guard and represent the estimated coefficients from the OLS regressions of the effects of cognitive ability, sociability, adaptability, an indicator variable for residing in Oslo at time of military enlistment and interaction terms of the Oslo-indicator with the different skill measures on an indicator variable for moving across local labor markets. Entries in column 4 include individuals who lived in a rural municipality at the time of enlistment and represent the estimated coefficients from the OLS regressions of the effects of cognitive ability, sociability, adaptability, and an indicator variable for being assigned the King's Guard on an indicator variable for moving from a rural to an urban area. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth in all specifications. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Heterogeneity

	Moved across LLM before 1980 (1)	Moved into cities before 1980 (2)	Moved across LLM before 1980 (3)	Moved into cities before 1980 (4)
Panel A: Birth Order				
	Firstborn Sons		**Second or Later Born Sons**	
Cognitive ability	0.059***	0.057***	0.051***	0.059***
	(0.005)	(0.006)	(0.004)	(0.005)
Sociability	-0.005	0.011*	0.004	-0.006
	(0.006)	(0.006)	(0.004)	(0.005)
Adaptability	0.044***	0.026***	0.041***	0.028***
	(0.004)	(0.005)	(0.004)	(0.004)
R-squared	0.123	0.138	0.125	0.132
N	9905	6619	13924	9602
Panel B: Socioeconomic Background				
	Low Socioeconomic Background		**High Socioeconomic Background**	
Cognitive ability	0.049***	0.050***	0.064***	0.064***
	(0.005)	(0.005)	(0.004)	(0.005)
Sociability	-0.003	0.001	0.002	-0.003
	(0.005)	(0.005)	(0.004)	(0.005)
Adaptability	0.049***	0.029***	0.036***	0.025***
	(0.004)	(0.004)	(0.004)	(0.005)
R-squared	0.079	0.128	0.168	0.139
N	11172	8673	12657	7548
Panel C: Macro-Regions				
	Southern, Middle, and Western Norway		**Northern Norway**	
Cognitive ability	0.059***	0.058***	0.049***	0.058***
	(0.003)	(0.004)	(0.009)	(0.008)
Sociability	-0.001	-0.001	0.009	-0.005
	(0.003)	(0.004)	(0.009)	(0.009)
Adaptability	0.040***	0.026***	0.047***	0.029***
	(0.003)	(0.004)	(0.008)	(0.007)
R-squared	0.129	0.143	0.042	0.042
N	20689	13182	3140	3039

Notes: Entries represent the estimated coefficients, with standard errors shown in parentheses, from the OLS regressions of the effects of cognitive ability, sociability, and adaptability on different mobility indicators. Columns 1 and 3 examine migration across local labor markets, and columns 2 and 4 examine rural–urban migration. The sample includes birth cohorts from 1932 and 1933. In columns 3 and 4, the sample only includes individuals who lived in a rural municipality at the time of enlistment. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth.

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Sibling Sample, Marriage Outcomes, and International Migration

	Brother Fixed Effects			
	Moved across LLM before 1960	Move into cities before 1980	Married in 1960	Emigrating to a foreign country
	(1)	(2)	(3)	(4)
Cognitive ability	0.085	-0.022	0.012***	0.006***
	(0.073)	(0.031)	(0.003)	(0.001)
Sociability	0.028	0.002	0.005	-0.001
	(0.036)	(0.015)	(0.003)	(0.001)
Adaptability	0.062**	0.033**	0.011***	0.003***
	(0.030)	(0.015)	(0.003)	(0.001)
Mean of dep. variable	0.49	0.25	0.62	0.01
R-squared (within)	0.191	0.106	0.036	0.009
N	230	208	23829	23829

Notes: Entries represent the estimated coefficients, with standard errors shown in parentheses, from the OLS regressions of the effects of cognitive ability, sociability, and adaptability on different outcomes. Columns 1 and 2 present brother fixed effects estimates for the probability of moving across local labor markets before 1980 or from a rural area to a city before 1980. Column 3 considers the probability of being married in 1960, and column 4 analyzes the probability of emigrating to a foreign country. Control variables include the occupation of the father, an indicator for the death of the father or mother or both parents, the parent's civil status, the individual's height in cm, and the individual's year of birth.

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$