The Role of Cognitive and Noncognitive Skills in Selecting into Migration*

Aline Bütikofer
Norwegian School of Economics

Giovanni Peri
University of California, Davis

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Abstract

We assess the importance of cognitive and noncognitive (soft) skills on geographic migrating using data that combine military enlistment information and administrative data for the male population born in 1932 and 1933 in Norway. The data measure 'sociability' and 'adaptability' skills based on detailed interviews with a psychologist at age 18. We find that adaptability has a significant and positive impact on the probability of moving out of one's local labor market or from rural to urban areas. High cognitive ability is also associated with a higher propensity to migrate. We find that adaptability has a particularly strong impact on migration for individuals with low cognitive skills implying a very strong positive selection of low skilled with respect to the (previously unobserved) adaptability skill. We also present evidence that adaptability has no significant effect on the earnings premium of those who migrate, while cognitive skills have a strong positive effect on earnings returns to migration. This evidence is consistent with adaptability skills mainly reducing the non-monetary migration costs, while cognitive skill mainly increase the earnings returns to migration.

1 Introduction

Recent economic research has found that besides cognitive skills, also noncognitive skills, often referred to as 'soft skills', such as the degree of sociability of an individual or his/her adaptability to new people and situations, are valuable characteristics in the labor market. While the traditional theory of human capital and schooling can be seen as emphasizing the role of cognitive abilities in enhancing the productivity of individuals, we are just beginning to understand the role of other, noncognitive abilities on labor productivity. These abilities may affect the marginal productivity of individuals (see Lindqvist and Vestman, 2011; Lundborg, Nystedt, and Rooth, 2014; Gensowski,

*Aline Bütikofer, Department of Economics, Norwegian School of Economics, Helleveien 30, 5045 Bergen, Norway. Email: aline.buetikofer@nhh.no. Giovanni Peri, Department of Economics, UC Davis, One Shields Avenue, Davis, CA 95616. Email: gperi@ucdavis.edu.

2014, among others), enhance their ability of accumulating human capital (Segal, 2013), or they may affect their occupational choice and specialization (see, e.g., Bacolod, Blum, and Strange, 2009). They may also differ between men and women more than cognitive abilities and hence drive, in part, their productivity differentials (Beaudry and Lewis, 2014). In the wake of this literature, we analyze how cognitive and noncognitive skills of individuals affect their geographic mobility. Interregional and rural-urban migration is a crucial way of realizing one's labor market potentials as well as a very important economic investment. While the literature has recognized for a long time the crucial importance of human capital (schooling) on increasing the propensity to migrate internally and internationally,[1] it is not known what part of this effect is due to cognitive and what part to noncognitive soft skills. This paper analyzes how cognitive and noncognitive skills, measured at 18 years of age, affect the migration behavior of an individual over his/her working career.

Understanding how cognitive and noncognitive abilities affect geographic mobility advances two lines of research. On one hand, we improve our understanding of migrant selection. If individual skills that increase the probability of migrating also make individuals more productive then this implies a positive selection of migrants along productivity measures. This suggests that migrants could be important economic contributors in the destination and their departure is a larger cost to the place of origin. In addition, if cognitive and noncognitive abilities that increase the probability to migrate make people more likely to succeed in the destination, this bodes well for their assimilation in the receiving economy. On the other hand, this paper improves our understanding of the channels through which cognitive and noncognitive skills affect individual income. Migration is an important investment and a mechanism through which people increase their permanent income. Migrants pay a current cost to move where their skills are paid more and hence their returns to abilities are higher. The connection between abilities and labor market success can be mediated by geographical mobility. Skills that reduce the cost of moving or increase the economic returns to moving may, in the long run, realize better employer-employee matches and more efficient allocation of productive resources, via higher mobility.

Whereas the correlation 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), there are, to our knowledge, only very few studies that analyze the connection between cognitive and noncognitive abilities and migration (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 (soft) noncognitive skills that we define as 'adaptability' and 'sociability' and one (hard) cognitive skill, the 'IQ' (intelligence quotient), all measured at age 18, affect the geographical mobility of individuals and in particular their probability to move out of their labor market region of origin during their working life. We investigate these effects by using detailed

[1]See for instance Malamud and Wozniak (2012) on schooling and internal migration and Grogger and Hanson (2011) on schooling and international migration.

population registry data from Norway from 1960 until 2010, which include annual information on the municipality of residence and labor market outcomes. These data can be linked to data on military enlistment for all 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, several scores assessing the cognitive ability of individuals as well as their psychological suitability to military service. The psychological suitability to military service is evaluated by military psychologists in a personal interview and the psychologists assessed in particular the recruits' adaptability and sociability.[2] These data are available for all male individuals reaching age 18 in year 1951 and 1953 and we can follow these individuals over their working life, starting in 1960 until their retirement.

This information allows us to analyze how IQ, adaptability, and sociability scores at age 18 affect the probability to migrate during the working life. We can also analyze whether the cognitive and noncognitive attributes of an individual interact with each other as complement or substitutes in determining the propensity to migrate. Besides establishing a link between skills and the probability to move 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, focusing on the 'soft' noncognitive skills it is important to understand whether they mainly affect the monetary return to migration or whether they reduce the (non-monetary) cost of migration. Within a simple variation of the Roy (1951) model of migration and selection a rational individual decides to emigrate if the expected returns from migration are larger than its (monetary plus non-monetary) costs of moving. We derive different predictions of the model on the migration probability and on the pre-post migration earnings differential depending on whether an individual's skills affect the returns to migration or if they affect the costs of migration. This model generates the robust prediction that the intensity of a skill that increases productivity (and hence the returns to migration) should affect positively the probability to migrate and the pre-post migration earnings differential. To the contrary, a characteristic that mainly affects the non-monetary cost of migration should have a positive impact on the migration probability but a negative or null impact on the pre-post migration earnings differential of the migrant.

We find that both the IQ and the soft 'adaptability' skill have a significant and positive impact on the probability to move across regions (or to move from rural to urban location) within the first decades of working life. Sociability, instead, does not seem to have any impact on the propensity to migrate. In addition, we find that adaptability has a particularly strong impact on migration for individuals outside the top quintile of cognitive ability distribution, suggesting that adaptability is relevant for deciding to migrate except when cognitive abilities are very high (and drive high probability of migration). Moreover, our empirical analysis reveals that adaptability significantly affects the probability of migrating but not the pre-post migration earnings differential consistently

[2] We follow previous work by Lindqvist and Vestman (2011) in considering that the military psychologists' assessment offers a reasonable and objective measure of noncognitive abilities.

with a channel that reduced non-monetary migration costs.

These results seem reasonable and interesting. First, a soft skill like adaptability that can be measured at age 18, turns out to be important in increasing the probability of migrating. Moving to a different region requires the ability to deal with new situations, new people and therefore better adaptability skills can certainly decrease adjustment costs and increase the propensity to migrate. Second, the importance of adaptability skills raises the question whether they can be increased in the population. The possibility of improving the adaptability skills of individuals through schooling, by exposing students to a varied and changing environment and by allowing them to interact with individuals with diverse and heterogeneous backgrounds, may increase the probability that they decide to migrate later in life and realize their best labor market options. Adaptability that spurs mobility would also improve the functioning of the labor markets by reducing the mobility costs. While it is hard to know how education could improve adaptability, the significant effect on migration that we find emphasizes the potential economic return in doing that.

The rest of the paper proceeds as follows. Section 2 summarizes previous literature analyzing 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. Section 7 provides a brief conclusion.

2 Previous Literature

There exist abundant literature on the link between migration and human capital. Part of it is based on variations of the selection model introduced by Roy (1951) and then developed by Borjas (1987) and Grogger and Hanson (2013) to analyze the skill selection of international migrants. Those models emphasize different type of selection across skills depending on the skill returns in the sending and in the receiving economies. In the context of internal migration, Borjas, Bronars, and Trejo (1992) find that persons are more likely to leave the 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 college versus high school educated individuals. Another strand of the literature focuses more on documenting the higher geographic mobility of college 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 as capturing the unobserved human capital characteristics of migrants. Hence, these papers characterize the migrant selection as positive or negative depending on the pre-migration wage relative to that of non-migrants. Much less common is to investigate the connection between cognitive and noncognitive skills and migration behavior. One reason is the extremely limited availability of measures of cognitive and noncognitive skills at the individual level. In many cases the skill content of individuals is derived by their occupational choice (e.g. Beaudry and Lewis, 2014), which is clearly an endogenous variable, and cannot be used to analyze the effects on the 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 form the German Socioeconomic Panel. 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. In addition, there are a couple of studies in the psychological literature investigating the relationship of self-assessed personality traits and migration. Examples include Jokela, Elovainio, Kivimäki, and Keltikangas-Järvinen (2008) who examine whether sociability and emotionality predicted migration propensity, selective urban to rural migration, and migration distance in a 9-year prospective study in Finland. The authors find that high sociability predicted migration to urban areas and longer migration distances. In addition, Jokela (2009) examined the role of personality in predicting the propensity to migrate within and between U.S. states. He shows that high openness and low agreeableness increased within- and between-states migration, while high extraversion increased within- but not between-states migration. Other mental traits were not related to migration probability. Our study is therefore the first using individual panel data from an administrative sources, covering two whole male cohorts of a country (Norway), and using a measure of noncognitive soft skills based on a personal interview (and not self-assessed or occupation-inferred) and their impact on migration propensity. Moreover, as these abilities are measured at age 18 and the individuals are followed over their whole working life, we can assess the long-run effects of different cognitive and noncognitive abilities on mobility outcomes over a long period.

While few studies have connected soft skills and migration, there is a growing literature on the impact of noncognitive skills on labor market outcomes of individuals. The majority of these papers, however, measures 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 they 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, assessed by a teacher, is negatively correlated with earnings and associated with lower educational attainment even after controlling for eighth-grade test scores and family background characteristics. Lindqvist and Vestman (2011) use Swedish data from the military enlistment, similar to the data we use in this paper, and find that low level of labor market attachment and low annual earnings depend more on 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. Our study uses data of quality comparable to Lindqvist and Vestman (2011) and it is the first to analyze, within the simple framework of a Roy model, the impact of cognitive and noncognitive skills on mobility of individuals.

3 Model

We consider a framework that modifies the typical model by Roy (1951). In this framework individuals differ in terms of a vector of observable productive characteristic $\underline{s}$ (think of cognitive skills as s_1, social skills as s_2, adaptability as s_3 and so on), and one unobservable productive characteristic ε whose distribution, conditional on the other characteristics, is a random normal with 0 average and standard deviation of one.[3] These individuals live in location H, they maximize their wage income and they are considering whether to migrate or not to location F. For simplicity, we consider that among all possible locations, F is the one that has the highest average productivity and returns to all skills and hence individuals only compare that location to their current one. The wage that individual i would receive if she remains in H and works there 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 while $\underline{\beta}^H = (\beta_1^H, \beta_2^H, \beta_3^H, ...)$ is the vector of linear returns to units of each individual skill s_{mi} in location H and $\underline{s}_i = (s_{1i}, s_{2i}, s_{3i}, ...)$ is the endowment of each skill of individual i. In expression (1), we assume that skills affect productivity linearly and independently of each other. This is a simplification and can be removed to analyze the 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 endowment of that skill. The wage that individual i gets if she were to move to F is, instead:

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

where μ_F is the average productivity of location F and $\underline{\beta}^F \geq 0$ and $\beta_\varepsilon^F \geq 0$ are the returns to individual observable and unobservable skills in location F. As a relevant case, we consider one in which the best potential location for a person, outside the current one, has a larger average productivity than location H ($\mu^F > \mu^H$), a larger return for the observable productive skills (each component of $\underline{\beta}^F$ is larger than the corresponding component of $\underline{\beta}^H$), and a larger return for the unobservable skill ($\beta_\varepsilon^F > \beta_\varepsilon^H$). This assumption is strong, but plausible and in line with what

[3] Skills may be correlated in their distribution across individuals. The term ε is the remaining skill, and conditional on observable skill endowments it is randomly distributed across individuals with 0 mean.

is observed across economies. It presumes that a highly productive location has higher average productivity and higher return to all skills than a lower productivity location.[4] It also implies that people move from low to high productivity locations and that the selection of migrants is positive on the observed and unobserved skills. We also assume that the cost of moving to any location for individual i is equal to C_i. C_i has two component C_M representing monetary costs expressed in units of labor income and common to all migrants and $c(\underline{s}_i)$ representing non-monetary costs that may depend on some (or all) of the individual skills $\underline{s}_i$. In particular, it is plausible to assume that $\partial c/\partial s_i \leq 0$ for all $i's$, so that higher endowment of cognitive, social or adaptability skills may reduce the non-monetary (psychological) costs of migration or have no effects on them.

Given this very simple set-up the decision of migrating of an income maximizing agent is driven by the comparison of the wage income at home (H) with the wage income at the most desirable 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 one obtains that individual i migrates if her 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 the function $c(.)$, the threshold ε^T for the non-observable skill so that individual i will migrate is decreasing in each component of the vector $\underline{s_i}$ so that $\partial\varepsilon^T/\partial s_{Mi} \leq 0$ for each characteristic s_{Mi}. An individual with higher ability of any kind 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 migrates.

Consider now individuals organized into groups that have a certain vector of observable characteristics $\underline{s_G}$. Within each group there are individuals with different unobservable characteristics ε_i and this characteristics are normally distributed across them with average 0 and standard deviation 1 and independently of the other characteristics. Then the probability that an individual in group G (i.e. with observable characteristics s_G) migrates 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, whose first derivative is strictly positive. Expression (5) implies that the probability of migrating $prob_i^{MIG}$ for

[4] Dustmann, Fadlon, and Weiss (2011) consider a model in which different location have different rates of returns for two separate skill. They consider all possible cases including one in which a location grants higher returns in one and lower returns in the other skill. In that case, the predictions on selection on unobservables are less clear.

individual i in group G is larger the larger any of the observable skill components $\underline{s_G}$ is. Interestingly, this simple model implies that looking at the probability of migrating of individuals as a function of their (cognitive, social, adaptive) abilities that may have a productivity effect or a migration cost reducing effect, one obtains a similar positive relation with migration probability.

Let us emphasize that there are two channels through which higher skills affect the probability of migrating and they both imply a non-negative effect under the assumptions of the model. One is through the term $-(\underline{\beta}^F - \underline{\beta}^H) * \underline{s}_i$ in expression (4) that implies a higher return to migration for individuals with higher value of any of the skill components $\underline{s}_i$ that have a positive productivity effect. This term also reduced the unobserved skill threshold increasing the probability of migrating. The other effect works through the term $c(\underline{s}_i)$ in expression (4) that implies a lower cost of migration associated to higher skills, a reduction of the migration threshold, and an increase in migration probability. Presumably, the impact of some skills, (possibly cognitive skills) on productivity is larger than their impact on costs while the impact of other skills, (possibly adaptability skills) are larger on moving costs than on productivity. Looking only at the direction of the impact on the probability of migration, however, one would not be able to separate those channels.

However, we can analyze the prediction of the model on the relationship between different skills $\underline{s}_i$ and the average migration premium for people who migrate to gain further insight. The migration premium is the difference in wage when migrating relative to staying, for individual i in group G, conditional on migrating. 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_m for the group will have on the expected return to migration for people who migrate. First, let's consider a skill s_m whose impact on productivity is zero, $\beta_m^F = \beta_m^H = 0$, but has an impact through reducing costs of migration $\partial c / \partial s_m < 0$. In this case, an increase in that skill will imply larger probability of migrating in (5), as $\partial \varepsilon^T / \partial s_{mi} < 0$. 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_m will reduce this term. Hence, if skill s_m only affects the cost of migrating, by decreasing it, and not the returns to migration the effect of an increase in such a skill on the expected return for people who migrate is negative.

Consider another skill $s_{m'}$ that only affects productivity and hence return to migration, so that, $\beta_{m'}^F - \beta_{m'}^H > 0$ and $\partial c / \partial s_{m'} = 0$. In this case the first effect of an increase in $s_{m'}$ 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 large enough value of $(\underline{\beta}^F - \underline{\beta}^H)$, namely if the effect on returns to migration is large enough, the first term will prevail and an increase in the productivity-enhancing skill $s_{m'}$ will have a positive impact on the average premium of migrants. On the other hand, this skill will also have a positive impact on probability of migrating $s_{m'}$.

Finally, we consider the impact of a skill that affects both, productivity and migration costs. The effect on expected returns to migration will depend on the relative strength of the two effects on productivity and on costs. A larger impact of such skill on the cost of migrating will reduce the expected return 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 skills will drive higher probability of migration, through both channels.

Hence we can summarize the implications of the model above into these two points:

- Considering 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 higher migration probability of group G', $prob_i^{MIG}(\underline{s_{G'}}) > prob_i^{MIG}(\underline{s_G})$, and higher expected return to migration for group $G', w_{G'}^F - w_{G'}^H > w_G^F - w_G^H$.
- Considering 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) then we should observe higher migration probability of group G', $prob_i^{MIG}(\underline{s_{G'}}) > prob_i^{MIG}(\underline{s_G})$, and equal or smaller expected return to migration for group $G', w_{G'}^F - w_{G'}^H \leq w_G^F - w_G^H$.

Our empirical analysis will put to the test these two propositions for different types of skills and we will infer from migration probabilities and from premium of migrants the role of different individuals skills such as cognitive ability, sociability and adaptability on productivity and on migration costs.

4 Data and Descriptive Statistics

The data we use are compiled from various sources. Our primary data source is the Norwegian Registry Data (from Statistics Norway), a linked administrative dataset that covers the whole population resident 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.[5] The data follow individuals over time in a longitudinal design and they provide information about place of birth, place of residence, educational attainment, labor market status, earnings, and a set of demographic variables as well as information on family background. This information is collected for each individual every year. To have information on individual cognitive and noncognitive skills we linked the registry data with detailed military enlistment data for two

[5]See Møen, Salvanes, and Sørensen (2003) for a detailed description of the data.

full cohorts of men born in 1932 and 1933 for whom these data are available. These two cohorts of men include all male individuals born in Norway between 1932 and 1933 who were subject to mandatory military enlistment in 1951 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 (which are a very small fraction of the cohorts under consideration). Moreover, the enlistment data also includes the place of residence at enlistment, which represents the location where an individual lived at age 18. Hence, from year 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 age 18. Educational attainment is taken from the educational database provided by Statistics Norway and from the enlistment records.[6] The earnings measure is not top-coded and includes labor earnings expressed in constant 2014 Norwegian Kroner (hence adjusted for inflation), taxable sick 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 demographics characteristics and skills for male Norwegian individuals born in 1932-33. Looking at the years of schooling completed at age 18 and overall we clearly see that the majority of individuals had already completed their schooling at enlistment: at enlistment, the average years of schooling were 8.4, the average completed years of education are 9.5 for the same sample of individuals. This reflects the fact that in the two considered cohorts only few individual had a college education. The average earnings in 1980 are NOK 325,442 (in 2014 values); in 1967, the first year when income data is available, the average earnings are NOK 239,388 (in 2014 values) reflecting the real growth in earnings for this group over time.

We use several different indicators of mobility: the first captures mobility by age 27-28 and it is a dummy equal to one if an individual resides in a different local labor market in 1960 than when he was 18 (at enlistment). 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).[7]

[6]Since 1974, educational attainment is reported annually by the educational institutions directly 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 that is considered to be very accurate (see, e.g., Black, Devereux, and Salvanes, 2005).

[7]We focus on migration across local labor markets rather than counties (Norwegian: fylke). Some large cities in

There are a total of 46 local labor market regions (see Figure A1).[8] These local labor market regions 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, which captures overall mobility by age 47-48. The average of these two variables (0.39 and 0.45 respectively) implies that 39% of the Norwegian male population born in 1932-33 moved out of the local labor market where they grew up (and resided at age 18) by age 28 and 45% of them had moved by age 48. These statistics confirm that the large part of mobility takes place when individuals are young, and that in this period Norwegian male individuals were quite mobile. Interestingly, 31% of individuals move permanently. That is, they move out of the local labor market where they resided at age 18 and never move back as of 2010 (or the year of death). The data also show that among those who move out of their labor market region of origin, 74% moved only once as of 1980. Only 5% of the movers moved three times or more. The average distance individuals move between age 18 and year 1980 is 470 kilometers which is a comparable to the distance between Paris and London or between Milan and Munich. The median distance is with 225 kilometers, which is substantially less and emphasizes that most of the moves are more local. In order to capture specifically mobility between farther locations, we also consider as additional indicator, which is equal to one for having moved to a different 'macro-region' (Norwegian: landsdeler) as of 1980. Norway is commonly divided into five geographical 'macro-region' (see Figure A2). These regions have a mere geographical characterization and no administrative purposes. As shown in Table 1, 19% of the Norwegian male population born in 1932-33 moved out of the macro-region where they resided at age 18 years of age by 1980. Hence, even if substantially lower than the shorter distance mobility, this longer distance mobility involved a significant group of individuals.

Finally, in terms of migration outcomes we consider the dummy variable that captures rural-urban migration. Statistics Norway divides municipalities in 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, while lower values are considered as 'rural'. The highest level of centrality includes urban settlements with a population of at least 50,000 as well as municipalities, which are located within 75 minutes travelling time from the centre of an urban settlement with a population of at least 50,000. By age 27-28, about 19 percent of individuals had moved from a rural to an urban location and by age 47-8 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 age of an individual. These features are consistent with male migration in the age range between 18 and 48 being mainly job driven: it is easier to change job when one is young, urban environment provides a larger opportunity for jobs, usually people move once or at most twice for a job opportunity.

Norway are situated right at county boarders and therefore across county migration might occur without substantial consequences to the working and social life. Boundaries of local labor markets, however, represent a larger changes in earnings, factor productivity, and firm innovation than county boarders.

[8]The archipelagos in the Arctic Ocean, Svalbard and Jan Mayen, are ruled directly on national level and are not included in the labor market regions.

4.2 Military Enlistment Data

Military enlistment and military service was mandatory for men and not for women in 1951 and 1953. Hence, our enlistment data include every single male individual who was 18 year old in 1951 and 1953. Before these young men could join the military service, their medical and psychological, suitability was assessed. In the 1950s, military enlistment centers called in about 20 men per day to be examined in these enlistment sessions. Each conscript was interviewed individually by an officer as well as a psychologist and examined by a doctor. Besides the interviews and medical tests, the enlistment procedure also included tests for physical fitness and cognitive ability, and a questionnaire aimed to reveal noncognitive skills and personality trains. Avoidance of military service was not possible by obtaining a low score on cognitive or noncognitive abilities. Only serious health issues such as tuberculosis infections or physical disabilities such as severe hearing problems were reasons for being exempted from military service. Among 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.

While medical tests were performed since the enlistment was instituted, tests of conscripts' cognitive and noncognitive ability were introduced in 1950 and 1951 respectively. The tests have changed substantially from their introduction until today. For each cohort of men, the tests are however the same. 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 at the military (Thrane, 1977). The tests lasted in total about 2 hours and 30 minutes including instructions and breaks and including answering the questionnaire on the personal situation.

4.2.1 Cognitive and Noncognitive Skills

The tests administered to determine cognitive skills consisted of four different components. The first two were aimed to assess general cognitive ability by testing logical-mathematical skills and spatial visualization skills. The third part consisted of a mechanical comprehension test and was aimed at assessing the knowledge of mechanics, that were important for military practices.[9] The last component was a test measuring processing speed (Thrane, 1977). As the first two tests are those measuring more closely math and analytical skills as opposed to test learned knowledge, we use them to measure cognitive ability in an index that mirrors IQ measures. The test for logical-mathematical skills measured a conscript's logic and abstract reasoning and the capacity to understand the underlying principles of some kind of causal system. This type of verbally formulated math problems have a long tradition in IQ tests for adults and were, for example,

[9] The mechanical comprehension test measured the conscripts' technical and in particular mechanical knowledge. The 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). This test was included as for many military jobs for which mechanical knowledge was important.

included in the Army Alpha test in order to evaluate U.S. military recruits during World War I. The test for spatial visualization ability is based on the J. C. Ravens' 'Progressive Matrices', which was used to classify military recruits in Britain during World War II. The test includes problems measuring abstract and inductive reasoning ability (see, e.g., Anastasi, 1968; Cronbach, 1964) and was developed in a way that prior education or knowledge should affect the results as little as possible. Only some verbal skills to understand the tasks are necessary.

Our data include the scores of these two subtest, which ranges from zero to 26 for the logical-mathematical skills test and from zero to 24 for the spatial visualization ability test. We add the two scores to construct the index for 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).

In 1951, a four-page questionnaire was introduced, which was aimed to reveal noncognitive skills and personality traits of the conscript. The questionnaire is based on the test developed by R. S. Woodworth for the U.S. military during World War I. The test was essentially an attempt to standardize a psychiatric interview and to adapt the procedure for mass testing. The Norwegian test included questions that elicit information to identify groups that may have problems adapting to new situations (see Lundgren and Olsen, 1952). Adaptability to new situations was mostly measures with so-called situational judgment tests, which were developed by the United States Army in the 1920s (see McDaniel, Morgeson, Finnegan, Campion, and Braverman, 2001). These tests present individuals with hypothetical but realistic scenarios and ask them to identify the most appropriate response. Moreover, the questionnaire included questions on behavior deviations, nightmare and other sleep disturbances, excessive fatigue and other psychosomatic symptoms, feelings of unreality, and motor disturbance such as tics and tremors (see Anastasi, 1968, page 438). The questionnaire also included questions on the living situation, education, job and satisfaction and on father's profession. The questionnaire is a standardized form of self-reported condition and might be important for mental health, physical health and social adaptability. There is no time limit to answer these questions and the conscripts are asked to answer as honestly as possible. For each question, one answer category was classified as showing potentially neurotic behavior. The psychologist analyzed conscripts with many answers hinting to some degree of neurotic disorder. In a study using the 1951 session data, Riis (1955) shows that the answers to 20 of these questions were a strong predictor for completing the fighter pilot education, or dropping out from it. Hence, some of these questions may reveal important noncognitive skills and personality traits with consequences on the future career.

As mentioned above, the conscripts are also individually interviewed by a psychologist. As a basis of the interview, the psychologist has information about the health, physical fitness as well as cognitive ability of a conscript and the answers to the questionnaire described above. The interview was semi-structured. The goal of the interview was to analyze whether a conscript's ability met the psychological needs for military service. The psychologists assign each conscript's sociability on a scale from zero to ten. 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 would increase the score. Motivation for military service did not affect the score (see, e.g., Cronbach, 1964). The ability to interact with others, to cooperate and to communicate effectively is a skill of potentially broad value. Psychologists found that high sociability is linked to professional success. In the context of military service, sociability was valued to increase a leader's ability to interact with his subordinates (see, e.g., Goleman, 2011). In addition, the psychologist assess a conscript's ability to adjust to a new environment. Generally, an individual is classified to be adaptable if she can modify her behavior to meet the demands of a new situation (Pulakos, Arad, Donovan, and Plamondon, 2000). Hence, if the situation or environment change, an individual must deal with the change in an effective manner. For the military, adaptability was relevant to assess a conscript's own ability to complete tasks and his interest in learning new tasks.[10] As sociability, adaptability may have a broad value as skill. Adaptability is important in a working environment where technological change, innovation and, in general, changes are paramount. An individual's adaptability is valuable to firms (Griffin and Hesketh, 2003) and may be an asset when people are exposes to new environments. Adaptability is reported on a scale from zero to ten. We use these two measures of noncognitive ability based on the psychologists' interviews and normalize both 0 to 10 scores to distributions with mean zero and unit variance.

Table 2 contains correlation coefficients for cognitive ability, sociability, adaptability all standardized to be have 0 average and standard deviation equal to 1, and the years of education at age 18. These raw correlations are interesting as they show three important facts. First, the two indices of noncognitive abilities have relatively low correlation (0.2 or lower) with cognitive skills at the individual level.[11] This is the first hint that they capture a genuinely different type of skills relative to cognitive ones, and cognitive and noncognitive skills are only mildly positively correlated. Second, the index of adaptability has very low correlation with sociability. This skill, that we call adaptability measures a trait that is not captured by the other indices and it is worth analyzing by itself in terms of its impact on the probability of moving. While such a skill is not available in most data, it seems that being able to deal with new situations, to adjust to new environments and to 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 and schooling is the highest. This

[10] 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).

[11] 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 version, Heckman, Stixrud, and Urzua (2006) report correlation coefficients for a set of different cognitive and noncognitive measures for men between 0.07 and 0.21.

reveals that education is mainly an indicator (or a result) of cognitive skills, but it does not proxy noncognitive skills as well.

As final summary statistics, we report in Table 3 the average value for the cognitive, sociability and adaptability indices separately for movers across counties and non-movers (as of year 1960). For each of the three skills we see a significant positive difference in average values for movers relative to non-movers (p-values for the difference are significant at 1% level). Once we standardize the difference by the standard deviation of the skill variable, we see that average cognitive ability is 0.28 standard deviations higher for movers than non-movers, sociability is 0.08 standard deviations higher for movers, and adaptability 0.07 standard deviations higher for movers. In general, it seems that there is positive selection of migrants according to each of these skills and this is compatible with our model of positive selection on all skills and it is compatible with the assumption that those skills increase the returns to migration or decrease the cost of it.

4.2.2 Parental Background

Migration propensity might 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 and we also include the father's work status and profession. We divide professions into high, medium and low socioeconomic status. As high status profession, we classify engineering and academic professions, and highly ranked jobs in the public administration. Skilled labor professions as mechanics or carpenters are classified as medium status professions. Low status professions include mostly professions related to agriculture, fishing, forestry, mining, and factory work. About 12.4 percent of fathers have high status professions, 41.2 percent have a medium status profession and about 96.3 percent of fathers were present in the household. We include these parental backgrounds variable 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:

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

whereas the variable $M_{i,t}$ represents a migration outcome at time t (that could be year 1960 or 1980) for individual i who was 18 years of age at time t_0. The migration outcome can either be a dummy for living in a different local labor market than at t_0, for living in a different 'macro-region' at t_0, 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 effect of cognitive skills, $C_{i,t0}$, sociability, $S_{i,t0}$, and adaptability, $A_{i,t0}$, as measured by the military recruitment test and standardized to have mean 0 and standard deviation equal to 1. Cognitive and noncognitive skills, as well as the control variables are measured at time t_0, which represents the year of enlistment when the individual was 18 years old. In the basic specification, we consider cognitive and noncognitive skills affecting the probability of migration via a linear term $\beta_C C_{i,t0} + \beta_S S_{Si,t0} + \beta_A A_{i,t0}$ consistently with the simple structure of the theoretical model. We will also consider nonlinear forms and specifications with interactions in robustness checks. $X_{i,t0}$ is a vector of controls for the individual i at time t_0, which includes region of residence at age 18, occupation of the father, indicator for death of the father, the mother or both parents, parent's civil status, height in centimeters at age 18, as a health indicator, and year of birth. Hence, all control variables are predetermined at the time of military enlistment. ε_i is a mean zero non observable 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 the individual, or a negative effect on the non-monetary costs of migrating, then the estimates of $\beta_{C,}$ 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 will 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, only for individuals who have migrated. This is a proxy for the 'migration premium', namely for the difference in wage that an individual would get by migration relative to what he gets in the place of origin. Here, the model predicts that the coefficient will be positive if the effect of a specific ability mainly works through affecting productivity. If, however, a specific ability mainly affect costs, the coefficient will be negative or zero as there will only be an effect through selection of migrants over 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 fixed. A concern affecting their 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 is 0.21 and the correlation of cognitive ability and adaptability is 0.12. One one hand, it can happen that the military psychologists knows the cognitive test scores of the conscript before assessing him, and this would affect the psychological evaluation of noncognitive skills. So the positive correlation only derives from measurement error and this could bring to measurement error bias and underestimate of the effect of noncognitive skills. On the other hand, higher noncognitive ability can determine better performance in cognitive tests and hence by controlling for cognitive performance one underestimates the effect of noncognitive ability. Borghans, Meijers, and ter Weel (2008), for example, show that individual behavior at cognitive tests depends on noncognitive skills. To put some bounds on these potential bias we estimate specifications that include either skill, cognitive ability, sociability, or adaptability in turn and specifications in which we include them together to provide bounds on the potential bias. Given their relative low correlation, it is unlikely that they affect each other much what would imply similar estimates when included together or one skill at a time.

6 Empirical Results

6.1 Effect of Cognitive and Noncognitive Ability on Migration

In this section, we show and discuss the basic association of cognitive and noncognitive ability on different measures of migration. We consider six different outcomes: two dummy variables indicating whether an individual changed local labor market between age 18 and 28 or between age 18 and 48, a dummy variable indicating whether an individual moved permanently after age 18, the number of moves across local labor markets from age 18, a dummy variable indicating whether an individual moved to a different macro-region after age 18, and a dummy variable indicating whether an individual migrated from a rural to an urban area after age 18.

The results for Regression 7 are presented in Table 4. Columns 1 and 2 show the effect on the probability of moving across local labor markets (as of 1960 or as of 1980). The estimated coefficients show that cognitive ability is positively and significantly associated with migration across local labor markets. In particular, an increase in cognitive ability by one standard deviation predicts an increase in the probability to move across local labor markets before 1960 by 5 percentage points. This is an increase of about 15 percent relative to the unconditional migration probability of 39 percent between age 18 and 1960. Similarly, an increase in cognitive ability by one standard deviation predicts an increase in the probability to move across counties before year 1980 by 6 percentage points or 13 percent relative to the unconditional migration probability over this time range (that equals 47 percent). Sociability has, overall, no significant impact on mobility across local labor markets. There is, however, more robust and statistically significant evidence that individuals with high adaptability are also more likely to move. One standard deviation change in adaptability increases the probability that an individual migrates between local labor markets before 1960 by 3.8 percentage point and the probability that an individual migrates between local labor markets before 1980 by 4.2 percentage points. Relative to the unconditional migration probability of 39 percent (Column 1) and 47 percent (Column 2), this indicates a 10 percent and a 9 percent increase, respectively. When entered linearly, adaptability skills have an impact on the probability of migration between two-thirds and three-quarter of the impact of cognitive skills.

In Column 3, we find similar results when investigating the probability of migrating permanently to a different labor market region. An increase in cognitive skills by one standard deviation predicts an increase in the probability to move out of the local labor market permanently, before 1980, by 5 percentage points. An increase in adaptability by one standard deviation increases that probability of migrating by 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 macro-region within Norway, which represents a more substantial 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 point when adaptability is increased by one standard deviation. Clearly, cognitive ability is the most important determinant of migration. As it is highly correlated to academic and schooling skills, these results confirm previous findings on positive selection of migrants in the literature. However, the new and equally interesting result is that adaptability is highly significant and relatively important in determining the probability of migrating. Sociability has a neglectible effect.

Columns 6 and 7 in Table 4 presents the results for Regression 7 with indicators for migration from rural into urban areas. The sample here is different and only includes individuals, which were growing up in rural areas. This group of individuals is certainly one for which economic success is strongly correlated with their ability to move to a more productive urban environment. Hence, mobility to a city may be a particularly important determinant of their working success. We find that adaptability has 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 to move into an urban area before 1980 by about 4.6 percentage points. This is an increase of about 18 percent relative to the unconditional migration probability. The same change in cognitive ability predicts an increase in the probability to move into an urban area before 1980 by 5.8 percentage points or 21 percent relative to the unconditional migration probability. Sociability is not a precise or robust predictor of rural-urban migration propensity.

Overall, the linear regressions including cognitive and noncognitive skills confirm the findings from the previous literature that there is a positive selection of immigrants in terms of cognitive skills (see, e.g., Malamud and Wozniak, 2012). The new finding is that adaptability measured at enlistment is also highly significant in determining the probability to migrate: one standard deviation increase in adaptability results in a 4 percent higher probability of migrating across local labor markets whereas the migration probability increases 5 to 6 percent for the same increase in cognitive skills.

Are smarter people receiving a higher adaptability score, so that part of the cognitive effect goes through higher adaptability and controlling for it underestimate the total effect of cognitive skills? Or are people that are more adaptable also smarter so that we are underestimating the total effect of adaptability? Or are these two skills not related to each other so that the partial effect estimated in Table 4 is the total effect? Cognitive ability and adaptability are positively but 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. That is, if the adaptability test captures cognitive ability, controlling for adaptability will bias the estimated effect of cognitive skills, and vice versa. We therefore estimate Regression 7 separately for each measure. Table 5 present the estimated effects when cognitive, sociability, and adaptability are each included separately in the regression. The estimated coefficients do not change much for cognitive ability and for adaptability. The association between sociability and the migration propensity is somewhat higher and significant if cognitive ability and adaptability are not included, implying that in this case some of the impact of those variables may be captured by sociability. The overall estimates are, however, unchanged and cognitive skills and adaptability turn out to have larger and more significant effects on propensity to migrate.

The basic set of control variables included in Tables 4 and 5 does not include the schooling level at time of enlistment. Schooling may have an important role in the formation and measurement of skills (see, e.g., Lindqvist and Vestman, 2011). The mandatory years of schooling for the cohorts born in 1931 and 1932 were seven. Hence, conscripts completed mandatory schooling about three years before the enlistment date. Conscripts who are still in school at enlistment have received substantially more schooling than conscripts with only mandatory schooling have. Conscripts with only mandatory schooling, have a 1.1 standard deviation lower cognitive ability score than conscripts with more than mandatory schooling. Men with more than mandatory education, score also higher in terms of noncognitive ability. With a difference of 0.04 standard deviations for sociability and 0.42 standard deviations for adaptability, the gap between men with mandatory schooling and men with more than mandatory schooling is however small. 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 will bias the total effect of cognitive ability on migration downward. Second, schooling might increase cognitive skills and different schooling level may be correlated to 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 time of enlistment could bias downward the partial effect of cognitive ability on migration. If schooling increases the cognitive skills, not controlling for the education level at age 18 may bias upwards the coefficient of interest. We therefore estimate Equation 7 where we either include a dummy variable for whether or not an individual has some education above mandatory schooling at enlistment[12] or the number of years of schooling at enlistment. Table 6 presents the results. Controlling for a dummy variable for whether or not an individual has some education above mandatory schooling at enlistment does not alter the results much (see Columns 2 and 6). When controlling for the number of years of education at enlistment the association between cognitive ability and migration is much weaker (see Columns 3 and 7). These findings reveal the high correlation between cognitive skills and schooling. If we believe that schooling is mainly 'sorting' individuals across cognitive skills and those are the only relevant skills determining return and costs of migration then we should think that the effect of pure cognitive skills on migration is 0.06 (Column 1). If instead we believe that schooling itself increases productivity or reduces costs

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

of migration then we should think that the pure impact of cognitive skills on migration probability is 0.035 (Column 3). Similarly for rural-urban migration the impact of cognitive skills can be as high as 0.06 (Column 5) not controlling for schooling, or 0.018 controlling for it (Column 7). More interestingly, however, we see that the relationship between adaptability and migration is not altered when controlling for different measures of schooling. Adaptability does not seem related to the level of schooling at age 18 (or later) and its impact on the propensity to migrate is around 0.02 to 0.04 for each increase by one standard deviation. This result also confer that migrant individuals are positively selected on this type of skills that are clearly different from cognitive skills or academic skills.

In Columns 1-3 and 5-8 of Table 5, all included controls are predetermined at the time of the draft. However, selection into higher education (for a relatively small group in this period as only 5% of people in our sample achieved college graduation) 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 affect mobility were by determining total schooling such a variable would absorb most of the skill impact. This is true for cognitive skills. When controlling for the completed years of education, the effect of cognitive ability becomes small. However, this is not true for adaptability. The association between adaptability and migration is equally strong as when not controlling for education at all. Hence, selection into higher education and into a job market for high-qualified workers might be a fundamental channel by which cognitive ability affect the migration decision but it is not likely to be a mechanism through which adaptability affects the migration.

6.2 Non-Linear Effects of Skills

The effect of cognitive ability and adaptability on the probability of migration may not be linear. As we have detected a significant and robust effects of those two skills on the probability of moving, we focus on those only in the rest of the analysis. While the existing literature has found positive selection of internal migrants, it has also pointed out that there could be a stronger effect for very high level of schooling (or IQ).[13] Hence, we consider nonlinear forms for function $f(\cdot)$ in Regression 7. Table 7 shows the results when we include quadratic terms of cognitive ability and adaptability. We find that the probability of migration across local labor markets and migration into cities is strictly convex in both cognitive ability and adaptability. However, the explained variance is only slightly higher in the regression models with the quadratic term.

We examine nonlinearity further as we are interested to know whether individuals with particularly high degrees of adaptability drive the results while at low levels such a variable does not really produce significant differences. We estimate a specification in which we split the cognitive

[13] For example, Glaeser and Mare (2001) discuss the selectivity of migrants in the context of rural-urban migration and Bütikofer, Salvanes, and Steskal (2015) discuss the positive selection on education and cognitive ability into urban migration in Norway.

ability measure and the adaptability measure into quintiles and we estimate a separate coefficient for each quintile, omitting the lowest one. These results are presented in Table 8 and focus on four migration outcomes. The two first Columns consider migration across labor market regions (before 1960 in Column 1 or before 1980 in Column 2), the third and the fourth Column focus on migration from rural to urban locations. Interestingly, we find strong evidence of a generalized convexity for cognitive ability. The estimates are increasing more than linearly in magnitude with quintile; in fact, they have a geometric type of effect, doubling from each quintile to the next. Considering Column 1, the probability of migrating is larger for individuals in the second quintile of cognitive ability, relative to the first, by only 1.1 percentage points, it increases by 3.5 points in the third, 7.3 points in the fourth and 14 points in the fifth. The pattern is very similar for the probability to migrate across labor market regions before 1980. For urban to rural migration, the increase is less pronounced for the second, third, and fourth quintile but more than twice as large for the fifth quintile. Adaptability looks different. While there is some positive effect on migration from being in the second to fourth quintile of the adaptability distribution these effects are similar to each other. People in the fifth (top) percentile of adaptability, instead, exhibit a much larger probability to migrate, significantly different from people in any other quintile. Whereas there is only a slightly larger probability to migrate for individuals with adaptability in the second, third and fourth quintile of the distribution relative to the propensity of individuals in the bottom quintile, individuals in the top quintile of the adaptability distribution are much more likely to relocate. The effect in this group is almost as large as the effect of being in the top cognitive skill group and it is very precisely estimated. Hence, it is clear that the adaptability measure is capturing a very specific skill and that people with very high endowment of such a skill are much more inclined to migrate to a different labor market region or to a city relative to others. These people can really have the spirit of 'pioneers'. While not necessarily the smartest people, they may genuinely have abilities that make them better at dealing with new environment and also more attracted by new opportunities.

6.3 Interactions between Skills

So far, we have considered cognitive skills and adaptability as independently (i.e. additively) affecting migration probability. It is however plausible that these two skills may interact with each other in more complex ways. In particular, it may be that individuals with high cognitive abilities are more likely to migrate, no matter what is their level adaptability. They may have large gains to migrating, they may know about good opportunities for their skills and hence this may push them to move independently of individual adaptability. To the contrary, individuals with lower cognitive ability may be much more dependent on their degree of adaptability in their decisions to migrate or not. Adaptability may reduce their discomfort in moving, may imply that they are looking more pro-actively. It is plausible that when people do not have extremely high cognitive abilities then having the extra advantage of high adaptability may be a crucial factor in their decision to migrate.

In order to explore this hypothesis we have partitioned the cognitive and adaptability skill continuum in three 'groups' defined as 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 nine separate effects). We report the coefficients after we standardize the coefficient on the dummy for the interaction between the two bottom skill quintiles to zero. The estimated effect for each dummy are presented in Table 9. 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, arrayed from left to right. 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 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 going from the dashed to the dotted and to the solid line. Second, increases in adaptability are much more relevant for individuals with low (dashed line) and intermediate (dotted line) cognitive ability and much less relevant for individuals with high cognitive ability (solid 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 to migrate for 47 percent. To the contrary, for individuals with cognitive ability in the top quintile, the level of adaptability does not seem to make any significant difference at all in 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, independently of their adaptability. These results are very interesting as they emphasize that, while there is a positive selection overall of migrants along cognitive skills and, in general, individuals with very high cognitive skills have higher probability to migrate, there is an even stronger selection of migrants with low to intermediate cognitive abilities on a skill, completely unobserved in previous studies, which is adaptability. Our results show that people with low cognitive skills are very likely to be selected among migrants only 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 are. Hence, an important consequence of this result is that whereas cognitive skills have very high correlation with schooling, adaptability does not. This implies that selection on one (previously) unobserved characteristic, namely the adaptability of individuals, for low skilled migrants is much more important than for high skilled migrants. If this characteristic helps individuals to adjust, to integrate and assimilate in the receiving economy and to succeed in any way, then low skilled (i.e. low cognitive skill) migrants have a much better chance, than comparable non-migrant, to do well and to succeed economically. Moreover, this result shows that individuals select themselves into migration with the same criteria that the receiving economy would use, if they could observe such skill, to maximize their probability of assimilation to the new circumstances and to a new working situation. Furthermore, this results compares well to the findings of Lindqvist and Vestman (2011) who show that noncognitive skills are a stronger predictor of labor force participation and wages of unskilled workers.

6.4 Early Mobility and Skills

Our data measure individual skills at age 18. While they certainly reflect some innate abilities, these measures are also affected by experience of the individual in his family as a child, and at school as a student. While we control for some characteristics of the family and we discuss the effects of including schooling as controls, we are also interested in analyzing whether moving as child, presumably with one's family, between birth and age 18, affects the cognitive and adaptability skills of a person. It is also important to analyze whether it 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 it may affect the likelihood of mobility as an adult. On the other hand, if mobility disrupts the learning process it may also affect cognitive ability. If higher adaptability is associated to early moves in life, than this skill may be transmitted to 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 moved across local labor markets between birth and the date of enlistment. Then we analyze if the inclusion of such a dummy affects the coefficient on sociability, adaptability or cognitive ability on the probability of migrating. The results, displayed in Table 10, show a significant positive association between cognitive ability and the probability of moving during childhood. Sociability and adaptability are not significantly affected by moving during childhood. Noncognitive ability does not seem to be affected by the experience of migrating as a child. The second regression analyzes whether, controlling for childhood moves reduced the impact of adaptability on the probability of migrating as an adult. In Table 11, we include a dummy for having moved as a child in Regression 7. We find that moving during childhood is significantly correlated with all migration measures considered. The coefficients on cognitive ability, sociability, and adaptability are however only altered to a minor degree by the inclusion of the dummy variable for moving during childhood. Hence, adaptability is not a less important determinant of migration when controlling for childhood mobility.

6.5 Birth Order

The place of a man in the household's birth order may influence his expectation of inheriting farmland in Norway and therefore his probability of migrating to another local labor market or into a city (see Abramitzky, Boustan, and Eriksson, 2012, for a discussion in the context of international migration). Hence, the migration pattern of first born sons and later born sons might differ substantially. Whereas the probability to migrate by 1980 for first born sons is 43 percent, the same probability is 46 percent for later born sons. The difference is just significant on a 5 percent significance level (p-value=0.0499). The probabilities for rural-to-urban migration are however not significantly different for first or later born sons. To test whether different skills matter for the migration decision of first born and later born sons, we estimate Regression 7 separately for the two groups. The results, displayed in Table 12, show that the association of cognitive ability, sociability, and adaptability on all considered migration outcomes are not significantly different for the two groups. Hence, cognitive and noncognitive skills are not of different importance for the migration decision of first born compared to later born sons.

6.6 Emigration

As mentioned in Section 4, the central population register includes an indicator identifying individuals who emigrated permanently to a foreign country after 1960. 372 individuals or about 1.2 percent of our sample emigrated during the observation period. To test whether cognitive and noncognitive skills are similarly important for the decision to emigrate, we estimate Regression 7 using a dummy variable indicating whether an individual emigrated to a foreign country as an outcome variable. The results presented in Table 13 show that an increase in cognitive ability by one standard deviation predicts an increase in the probability to emigrate by 0.6 percentage points and an increase in adaptability by one standard deviation predicts an increase in the probability to emigrate by 0.3 percentage points. Although the estimated coefficients are small, they indicate a 50 percent and a 25 percent increase relative to the unconditional emigration probability of 1.2 percent. Sociability has no significant association with the probability to emigrate. Hence, the importance of skills determining the decision to emigrate are similar to the importance of skills determining geographic mobility within Norway.

6.7 Skills and Earnings Premium to Migration

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. More interestingly, we have also found that individuals with medium to low cognitive skills are highly selected into immigration if they have very high levels of adaptability skills. Building on the implications of the model developed in Section 3 we now test whether such higher migration probability is consistent with cognitive ability and adaptability increasing return to migration or with them decreasing the non-monetary costs of migration. In particular, we analyze whether cognitive ability and adaptability increase the return to migration, measured as the difference in (log) earnings that the individual was receiving right before (or three years before) migration and right after (or three years after) migration to a different local labor market or from a rural to a urban location. The model in Section 3 predicts that if the skill under consideration mainly affects productivity and hence returns to migration, one would find a positive correlation between such skill and the earnings premium to migration. If the skill mainly affects non-monetary costs of migration, one should find a negative or null correlation between the skill and the earnings premium from migration, but still a positive effect on the migration probability. Table 14 presents the coefficients from a specification similar to Regression 7 where the dependent variable is the pre-post migration earnings difference for the individual.[14] In Columns 1 and 2, we take the log difference between year-before and the year-after migration (for migration across local labor markets or rural-urban migration), while in Columns 3 and 4 we take the earnings differentials three years before and three years after migration. Differences are taken in logs and we consider the three year distance as a way of avoiding the effects of pre-migration recessions or an individual shock that could push people to moving and, at the same time, affecting negatively the pre-migration earnings.[15] The results are very clear: cognitive ability affects significantly and positively the pre-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 returns to moving to a new local labor market. The difference is between 0.2 and 0.4 logarithmic points (between 22 and 41 percent) and highly significant. This is consistent with cognitive ability mainly affecting productivity and through the channel of the earnings returns to migration. On the other hand, the measure of adaptability does not affect the pre-post migration earnings difference. People that are more adaptable are more likely to migrate but conditional on migrating and having positive earnings prior to moving, higher adaptability does not provide higher earnings premium. This is consistent with adaptability mainly affecting the non-monetary cost of migration instead. The effects is zero rather than negative confirming that there is not strong negative selection of migrants on non-observable productive characteristics (associated with higher adaptability), but adaptability per se does not affect the pre-post earnings premium: This reveals that it must affect migration through non-monetary costs.

Further analysis on the impact of adaptability on the post-migration assimilation and success on the labor market is an interesting extension on which we are working.

7 Conclusion

In this paper, we combine measures of cognitive and noncognitive abilities of individuals, tested at 18 years of age, and data on their subsequent working life. For the first time, characteristics

[14]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 correlate with earnings.

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

that have been considered as unobservable, but are potentially important in production and career choices, such as sociability and adaptability can be observed and measured together with many years of working experience. For our sample, the Norwegian male population born in 1932 and 1933 we have analyzed how cognitive and noncognitive skills affect their migration behavior. This allows us to infer how migrants are selected on cognitive and (so far unobserved) noncognitive skills. Our results confirm that cognitive skills, which are highly correlated with schooling, have a strong positive effect on the probability of migrating, which was a known fact in the literature on internal and international migration: migrants are positively selected on schooling and cognitive skills. We are the first, however, to find a second important result, namely that people with high 'adaptability' skills, measured using tests assessing their ability to cope with the new environment and situations, have also a much higher probability to migrate. In particular among low educated, low cognitive ability people, those with high values of the adaptability skill are much more likely to migrate than the rest of the population. In order to understand if cognitive skills and adaptability affect the returns or the costs of migration we develop a simple variation of the Roy model that predicts that a skill increasing the earnings returns to migration would increase probability of migration and also increase, conditional on migrating, the pre-post migration earnings. To the contrary, skills decreasing the (non-monetary) costs of migration increase the probability of migration but, conditional on migrating, would not be associated with larger pre-post migration earnings premium.

We find that both cognitive ability and adaptability have a significant and positive impact on the probability that the individual migrates to another location in the first decades of his working life. In addition, we present empirical evidence that cognitive skills also have a significant positive effect on the pre-post migration earnings differential, while adaptability does not. This evidence is consistent with adaptability being a skill that mainly reduces the non-monetary migration costs of migrants. Adaptability, however, may increase the capacity of a migrant to assimilate, to integrate and to succeed in the long run. Hence, the strongly positive selection of migrants on 'adaptability', especially strong for low skilled individuals, on bodes well for their ability to succeed and integrate in the host economy.

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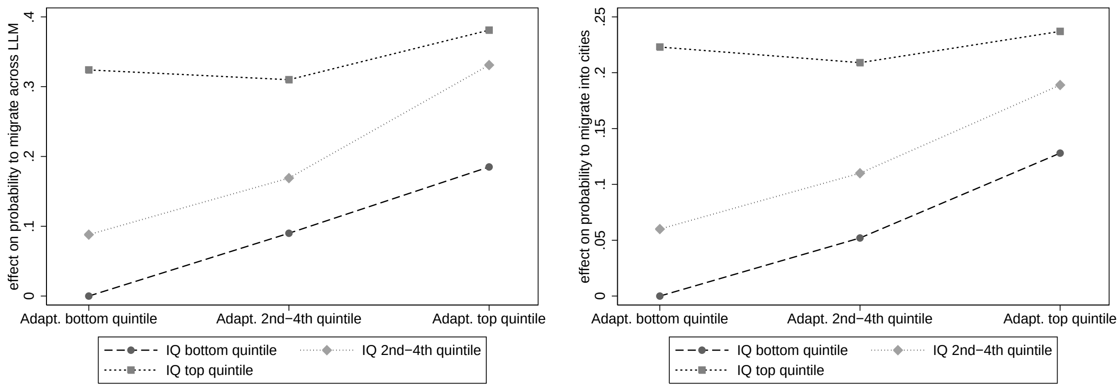
8 Tables and Figures

Figure 1: Probability of Moving Across Counties and Moving into Cities: Interactions of Cognitive Ability and Adjustability



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 9. The left figure shows how the probability of moving across counties changes with adaptability for different levels of cognitive ability. The right figure shows how the probability of moving into cities changes with adaptability for different levels of cognitive ability.

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 18	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
Number of observations	30387	

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

Table 2: Correlation Coefficients

	Cognitive ability	Sociability	Adaptability	Years of education at enlistment
Cognitive ability	1.000			
Sociability	0.209	1.000		
Adaptability	0.123	-0.056	1.000	
Years of education at age 18	0.680	0.250	0.131	1.000

Notes: Entries represent correlation coefficients for cognitive ability, sociability, and adaptability all standardized to zero mean and unit variance. Years of education are measured at enlistment at age 18.

Table 3: Differences Between Movers and Stayers

	Across LLM movers				Into city movers			
	Stayers (1)	Movers (2)	Difference (3)	p-value (4)	Stayers (5)	Movers (6)	Difference (7)	p-value (8)
Cognitive ability	19.63	22.28	-2.65	0.00	19.23	18.75	0.49	0.00
Sociability	4.92	5.03	-0.11	0.00	4.92	4.99	-0.07	0.02
Adaptability	4.82	4.94	-0.12	0.00	4.78	4.94	-0.17	0.00

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

Table 4: Estimated Association of Cognitive Ability, Sociability, and Adaptability on the Probability of Moving across Local Labor Markets (LLM) and Moving into Cities

	Moved across LLM before 1960	Moved across LLM before 1980	Moved across LLM before 1980 permanently	Number of moves before 1980 across LLM	Moved across region before 1980	Moved into cities before 1960	Moved into cities 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)
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 OLS regression of the effect of cognitive ability, sociability and adaptability on different mobility indicators. Columns 1-4 look at migration across local labor markets, Column 5 looks at migration across macro-regions, and Columns 6 and 7 look at rural-urban migration. The sample includes birth cohorts 1932 and 1933. In Columns 6 and 7, the sample only includes individuals who lived in a rural municipality at time of enlistment. Control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Separately Estimated Association of Cognitive Ability, Sociability and Adaptability and on the Probability of Moving across Local Labor Markets (LLM) and Moving into Cities

	Moved across LLM before 1960	Moved across LLM before 1980	Moved across LLM before 1980 permanently	Number of moves before 1980 across LLM	Moved across region before 1980	Moved into cities before 1960	Moved into cities 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 in parentheses from OLS regression of either the effect of cognitive ability, sociability and adaptability on different mobility indicators. Columns 1-4 look at migration across local labor markets, Column 5 looks at migration across macro-regions, and Columns 6 and 7 look at rural-urban migration. The sample includes birth cohorts 1932 and 1933. In Columns 6 and 7, the sample only includes individuals who lived in a rural municipality at time of enlistment. Control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Estimated Association of Cognitive Ability, Sociability, and Adaptability on the Probability of Moving across Local Labor Markets (LLM) and Moving into Cities when 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 OLS regression of the effect of cognitive ability, sociability and adaptability on different mobility indicators. Columns 1-4 look at migration across local labor market and Columns 5 and 6 look at rural-urban migration. Columns 1 and 5 do not include control variables for education and reflect the main specification of Table **??**. In Columns 2 and 6, a dummy variable indicating whether an individual has some secondary education at time of enlistment (at age 18) 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 time of enlistment (at age 18) is included in the regression and in Columns 4 and 8, the completed years of education is included in the regression. The sample includes birth cohorts 1932 and 1933. In Columns 5-8, the sample only includes individuals who lived in a rural municipality at time of enlistment. Further control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Quadratic Functional Form: Estimated Association of Cognitive Ability and Adaptability on the Probability of Moving across Local Labor Markets (LLM) and Moving into Cities

	Moved across LLM		Move into cities	
	before 1960	before 1980	before 1960	before 1980
	(1)	(2)	(3)	(4)
Cognitive ability	0.051***	0.057***	0.048***	0.060***
	(0.003)	(0.003)	(0.003)	(0.004)
Cognitive ability squared	0.008***	0.011***	0.013***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
Adaptability	0.039***	0.043***	0.019***	0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
Adaptability squared	0.002	0.004**	0.010***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.123	0.124	0.172	0.137
N	24154	24154	16451	16451

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

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

Table 8: Non-parametric Functional Form: Estimated Association of Cognitive Ability and Adaptability on the Probability of Moving across Local Labor Markets (LLM) and Moving into Cities-Percentile

	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 in parentheses from OLS regression of the effect of different cognitive ability quintiles and adaptability quintiles on different mobility indicators. Columns 1 and 2 look at migration across local labor markets and Columns 3 and 4 look at rural-urban migration. The sample includes birth cohorts 1932 and 1933. In Columns 3 and 4, the sample only includes individuals who lived in a rural municipality at time of enlistment. Control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.

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

Table 9: Interactions Between Cognitive and Noncognitive Skills: Estimated Association of Cognitive Ability, Adaptability, and their Interaction on the Probability of Moving across Local Labor Markets (LLM) and Moving into Cities

	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 in parentheses from OLS regression of the effect of different cognitive ability quintiles and adaptability quintiles as well as interactions of these on different mobility indicators. Columns 1 and 2 look at migration across local labor markets and Columns 3 and 4 look at rural-urban migration. The sample includes birth cohorts 1932 and 1933. In Column 2, the sample only includes individuals who lived in a rural municipality at time of enlistment. Control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.

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

Table 10: Reverse Causality: Association Between Moving During Childhood and Cognitive and Noncognitive Ability

	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 in parentheses from OLS regression of the effect of a variable indicating whether an individual was moving during childhood on different cognitive ability (Columns 1), sociability (Column 2), and adaptability (Column 3). The sample includes birth cohorts 1932 and 1933. Control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.

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

Table 11: Estimated Association of Cognitive Ability, Sociability, Adaptability, and Childhood Mobility on the Probability of Moving across Local Labor Markets (LLM) and Moving into Cities

	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	0.046***	0.053***	0.049***	0.058***	0.038***	0.045***	0.057***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)
Sociability	0.004	0.001	0.003	-0.011**	0.001	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)
Adaptability	0.036***	0.040***	0.032***	0.021***	0.032***	0.014***	0.025***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
Childhood mobility	0.555***	0.506***	0.556***	0.031***	0.730***	0.111***	0.084***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.004)	(0.007)	(0.007)
R-squared	0.429	0.389	0.366	0.037	0.574	0.184	0.141
N	23829	23829	23829	18220	23829	16221	16221

Notes: Entries represent the estimated coefficients with standard errors in parentheses from OLS regression of the effect of cognitive ability, sociability, adaptability, and childhood mobility on different mobility indicators. Columns 1-4 look at migration across local labor markets, Column 5 looks at migration across macro-regions, and Columns 6 and 7 look at rural-urban migration. The sample includes birth cohorts 1932 and 1933. In Columns 6 and 7, the sample only includes individuals who lived in a rural municipality at time of enlistment. Control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.

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

Table 12: Estimated Association of Cognitive Ability, Sociability, and Adaptability on the Probability of Moving across Local Labor Markets (LLM) and Moving into Cities by Birth Order

	Moved across LLM before 1960	Moved across LLM before 1980	Moved across LLM before 1980 permanently	Number of moves before 1980 across LLM	Moved across region before 1980	Moved into cities before 1960	Moved into cities before 1980
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: First Born Sons							
Cognitive ability	0.051***	0.059***	0.047***	0.064***	0.047***	0.044***	0.057***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)	(0.006)
Sociability	0.003	-0.005	-0.005	-0.017**	-0.005	0.015**	0.011*
	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)
Adaptability	0.039***	0.044***	0.035***	0.009	0.030***	0.020***	0.026***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
R-squared	0.119	0.123	0.075	0.040	0.084	0.176	0.138
N	9905	9905	9905	7615	9905	6619	6619
Panel B: Second or Later Born Sons							
Cognitive ability	0.051***	0.057***	0.059***	0.055***	0.043***	0.048***	0.059***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Sociability	0.004	0.004	0.007	-0.006	0.002	-0.009**	-0.006
	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)
Adaptability	0.038***	0.041***	0.035***	0.031***	0.027***	0.014***	0.028***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)
R-squared	0.126	0.125	0.085	0.036	0.077	0.168	0.132
N	13924	13924	13924	10605	13924	9602	9602

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

Table 13: Estimated Association of Cognitive Ability, Sociability, and Adaptability on the Probability of Emigrating

	Emigrating to a foreign country
Cognitive ability	0.006***
	(0.001)
Sociability	-0.001
	(0.001)
Adaptability	0.003***
	(0.001)
R-squared	0.009
N	23829

Notes: Entries represent the estimated coefficients with standard errors in parentheses from OLS regression of the effect of cognitive ability, sociability and adaptability on the probability of emigrating to a foreign country. Control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.

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

Table 14: Estimated Association of Cognitive Ability, Sociability, and Adaptability and Log Earnings Difference Before and After Moving across Local Labor Markets (LLM) or Moving into Cities

	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

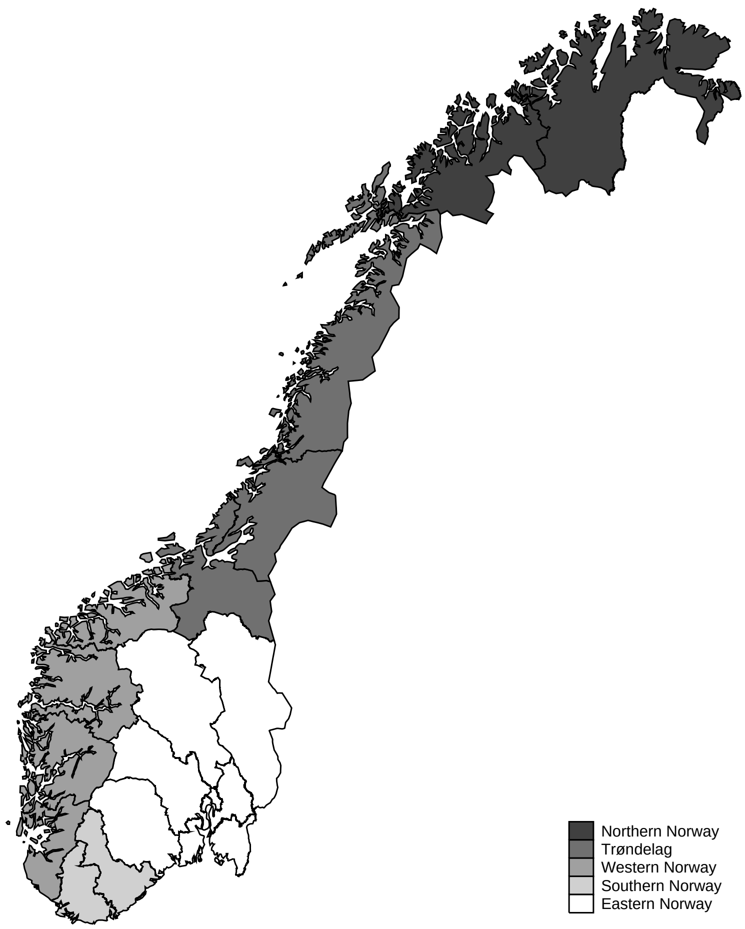
Notes: Entries represent the estimated coefficients with standard errors in parentheses from OLS regression of the effect of cognitive ability, sociability and adaptability on log earnings differences one year prior compared to one year after the move (Columns 1 and 2) and log earnings differences three years prior compared to three years after the move (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 are moving across counties. Columns 2 and 4 focus on individuals who lived in a rural municipality at time of enlistment and moved to urban areas later. Control variables: occupation of the father, indicator for death of father or mother or both parents, parent's civil status, height in cm, and year of birth.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix

Figure A1: Local Labor Markets

Notes: The map displays the 46 local labor markets. 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 outside not included in the labor market regions.

Figure A2: Macro-regions



Notes: The map displays the five different macro-regions (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 ruled directly on national level.