Journal of Comparative Economics 48 (2020) 144–162

Contents lists available at ScienceDirect

Journal of Comparative Economics

journal homepage: www.elsevier.com/locate/jce

The impact of non-cognitive skills and risk preferences on rural-to-urban migration in Ukraine

Sinem H. Ayhan[*,a,b], Kseniia Gatskova[c], Hartmut Lehmann[b,d,e]

[a] *Mercator Research Institute on Global Commons and Climate Change (MCC), EUREF Campus 19, Torgauer Str. 12-15, Berlin 10829, Germany*
[b] *IZA, Bonn, Germany*
[c] *Leibniz Institut für Ost- und Südosteuropaforschung (IOS), Landshuter Str. 4, Regensburg 93047, Germany*
[d] *Department of Economics, University of Bologna, Strada Maggiore 45, Bologna 40125, Italy*
[e] *National Research University Higher School of Economics, Moscow, Russia*

A R T I C L E I N F O

Keywords:
Migration
Non-cognitive skills
Big five
Risk attitudes

JEL classification:
J61
D03
D81
R23

A B S T R A C T

This paper provides evidence on the impact of non-cognitive skills and attitudes towards risk on the decision to migrate from rural to urban areas. Our analysis is based on a unique four-wave panel of the Ukrainian Longitudinal Monitoring Survey for the period between 2003 and 2012. Adopting the Five Factor Model of personality structure, and using it in the evaluation of non-cognitive skills, our results suggest that the personality trait *openness to new experience* increases the probability of migration. On the other hand, the non-cognitive skills *conscientiousness and agreeableness* are found to be negatively associated with the propensity to migrate. The impact of an increased willingness to take risks is more complex in that it increases the proclivity to move from rural areas to cities but lowers the migration intention from rural areas to towns. The effects are quantitatively significant and are robust to several sensitivity checks, including tests of reverse causality.

1. Introduction

A growing body of economics literature has been investigating the role of non-cognitive skills, often referred to as soft skills or personality traits, in predicting micro-economic behavior. In this literature non-cognitive skills, besides cognitive abilities, are documented as important determinants of labor productivity, wages, occupational choices and job search behavior (see Kautz et al., 2014 for a summary). Conceivably, geographic mobility is among those life outcomes which non-cognitive skills might predict. Yet only little is known about the role of non-cognitive skills for individual migration decisions (e.g., Bütikofer and Peri, 2016, Caliendo et al., 2016). Our study contributes to this scarce literature by providing evidence on the impact of non-cognitive skills on the decision to migrate within a transition country. The country of our study, Ukraine, is according to World Bank rankings in the upper bracket of lower middle-income countries. The paper shows that non-cognitive skills have an impact on rural to urban migration in a country of this income level. Our estimation results also provide evidence that individuals in better off households are more likely to migrate. Hence it is inconceivable that poverty is the main driver of rural to urban migration in Ukraine and that our findings stem from an effect of poverty on non-cognitive skills, and only subsequently on the decision to migrate.

Considering migration behavior within a resource allocation framework, people migrate to realize their labor market potential as far as its benefits outweigh the costs. The costs of migration increase with greater uncertainty about other locations, particularly

* Corresponding author.
E-mail addresses: ayhan@mcc-berlin.net (S.H. Ayhan), gatskova@ios-regensburg.de (K. Gatskova), hartmut.lehmann@unibo.it (H. Lehmann).

https://doi.org/10.1016/j.jce.2019.09.001
Received 17 July 2018; Received in revised form 5 August 2019; Accepted 9 September 2019
Available online 17 September 2019

about the housing market, labor market and education opportunities. In this respect, risk attitudes have a high predicting power in explaining the migration decision as recently documented by Jaeger et al. (2010) and Bauernschuster et al. (2014). Apart from the mobility costs due to market imperfections or the time and effort spent to search for and get familiar with a new job, there are other non-monetary considerations involved in migration such as the emotional burden of leaving familiar surroundings, family and friends, and adapting to a different cultural environment. These so-called "psychic" costs might increase the costs of moving perceived by individuals (Sjaastad, 1962).

While the non-pecuniary costs of migration are real costs, they are not easy to measure, since they are subject to a subjective evaluation by each person. Self-assessment of these costs may be quite different even among persons with very similar observable demographic and socio-economic characteristics. We argue that how individuals perceive these costs might be related to personality characteristics. Certain characteristics such as openness to new experience may help people perceive these costs to be lower, while other skills may make people strongly attached to their communities and thus perceive the costs of leaving as higher. Here, we pursue the question what types of non-cognitive skills might make individuals perceive a lower (higher) cost and thus generate more (less) willingness to migrate.[1]

Not only perceived costs but also the expectation of future benefits is a crucial factor in the migration decision. As first suggested by Harris and Todaro (1970), individuals in the countryside are considering moving to urban areas because they expect to earn higher wages in the formal urban sector. The wage disparity could be linked to differences in the productivity of non-cognitive skills in urban areas, which would represent the so-called "non-behavioralâg explanation of the findings. However, not everyone moving to an urban area finds a formal sector job, many of the migrants end up in informal employment. Even if the expected wage of migrants therefore does not exceed the wage earned in the rural area, there can be large migratory flows from the countryside to cities since many individuals are convinced that they will find formal employment. It seems reasonable to assume that personality traits and risk preferences can influence the assessment of future gains connected with the migration decision. In the case of risk preferences, it seems intuitive that risk-loving persons have a more optimistic assessment of potential future gains than risk averse individuals do. Therefore, considering the channel of potential benefits, our prior would be that there is a positive correlation between the willingness to take risks and the decision to migrate.

On the other hand, there is no literature in a transition or developing context that links personality traits to the expectation of future benefits arising from rural to urban migration. We can moot, though, that individuals who, for example, are open to new experiences assess the potential gains more positively than persons who do not exhibit this trait. It strikes us also as reasonable to assume that very conscientious people regard potential future gains arising from migration with more scepticism than persons who lack conscientiousness. Therefore, openness to new experiences should be positively, conscientiousness negatively linked to the decision to migrate.

In this paper, we do not develop a theoretical model that shows the link between non-cognitive skills and rural-to-urban migration. Our goal is to identify those non-cognitive skills that are important predictors of migration in a consistent fashion. We would argue that the link between non-cognitive skills and risk preferences and migration could work through the channel of perceived costs and/or through the channel of expected benefits. However, the data at our disposal do not allow us to distinguish between these two channels.

The focus of this study is rural-to-urban migration in Ukraine. Rural-to-urban migration is an especially important type of mobility in a transition country context, since it has the potential to foster economic growth by reallocating workers from economically lagging-behind regions to large urban centers, where returns to human capital are higher. For the empirical analysis, we use the four waves of the Ukrainian Longitudinal Monitoring Survey (ULMS). In addition to rich information on individual and labor market characteristics, the ULMS includes direct measures of attitudes towards risk in the survey years of 2007 and 2012 and a module with 24 items on non-cognitive skills added in 2012. Using this skill module we assess non-cognitive skills based on the widely accepted 'Big Five' taxonomy developed in the personal psychology literature (Goldberg, 1990; John and Srivastava, 1999; Lang et al., 2011) and well taken in the economics literature (e.g., Borghans et al., 2008a, Gill and Prowse, 2016). The taxonomy measures five character skills: openness, conscientiousness, extraversion, agreeableness, and neuroticism. We propose a mapping of the 24 items into the Big Five domains, utilizing the facets of these domains characterized by John and Srivastava (1999).

Our results suggest that openness to new experience increases the probability of an individual to migrate from rural to urban areas. On the other hand, conscientiousness and agreeableness are negatively correlated with the propensity to migrate. The effects are driven both by movements from rural areas into large cities and by movements from rural areas into towns. However, we find no consistent evidence supporting an association of neuroticism and extraversion with the migration propensity. The willingness to take risks has countervailing effects when it comes to moves into cities and moves into towns, impacting on migration positively in the former case and negatively in the latter. The magnitudes of the impacts of non-cognitive skills and risk attitudes are at any rate substantial considering unconditional rural-to-city and rural-to-town migration probabilities of about 1.5% each. Our results are also consistent with the previous evidence by Jaeger et al. (2010) and Bauernschuster et al. (2014), showing that risk-loving people are more likely to migrate. Performed tests also indicate that a full model, which uses the Big Five factors and risk preferences jointly, fits the data better than models that use them separately. Moreover, we provide evidence that the estimated effects of personality and risk attitudes are not driven by reverse causality.

To the best of our knowledge, this is the first economic study that explores the effects of the Big Five factors on migration

[1] One way to measure relative non-monetary costs could consist in looking at relative reservation wages in the destination region of those who migrate. Unfortunately we do not have data that allow us to measure relative costs in this way and relate them to non-cognitive skills

decisions in a middle income country. In addition, we use measures of personality traits and measures of risk preferences jointly as predictors of the probability to migrate and show that these measures are complementary rather than substitutes. Finally, in spite of its importance the nexus between non-cognitive skills and migration has been little studied in the literature because of data limitations; hence, our study provides important and very consistent evidence regarding this understudied topic.

In the following section, we provide some background information about demographic developments and migration patterns in Ukraine. Section 3 presents a brief summary of the pertinent literature on the link between non-cognitive skills and life outcomes and embeds our paper into this literature. Section 4 introduces the data, motivates the variables used in the regression analysis, and discusses our research strategy. The following section presents the main estimation results and provides some extensions and robustness checks. Finally, Section 6 discusses the results and offers some conclusions.

2. Demographic developments and internal migration in Ukraine

In the last three decades, very little research has been done on internal labor mobility in Ukraine and many questions related to its different aspects remain unanswered. To put our paper into context, we provide a brief overview of the major economic and demographic developments and of internal migration trends in Ukraine.

During the independence years Ukraine's population contracted by roughly 9 million people from 51,9 million in 1991 to 42,8 million in 2016 (State Statistics Service of Ukraine[2]). This enormous population drop may jointly be explained by a combination of three major factors: low fertility rates (1.5 children per woman[3]), high mortality levels (deficit of births over deaths reached 158,711 persons in 2013) and international out-migration (Danzer and Dietz, 2014). These demographic trends were nurtured by unfavorable economic conditions that led to an overall impoverishment of the population. In the 1990s, the country experienced a period of hyperinflation and an enduring economic recession with real GDP falling by over 60%, resulting in high rates of poverty. Among especially affected population groups were families with children and the less educated as well as the rural population (Brück et al., 2010). Although the situation slightly improved in the period of moderate economic growth in the later years, economic shocks such as the global financial crisis, which hit Ukraine in 2008–2009, and the military conflict with Russia, which started with the Russian annexation of Crimea in 2014, led again to a sharp drop in the welfare of the population.

Given the weak economic performance of Ukraine, large internal migration from rural to urban areas could boost economic growth in a major way. However, potentially beneficial large migration flows are absent in Ukraine since there is a number of important barriers to internal mobility. These include a complicated population registry system, ineffective public employment policy, underdeveloped housing and credit markets, non-portability of social benefits and wide-spread skills mismatch.[4] As a result, the population of Ukraine is considerably less geographically mobile than one would expect given the high economic disparities across regions and between rural and urban areas.[5] While Kyiv is the largest magnet for internal labor migrants in the country, internal migration in Ukraine is not always directed from economically lagging to better developed industrial regions but happens mostly within the same region - from rural to urban areas - or between neighboring regions with similar levels of socioeconomic development (Koettl et al., 2014, Kupets, 2014).

The share of the urban population in Ukraine has been growing slowly in the last decades: it increased from 66.9% in 1989 to 69.2% in 2016. This process is driven by internal movements of mostly young people from rural areas to the cities in search of better economic opportunities. In general, rural areas in Ukraine provide a much poorer standard of living, worse quality of facilities and infrastructure and fewer opportunities for skills acquisition and employment as compared to large urban centers. Hence, economic disparities between rural and urban settlements encourage many people to engage in one of two popular types of internal mobility: permanent movements from rural areas to larger urban centers or commuting between the (rural) place of residence and the (urban) location of work[6] In our paper, we focus on the group of internal migrants who change their residence and move from rural areas into towns and cities.

3. Our study and the literature on non-cognitive skills and life outcomes

Economic research analyzing the impact of non-cognitive skills on life outcomes has rapidly expanded since the 2008 special issue of the Journal of Human Resources edited by Weel (2008). In this special issue, Borghans et al. (2008a) link the evidence from the psychology of personality traits to economics. For instance, Borghans et al. (2008b) focus on the relationship between interpersonal styles (caring and directness) and labor market outcomes. Kautz et al. (2014) present a summary of the evidence from the economics literature on the predictive power of non-cognitive skills for a wide range of life outcomes, including educational achievement, labor market outcomes, health, and criminal behavior.

[2] http://www.ukrstat.gov.ua/, retrieved on 25 January 2017.

[3] Fertility rate for 2013 according to the State Statistics Service of Ukraine. The fertility rate is traditionally lower in urban (1.365) than in rural areas (1.825).

[4] Lack of appropriate skills in rural areas is one of the factors that hinder internal migration, which otherwise would be an expected response to spatial earnings differentials. Some agriculture-dominated regions employ low-skilled workers that cannot easily become qualified for employment in high-wage industrial sectors in other regions (Koettl et al., 2014).

[5] Despite a relatively low level of internal mobility due to institutional obstacles in Ukraine, people still decide to move from rural to urban areas and the effect of non-cognitive skills as factors affecting these decisions may be efficiently studied in settings, where migration decisions are related to high costs.

[6] The total number of commuters reached 2.6 million individuals in 2010, which amounted to 13.2% of the total number of employed persons.

Much less is known about the impact of non-cognitive skills on migration behavior. To the best of our knowledge, there are only two economic papers on the impact of non-cognitive skills on the decision to migrate. Bütikofer and Peri (2016) investigate the importance of cognitive and non-cognitive skills on the probability of migrating out of one's region of origin for the male population in Norway. Focusing on two aspects of non-cognitive skills, 'adaptability' and 'sociability', they find that adaptability has a particularly strong impact on migration for individuals with low cognitive skills. On the other hand, Caliendo et al. (2016) investigate the predicting role of locus of control in internal migration decisions within Germany. Their findings suggest that those with an internal locus of control are predicted to search a job more intensely across larger geographic areas because they expect higher returns to their search effort.

In contrast to the scarce evidence on non-cognitive skills and migration in economic research, it has been relatively extensively studied in psychology. These psychological studies generally rely on the Big Five factor model. Using a sample of Finnish twins, Silventoinen et al. (2008) find extraversion and neuroticism positively correlated with the migration propensity to neighboring Sweden. In another study using Finnish subjects, Jokela et al. (2008) point to sociability as an important determinant of internal rural-to-urban migration. On the other hand, some evidence from the U.S. suggests that high openness and low agreeableness increase the propensity to migrate within- and between-states, while extraversion can only predict within-state migration (Jokela, 2009). Focusing on two elements of the Big Five, Canache et al. (2013) find only a modest positive influence of openness and extraversion on the intention to emigrate from Latin American countries. While for openness the greatest effect is seen among relatively well-educated respondents, for extraversion it is rather a compensating effect in that low-educated respondents are less likely to intend to emigrate, but the education gap shrinks as extraversion rises. Another study, examining the impact of the Big Five factors on the intention to emigrate and using a Lithuanian student sample, finds no evidence for extraversion to have predictive power. The results of Paulauskaite et al. (2010) suggest conscientiousness and openness the only two traits to be linked with migratory intentions. The cited psychological studies do not arrive at clear-cut conclusions regarding the link between the Big Five and migration. This might be the result of methodological deficiencies or of very specific samples used in the analysis.

We rely on a Big Five factor model for the analysis of the impact of non-cognitive skills on rural-to-urban migration. But the focus of our study is not limited to this, since we analyze the impact of non-cognitive skills together with the attitudes towards risk on migration behavior. Our study draws on Jaeger et al. (2010) who provide direct evidence on risk attitudes and internal migration. Using data from the German Socio-Economic panel they find that individuals who are more willing to take risks are more likely to migrate between labor markets in Germany. Non-monetary costs due to general uncertainty (imperfect information) about other locations are considered to be the channel through which risk attitudes determine intra-country mobility. A more recent study by Bauernschuster et al. (2014) using the same data source focuses on internal migration in order to explore the reason why more educated and risk-friendly persons move more easily over longer distances. Their findings suggest less sensitivity among those people to the cultural costs of migration proxied by linguistic variation within Germany, while costs related to geographical distance do not play a role in explaining the higher mobility of higher educated and risk-loving persons.

As documented by Jaeger et al. (2010) and Bauernschuster et al. (2014), because risk lovers are more able to deal with uncertainties connected to moving to a new place, the obvious expectation would be to find a positive relationship between the willingness to take risk and the migration propensity. For non-cognitive skills the relationship is not so self-evident given the ambiguity of the previous evidence from the psychology research. Arguably, we may anticipate that skills that reduce the cost of mobility would increase the probability of migration. For instance, openness to experience is expected to help adapt to a new environment and a different culture, and hence decrease the psychic costs of migration and increase the probability of moving. On the other hand, a skill such as conscientiousness described by the tendency to be organized, responsible, and hard-working as well as by a high valuation of persistence and predictability is expected to be negatively associated with the decision to migrate (John and Srivastava, 1999; Kautz et al., 2014). Moving to another place per se contains unpredictability (uncertainties) and inconsistency as it opens a new episode in life. Therefore, conscientious people might perceive moving as relatively costly.

It is not straightforward to anticipate the direction of the relationship for the other three traits. For extraversion the first effect that comes to mind is to increase the migration propensity, because extraverted people have better communication abilities which would help them easily adapt to a new environment. On the other hand, it is reasonable to argue that social people feel more attached to their own communities as well as more able to increase their well-being in their present places (John and Srivastava, 1999; Jokela, 2009; Paulauskaite et al., 2010). Taken together, these facets of extraversion might counterbalance each other and as a result there will be no significant effect on the migration decision observed.

Countervailing effects might also arise for agreeableness and neuroticism.[7] More agreeable individuals can more easily conform to different norms of a new environment so that the cost of adaptation would be lower for them. However, those people are also likely to be pleasant and satisfied with their existing lives and have a stronger emotional attachment to their own communities (Jokela, 2009). The latter facet would make them less willing to leave their current place. Similarly, some facets of neuroticism (emotional instability) such as proneness to anxiety and fear, low self-esteem, and vulnerability to stress are expected to make individuals less able to start over a life in a new place. Meanwhile, some other facets of neuroticism such as pessimism, hostility, and irritability might bring about a lower level of satisfaction with their current jobs, neighborhoods or lives as a whole, which would instigate the decision to migrate (Jokela, 2009).Our analysis helps to shed light on those facets of the Big Five factors that dominate the decision to migrate in our data sample.

[7] The evidence is more clear-cut in the context of other micro-economic behavior. For instance, in their recent study, Gill and Prowse (2016) link the Big Five to economic behavior and find that more agreeable and less neurotic individuals perform and learn better in strategic games.

4. Data, descriptive evidence and empirical strategy

4.1. Data

For the estimation of the impacts of non-cognitive skills and risk preferences on the rural-to-urban migration decision we make use of panel data from the Ukrainian Longitudinal Monitoring Survey (ULMS). The panel survey launched in 2003 was also carried out in 2004, 2007 and 2012. The ULMS is the only panel data set for Ukraine, which is accessible to researchers worldwide and is representative at the national level (see Lehmann et al., 2012). Our sample consists of individuals between the age of 15 and 72. The survey instrument contains an individual questionnaire soliciting information on socio-demographic and labor force characteristics, labor market status, skills, preferences and attitudes, as well as a household questionnaire on the structure of the household, housing conditions, income, assets and expenditures.

For the outcome variable of interest, namely rural-to-urban migration, we exploit the survey question related to the "type of settlement of the current place of residence" which is asked in all four waves of the panel survey. Possible answer categories include six types of settlement: village, rural-type settlement, small town (population up to 20 thousands), medium town (population of 20–99 thousands), city (population of 100–499 thousands) and large city (population more than 500 thousands). While we consider villages and rural-type settlements as belonging to a 'rural' area, towns (small- and medium-size) and cities (medium- and large-size) are categorized as 'urban' areas. The dependent variable thus comprises a binary indicator, which takes a value of 1 if the respondent changes the type of settlement from a rural area to an urban area between two survey periods and a value of 0 if the respondent resides in a rural area both in the current and last survey period.[8,9]

One important feature of the ULMS is its collection of information on non-cognitive skills in the wave of 2012, where a set of questions regarding non-cognitive skills was added to the survey. The questions, based on the World Bank's 24-item STEP survey questions regarding non-cognitive skills (Pierre et al., 2014), asks respondents how they perceive themselves. Respondents are asked, for instance, whether they are talkative, are interested in learning new things, tend to worry, and so on. Responses are ranked on a 4-point scale: "1 Almost always", "2 Most of the time", "3 Some of the time" and "4 Almost never". We transform the ranking in a way that a higher ranking refers to a higher value for the corresponding characteristic (1 = Almost never–4 = Almost always). In the assessment of non-cognitive skills, we map these 24 items into the Big Five factors model, with openness, conscientiousness, extraversion, agreeableness, and neuroticism as the five personality constructs. The Big Five personality factors represent a widely accepted, comprehensive, and ample frame for delineating the structure of core personality traits over adulthood (Lang et al., 2011: 550). Given its universal structure validated by numerous empirical studies from different cultures as well as its rank order stability over the life cycle, we prefer the Big Five Factor model to the usage of single traits such as self-efficacy or self-esteem, which show less rank order stability (Goldberg, 1990; John and Srivastava, 1999; Lang et al., 2011).

Our mapping into the Big Five factor model largely benefits from the domains characterized by John and Srivastava (1999) and Kautz et al. (2014). Table 1 presents the original table of the 24 items and the corresponding Big Five factors into which these items are mapped. While generating the Big Five constructs, the scale of some items –those denoted by '*'– are reversed for the sake of coherence with the defining construct. Each of the Big Five factor is the simple average of the corresponding items and the averages are standardized with a mean of zero and standard deviation of 1. Because the information on non-cognitive skills is only available in the survey year of 2012, we treat the Big Five personality constructs as fixed over the sample period. Whether this assumption is plausible is taken up in the robustness section of the paper. It is also worthy of note that the treatment of the non-cognitive skills fixed over the period requires us to use a balanced panel straddling the years 2003 to 2012.[10]

The ULMS also introduced a module on risk preferences in 2007 and 2012, identical to the module in the German Socio-Economic Panel (SOEP). Respondents are asked about their willingness to take risks in general and in life-specific domains.[11] In our empirical analysis we only use the general risk measure. The general risk question asks: "How do you see yourself: are you generally a person who is willing to take risks or do you try to avoid taking risks?" The answer can be on an 11-point Lickert scale, from 0 "completely unwilling to take risks" to 10 "completely willing to take risks". In our main regressions we rely on a dichotomous variable, the risk preference indicator, which takes the value of 1 if the respondent chooses a value of 6 or higher on the 0-to-10-scale. This mitigates potential problems from different use of scales, as explained by Jaeger et al. (2010).[12]

Similar to the Big Five measures, we treat preferences as (partly) fixed over the sample period. In particular, we assign the values of risk preferences measured in 2007 to the previous survey years of 2003 and 2004, and address the potentially arising reverse

[8] The migration dummy takes the value 1 only in the year when the move occurs. For example, if a person moved between 2003 and 2004, the respondent will be assigned a value of 1 only for the year 2004 and a missing value in the years of 2007 and 2012.

[9] Given the construction of the dependent variable, a potential concern is measurement error due to 'round-tripping'. Given that there are up to 5-year brackets between two survey periods, it is possible to experience multiple movements within such a relatively long period. Therefore, our dependent variable could underestimate the rural-to-urban migration if movers migrate back to the rural area between two survey periods. A preliminary check performed by us, which employs information on moves between reference weeks, indicates that 'round-tripping' is negligible. Less than 5% of the rural-to-urban movers experience round-tripping.

[10] We did not pursue exploratory factor analysis since the cited literature provides us with a very intuitive and clear guidance regarding the mapping of the 24 items into the Big Five factors. Exploratory factor analysis is particularly useful when researchers have only vague notions of how to project high-dimensional data onto a lower dimensional space, which is not the case here.

[11] These life-specific domains are: financial matters, career, health, sports and leisure, as well as car driving.

[12] The risk index, which measures risk attitudes on the 11-point scale is only used for some robustness checks.

Table 1
Mapping 24 items into the Big Five factors.

How do you see yourself?	
3 Do you come up with ideas other people haven't thought of before? 11 Are you very interested in learning new things? 14 Do you enjoy beautiful things, like nature, art and music?	Openness
2 When doing a task, are you very careful? 6 Do you finish whatever you begin? 8 Do you work very hard? For example, do you keep working when others stop to take a break? 12* Do you prefer relaxation more than hard work? 13 Do you enjoy working on things that take a very long time (at least several months) to complete? 17 Do you work very well and quickly? 21 Do you think carefully before you make an important decision?	Concientiousness
1 Are you talkative? 4* Do you like to keep your opinions to yourself prefer to keep quiet when you have an opinion? 20 Are you outgoing and sociable, for example, do you make friends very easily?	Extraversion
9 Do you forgive other people easily? 16 Are you very polite to other people? 19 Are you generous to other people with your time or money? 23 Do you ask for help when you dont understand something?	Agreeableness
5* Are you relaxed during stressful situations? 7 Do people take advantage of you? 10 Do you tend to worry? 15* Do you think about how the things you do will affect you in the future? 18 Do you get nervous easily? 22 Are people mean/not nice to you? 24* Do you think about how the things you do will affect other?	Neuroticism

causality issue in Section 5.

4.2. Descriptive statistics

Table 2 presents summary statistics of the variables used in the regression analysis for rural-to-urban movers, rural stayers, and the urban sample. The former two make up our sample for analysis. Since the 2012 survey is the only year with complete information on both non-cognitive skills and preferences, the statistics reported in Table 2 are for 2012. However, we also present summary statistics of other years for the available variables in Table A.1 in the appendix. Table 2 shows those rural-to-urban movers who moved between 2007 and 2012, the period encompassing the Great Recession. If we compare this table with Table A.1, we see that between 2007 and 2012 the number of moves was particularly small compared to the period between 2003 and 2004. This lower

Table 2
Summary statistics (2012).

	Urban sample			Rural stayers			Movers into urban			Mean differences between	
	(1)			(2)			(3)			(2)and (3)	
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Diff.	Std. Dev.
Age	3644	42,84	16,13	2308	47,31	14,98	48	32,44	13,00	14,87	2,18
Female	3644	0,56	0,50	2308	0,59	0,49	48	0,58	0,50	0,01	0,07
Ukranian language	3644	0,30	0,46	2308	0,68	0,47	48	0,42	0,50	0,26	0,07
Married	3643	0,62	0,48	2308	0,66	0,47	48	0,77	0,42	−0,11	0,07
Number of children	3640	1,23	0,95	2308	1,67	1,05	48	0,88	0,87	0,79	0,15
Education level	3637	3,03	0,88	2305	2,77	0,86	48	3,23	0,93	−0,46	0,13
Employed	3644	0,51	0,50	2308	0,45	0,50	48	0,71	0,46	−0,26	0,07
Household income	3644	4894,72	3484,40	2308	3648,39	2497,21	48	4198,10	2212,40	−550,82	363,39
Risk indicator	3527	0,22	0,42	2270	0,18	0,39	48	0,23	0,42	−0,04	0,06
Risk index	3527	3,62	2,71	2270	3,20	2,64	48	3,75	2,61	−0,55	0,38
Openness	3643	3,05	0,54	2308	3,01	0,57	48	3,19	0,52	−0,18	0,08
Conscientiousness	3643	2,87	0,47	2308	2,99	0,44	48	2,94	0,48	0,05	0,07
Extraversion	3643	2,63	0,62	2308	2,65	0,60	48	2,66	0,61	−0,01	0,09
Agreeableness	3641	2,85	0,52	2303	2,96	0,49	48	3,05	0,52	−0,09	0,07
Neuroticism	3643	2,09	0,41	2308	2,10	0,40	48	2,02	0,41	0,08	0,06

Source: Authors' tabulations from the 2012 wave of the ULMS.

number could be related to less mobility in times of economic crisis. Another reason for this drop in numbers could be a selection issue. Nearly all the rural-to-urban movers whom we observe are part of the original sample that was surveyed in 2003. It is certainly feasible that those with the largest propensity to move to an urban environment moved early in the reported period and once we arrive in 2007 the pool of those willing to move has nearly been depleted. This potential explanation strongly influences our research strategy that we discuss below.

The urban sample is composed of those who were born and currently reside in urban areas as well as those who moved into urban areas. Table 2 demonstrates that the urban sample is significantly younger than the rural sample. Furthermore, about 70% of the urban sample prefer to communicate in Russian; these respondents are likely to be concentrated in the center and east of the country. In line with expectations, the education level and employment rate among the urban sample is higher than among rural stayers. Consistent with these patterns, compared to rural stayers, the movers into urban areas are much younger, relatively more educated, more likely to be married but have less children, more likely to be employed and more likely to prefer Russian for communication.

Table 2 also shows the average values of the Big Five factors (on a 4-point scale) separately for movers and stayers. We see a positive and statistically significant difference in the average value of openness and agreeableness for movers relative to stayers. As for conscientiousness and neuroticism movers score, on average, lower than stayers. The negative difference for each of these two skills is also statistically significant. However, as far as extraversion is concerned, the difference between movers and stayers is not statistically significant. Next, we present how attitudes towards risk are distributed between rural-to-urban movers versus stayers. As shown in Table 2, 23% of movers score their risk attitudes 6 or higher on the 11-point scale, which is about 5 percentage points higher than rural stayers. The measured risk preferences show lower scores among movers compared to stayers in 2007. The difference between the two survey years are mainly driven by movers who scored significantly lower in 2007 than 2012. The difference is more apparent for the index measure, thus we rely in our analysis on the dichotomous indicator variable as it can better mitigate the potential measurement error problem. A relevant concern can also be reverse causality, in that the migration experience might have led to an increase in the willingness to take risks or might have prompted respondents to reveal themselves as more risk loving. We discuss this potential endogeneity problem due to reverse causality in Section 5.

Finally, we examine the distribution of the responses to the general risk questions for the rural and urban samples in 2007 and 2012. As shown in Fig. 1, the average of the risk index is higher in the urban than in the rural sample in both survey years. While the largest difference between the rural and urban residents is among the most risk-averse group in 2007, we do not see such a marked difference in 2012.

4.3. Empirical strategy

To investigate the impact of non-cognitive skills and risk preferences on the probability of migration, we estimate the following basic specification of a probit model:

$$Y_{i,t} = \alpha + N_i'\beta + \gamma P_{i,t+\tau} + X_{i,t-1}'\delta + \epsilon_{i,t} \tag{1}$$

where $\tau = \{0, 1, 2\}$.

$Y_{i,t}$ indicates a dummy variable which takes the value of 1 if the respondent i resides in the urban area during the reference week of survey period t, but was residing in a rural area during the reference week of the previous survey period, at time $t-1$.[13] It takes the value of 0 if the respondent's current and last settlements are both in the rural area. N_i is a vector of non-cognitive skills represented by the Big Five which are standardized to have a mean of 0 and standard deviation equal to 1. Because we observe responses to non-cognitive skill questions only in 2012, we assume them as time-invariant characteristics of the individual. In the next section we perform a robustness check which shows that this is a reasonable assumption. The variable $P_{i,t+\tau}$ is the risk indicator which takes the value of 1 for risk index values greater than 5 (on a scale of 0 to 10). The risk measure is observed in 2007 and 2012 surveys. For the most part, we assign the values of risk preferences measured in 2007 to the previous survey years of 2003 and 2004. However, when the risk measure is not available in 2007 we use the risk measure of 2012. In the most extant basic specification, $X_{i,t-1}$ is a vector of individual characteristics with dummy variables for female, married, employed, educational attainment and Ukrainian as the preferred language of the interview, as well as continuous variables including age, age squared, the number of children in the household and the log of household income. For the time-varying covariates we rely on information from the previous survey year in order to rule out reverse causality problem. In particular, the covariates are measured at time $t-1$, before migration happens (which is measured at time t). This implies that the estimation sample only comprises data from the survey years of 2004, 2007, and 2012. Finally, $\epsilon_{i,t}$ is a white noise error term.

The estimated coefficients of β capture the impact of non-cognitive skills on the propensity to move from rural to urban areas, holding risk attitudes and other individual characteristics constant. As we discussed in the previous descriptive section, most of the moves from rural to urban locations occurred before 2007, i.e., before the respondents provided self-assessed measures on risk preferences. One research strategy might consist in limiting our analysis to the period 2007–2012; this way we would condition on risk measures provided in 2007 that were solicited before any rural-to-urban move occurred. However, with this strategy we would ignore most of the moves that we can observe in the data set, missing all those movers who might have had a particularly high propensity to change their residence from rural to urban. We, therefore, rely on an empirical model that uses the risk measure as an explanatory variable even if migration occurred before respondents were asked about their risk preferences. As this raises reverse

[13] In subsequent periods the dependent variable takes the value 1 if the respondent ever moved.

causality issues, we perform a number of reverse causality tests and also report the results when the analysis is restricted to migration episodes between 2007 and 2012. Since these latter results are qualitatively similar to the results when all moves are considered and since the reverse causality tests do not point to reverse causality we are confident that our research strategy that uses the fullest information available is the most appropriate one.

5. Main results and extensions

5.1. The big five

Table 3 presents marginal effects of a probit model that estimates the probability to migrate from rural to urban areas. Because of substantial differences in the institutional and economic structures of cities and towns, the decision to move into a city may require distinctive personality characteristics than moving into a town. Therefore, we break down the results by rural-to-city and rural-to-town migration, presented in Table 3 in columns (4)–(6) and columns (7)–(9), respectively. Table 3 displays results for different sets of control variables. While in columns (1), (4) and (7) we do not control for any demographic and socio-economic characteristics but only the Big Five, columns (2), (5) and (8) also include pre-determined (demographic) characteristics such as gender, age, age squared and Ukrainian language[14] as covariates, and columns (3), (6) and (9) additionally include socio-economic controls that may be jointly determined with the migration decision, including marital status, number of children, employment status, log of household

Table 3
Effects of the Big Five on migration.

	(1) rural-urban	(2) rural-urban	(3) rural-urban	(4) rural-city	(5) rural-city	(6) rural-city	(7) rural-town	(8) rural-town	(9) rural-town
Openness	0.008***	0.003*	0.001	0.004***	0.002**	0.001*	0.003**	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Conscientiousness	−0.013***	−0.008***	−0.008***	−0.008***	−0.005***	−0.004***	−0.005***	−0.002**	−0.002**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Extraversion	−0.002	−0.002	−0.000	−0.002*	−0.002**	−0.001*	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agreeableness	−0.008***	−0.005***	−0.005***	−0.003**	−0.002	−0.001	−0.004***	−0.003***	−0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neuroticism	−0.004*	−0.003	−0.002	−0.002	−0.001	−0.001	−0.003*	−0.002*	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		−0.001*	−0.002**		−0.001**	−0.001*		0.000	−0.000
		(0.001)	(0.001)		(0.000)	(0.000)		(0.000)	(0.000)
Age squared		0.001	0.002*		0.001	0.001		−0.000	0.000
		(0.001)	(0.001)		(0.001)	(0.001)		(0.000)	(0.001)
Female		0.001	0.002		0.001	0.001		0.000	0.001
		(0.003)	(0.003)		(0.002)	(0.001)		(0.002)	(0.002)
Ukrainian language		−0.041***	−0.034***		−0.012***	−0.008***		−0.029***	−0.024***
		(0.005)	(0.005)		(0.003)	(0.002)		(0.004)	(0.004)
Married			0.000			−0.002			0.002
			(0.003)			(0.002)			(0.002)
Number of children			−0.002			−0.002			−0.000
			(0.002)			(0.001)			(0.001)
Employed			0.001			−0.001			0.002
			(0.003)			(0.002)			(0.002)
Log of household income			0.007***			0.003***			0.003**
			(0.002)			(0.001)			(0.001)
Education: Secondary			0.002			0.005**			−0.004*
			(0.003)			(0.002)			(0.002)
Education: Vocational			0.010***			0.006***			0.002
			(0.003)			(0.002)			(0.002)
Education: Higher			0.018***			0.007**			0.007*
			(0.006)			(0.003)			(0.004)
Observations	5729	5729	5729	5644	5644	5644	5649	5649	5649

Note: The table shows marginal effects from probit estimation, evaluated at sample mean. The Big Five factors –openness, conscientiousness, extraversion, agreeableness, neuroticism– are standardized averages with a mean of 0 and standard deviation of 1. The covariates of *age, age squared, number of children* and *log of household income* are continuous variables, while *female, Ukrainian language, married* and *employed* refer to dummy variables. The control for *education* is a categorical variable with the reference category of basic secondary level education. These control variables are lagged, i.e. the values are taken from the previous wave. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *a*

[14] We consider the pre-determined characteristics exogenous, bearing in mind that the language may determine an individual's initial place of residence. On the other hand, we take language chosen for the interview as a good proxy of ethnicity, a characteristic certainly exogenous to the migration decision.

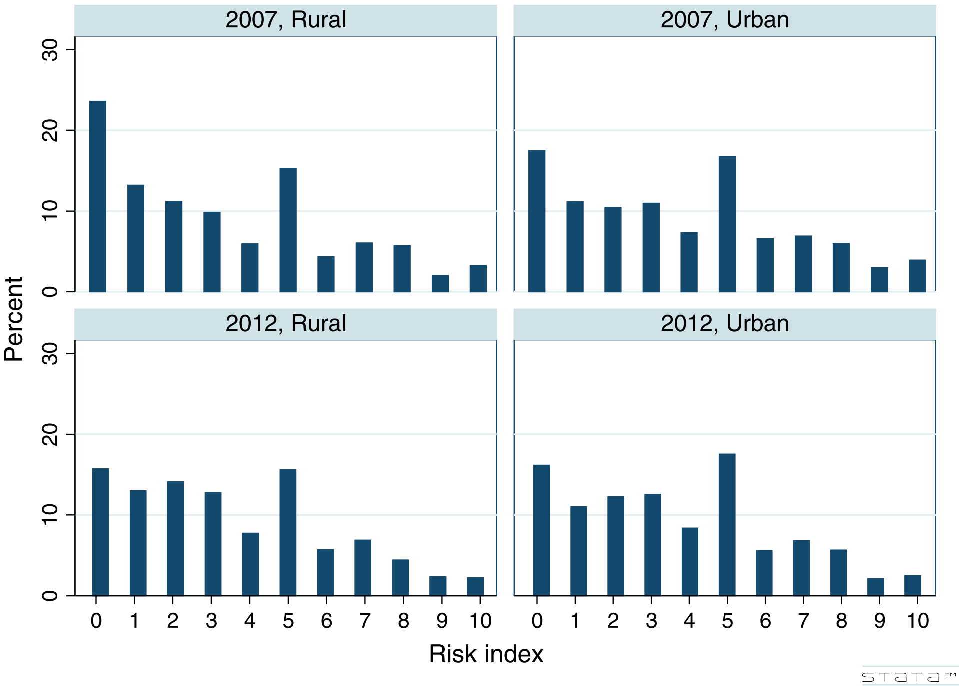

Fig. 1. General risk index in urban and rural areas, in 2007 and 2012.

income, and dummies of educational attainment.[15]

In all nine specifications we find statistically significant evidence that conscientiousness is negatively related to rural-to-urban migration. For instance, in column (2) where we only control for the pre-determined characteristics, we estimate that one standard deviation increase in conscientiousness is associated with a 0.8 percentage points lower probability of moving from rural to urban areas. Breaking the results down, this corresponds to 0.5- and 0.2- percentage points lower probability of rural-to-city migration and rural-to-town migration, respectively (columns 5 and 8). A coefficient on agreeableness of a smaller size (0.5) is also linked to a fall in the probability of moving into an urban area. This effect of agreeableness on rural-to-urban migration is roughly evenly split between moves to cities and moves to towns. A much smaller negative effect is given by extraversion, since a one standard deviation increase in extraversion lowers the likelihood to move to urban areas by 0.2 percentage points, and the effect is salient only for rural-to-city migration.

The only personality traits that is positively associated with the willingness to move is openness. We find that individuals who rate themselves as (one standard deviation) more open to new experiences have a 0.3 percentage point higher probability of moving from rural to urban locations, which is more marked in rural-to-city moves. Finally, neuroticism is found to be uncorrelated with any type of migration once we include demographic covariates. All these estimated effects are substantial given the unconditional migration probability of 3% from rural to urban areas, which is evenly split between rural-to-city and rural-to-town moves.[16]

The inclusion of demographic and socio-economic characteristics as control variables substantially reduces the size of the marginal effects of personality traits. However, for all the originally significant traits the effects remain statistically significant, and the signs of the marginal effects of the controls are generally in line with migration theory. Net household income, educational attainment and the Ukrainian language are the variables which have the highest and most consistent explanatory power. The probability of rural-to-urban migration is approximately 4 percentage points lower among those who prefer to communicate in Ukrainian rather than in Russian. As for moving into cities or towns, the effect is smaller, yet strongly significant. The probability of migration increases with the education level, and it is the highest among university graduates, who are around 2 percentage points more likely to migrate. The impact of household income is also positive: members of financially better-off families are more likely, arguably more

[15] Since in many countries rural-to-urban migration is driven by individuals moving for education, we ideally would like to identify those who move for educational purposes. Since the construction of the migration variable does not allow us to determine the reason of migration, we estimate the probability to move to urban areas without and with dummies of educational attainment and establish whether the inclusion of these dummies changes the coefficient estimates on the non-cognitive skills measures. The results are very similar to those presented in columns (3), (6), and (9), thus we prefer to present the results of the full specification. The results are available upon request from the authors.

[16] Breaking down the absolute number of 172 rural-to-urban movers (as reported in Tables 2 and A.1) by type of migration, there are in total 85 rural-to-town and 87 rural-to-city movers over the period.

Table 4
Age-free effects of the Big Five on migration.

	(1) rural-urban	(2) rural-urban	(3) rural-urban	(4) rural-city	(5) rural-city	(6) rural-city	(7) rural-town	(8) rural-town	(9) rural-town
Openness	0.005**	0.003*	0.001	0.002*	0.002**	0.001*	0.003*	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Conscientiousness	−0.012***	−0.008***	−0.009***	−0.007***	−0.005***	−0.005***	−0.005***	−0.002**	−0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Extraversion	−0.002	−0.002	−0.001	−0.003**	−0.002**	−0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agreeableness	−0.006***	−0.005***	−0.005***	−0.003	−0.002	−0.002	−0.004***	−0.003***	−0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Neuroticism	−0.004*	−0.003*	−0.003*	−0.001	−0.001	−0.001	−0.003*	−0.002*	−0.002*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Covariates									
Set 1	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Set 2	No	No	Yes	No	No	Yes	No	No	Yes
Observations	5729	5729	5729	5644	5644	5644	5649	5649	5649

Note: The table shows marginal effects from probit estimation, evaluated at sample mean. The Big Five factors –openness, conscientiousness, extraversion, agreeableness, neuroticism– are the predicted residuals from the regressions of the Big Five on age and age square. The predicted residuals are standardized with a mean of 0 and standard deviation of 1. *Set 1* represents covariates of age, age square, female and Ukrainian language, while *Set 2* refers to covariates of married, number of children, education level, employed, and log of total household income. These control variables are lagged, i.e. the values are taken from the previous wave. Bootstrapped standard errors in parentheses (with a replication number of 500); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

able, to migrate into cities. The signs of the marginal effects of education and income covariates are generally in line with migration theory. In the case of Ukraine, where returns to education are higher in urban than in rural areas,[17] better skilled migrants are self-selected into migration. At the same time, lower-income individuals often cannot afford to cover the migration costs. On the other hand, gender, marital status, and employment status do not predict the propensity to migrate. Finally, adding educational dummies in the regressions alters the magnitude of the effect of non-cognitive skills on rural to urban migration only very marginally. Hence, our results are not driven by a strong correlation of educational attainment, cognitive ability and personality traits. Instead, personality traits are important drivers of rural-to-urban migration in their own right. Although the magnitudes of the effects of socio-demographic variables are larger than those of the non-cognitive skills, the signs and significance of the latter are considerably stable across the various specifications.

We assume stability of the Big Five personality traits over the panel period. Reverse causality could be a concern for these skills, despite the sound evidence in the personal psychology literature regarding rank order stability over time and relatively little malleability of these skills after adolescence (Lang et al., 2011). We cannot test the presence of reverse causality in personality traits and hence internally check the validity of our assumption given the lack of repeated information on personality traits in the ULMS. We, instead, implement an approach suggested by Groves (2005) and Heineck and Anger (2010) to validate our results. In particular, we predict residuals from the regression equation (2) of the Big Five factors on age, age squared and age cubed.

$$N_i = \alpha_0 + \alpha_1 age_i + \alpha_2 age_i^2 + \alpha_3 age_i^3 + u_i \tag{2}$$

where N_i is a vector of the Big Five as described in Eq. (1) and *age*, age^2 and age^3 denote the age variable as a third order polynomial. We plug the predicted residuals $\hat{u}_i$ into Eq. (1), replacing the vector N_i and estimate the impact on the migration behavior. The idea behind this approach is to net out the age effect of non-cognitive skills, so that the estimated impact is a time-invariant (age-free) component of personality. Table 4 shows very similar results to our basic specifications in Table 3: the signs of the coefficients on non-cognitive skills and their magnitudes are the same and in almost all cases the significance is preserved. So, after we have 'de-aged' our measures of non-cognitive skills, openness, conscientiousness, and agreeableness remain important predictors of rural-to-urban migration Hence, our initial assumption of the time-invariance of the Big Five factors, in particular their non-malleability with age, taken from the psychology literature, seems to hold with our data.

5.2. The big five and risk preferences

Table 5 extends the model by including the risk preference measure as a covariate. The inclusion of the risk variable in the analysis does not change the impact of personality traits in a substantial way as a comparison of Tables 3 and 5 shows.[18] This suggests that the Big Five traits, and risk preferences represent distinctive features of personality and that they operate as complements when

[17] Table B.1 in the online appendix provides estimates of average monthly wages for workers with secondary education, vocational education and higher education for the four waves of the ULMS. These estimates demonstrate that for all three levels of educational attainment and in any given year wages are substantially higher in urban than rural areas. The online appendix is available at http://ftp.iza.org/dp10982_app.pdf.

[18] Table A.2 in the appendix provides the results of the four specifications using OLS estimation, which for the most part give very similar impacts as in Table A.5.

Table 5
Effects of the Big Five and risk on migration.

	(1) rural-urban	(2) rural-urban	(3) rural-urban	(4) rural-city	(5) rural-city	(6) rural-city	(7) rural-town	(8) rural-town	(9) rural-town
Openness	0.007***	0.003*	0.001	0.004***	0.002**	0.001*	0.003**	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Conscientiousness	−0.013***	−0.008***	−0.008***	−0.008***	−0.005***	−0.004***	−0.005***	−0.002**	−0.002**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Extraversion	−0.002	−0.001	−0.000	−0.003**	−0.002**	−0.001*	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agreeableness	−0.008***	−0.005***	−0.005***	−0.003**	−0.002	−0.001	−0.004***	−0.003***	−0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neuroticism	−0.004*	−0.003	−0.002	−0.001	−0.001	−0.001	−0.002*	−0.002*	−0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Risk indicator	−0.001	−0.001	−0.001	0.008**	0.005**	0.003*	−0.009***	−0.005***	−0.004**
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Covariates									
Set 1	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Set 2	No	No	Yes	No	No	Yes	No	No	Yes
Observations	5692	5692	5692	5608	5608	5608	5612	5612	5612

Note: The table shows marginal effects from probit estimation, evaluated at sample mean. The Big Five factors –openness, conscientiousness, extraversion, agreeableness, neuroticism– are standardized averages with a mean of 0 and standard deviation of 1. The *risk indicator* is a dummy variable for values greater than 5 on a 11-point scale. The covariates of *age, age square, number of children* and *log of household income* are continuous variables, while *female, Ukrainian language, married* and *employed* refer to dummy variables. The control for *education* is a categorical variable with the reference category of basic secondary level education. These control variables are lagged, i.e., the values are taken from the previous wave. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

explaining the propensity to migrate.

In line with the previous literature, we find that individuals who are relatively more willing to take risks are more likely to migrate. This positive effect is present only for rural-to-city migration. The probability of moving into cities is 0.5 percentage points higher for relatively more risk-loving people, controlling for demographic and socio-economic characteristics. In contrast, we find a strong negative association between risk willingness and rural-to-town migration. This might be an indication that the push and pull factors regarding rural-to-town migration are very different from the push and pull determinants of moves from rural to city locations.[19]

Search models predict that mobility across jobs and across space falls when local macroeconomic and labor market conditions become more adverse (Pissarides, 1994). As an extension of the model that includes both personality traits and risk preferences, we, therefore, include the unemployment rate or the log of GDP, both at the *oblast* level in Table A.3 in the annex, in order to control for local macroeconomic or labor market conditions.[20][21] Table A.3 presents the impact of the Big Five together with risk preferences when we add either the regional unemployment rate or the regional GDP growth rate. A comparison with Table 5 makes it clear that the inclusion of either of the macro indicators does only marginally change the coefficient estimates on non-cognitive skills and risk preferences. This suggests that regional controls are orthogonal to the Big Five and risk preferences and that these preferences and a subset of the Big Five, namely openness, conscientiousness and agreeableness consistently predict internal migration from rural areas to cities. When it comes to rural-to-town migration, we see a consistently estimated negative impact of conscientiousness, agreeableness and risk preferences, while openness is positively correlated with moves into towns. Table A.3 also demonstrates that internal migration is pro-cyclical since adverse regional labor market and macroeconomic conditions lower spatial mobility. It is also noteworthy that regional macroeconomic and labor market conditions affect rural-to-city and rural-to-town migration in roughly equal measure and in the same direction. This last result confirms that workers tend to stay put when macroeconomic and labor market conditions get worse and that this heightened reluctance to move is independent of the potential destination.[22]

[19] We spent considerable time exploring the available data to check whether these countervailing effects of risk attitudes on rural-to-town versus rural-to-city moves are due to some fluke in the data, for example, âæinfluential points.âg We found no evidence for this. At the same time, the scarce literature on spatial mobility in Ukraine gives us no sound guidance why these countervailing effects might occur. We can speculate about the motives of rural-to-town versus rural-to-city movers but are unable to test empirically any hypotheses about these motives with the data at hand. Investigating the reasons for these countervailing effects with appropriate data is, therefore, an interesting future research topic.

[20] There are 24 Oblasts in Ukraine, forming the largest administrative units. Oblasts are larger than, e.g., counties in the U.S. but smaller than, e.g., lands in Germany. The macroeconomic measures introduced in Table A.3 are hence only rough proxies for local macroeconomic and labor market conditions. Since most migration, however, takes place within oblasts, we can suppose that internal migration is pro-cyclically related to macroeconomic measures at the oblast level in Ukraine.

[21] One way to capture regional unobserved heterogeneity that serves as a push factor for migrants is to include regional fixed effects. We did not include them in our specifications because the aim is to explore the role of non-cognitive skills in rural-to-urban migration, which is likely to occur within as well as between oblasts. If we had included fixed effects, we would have estimated the effects within the oblast losing the variation coming from between-oblast movements.

[22] The theme of the paper is the nexus between personality traits and risk preferences and an individual's decision to migrate from a rural to an

Table 6
Effects of the Big Five and risk on migration: Migration occurs between 2007–2012, after risk is measured in 2007.

	(1) rural-urban	(2) rural-urban	(3) rural-urban	(4) rural-city	(5) rural-city	(6) rural-city	(7) rural-town	(8) rural-town	(9) rural-town
Openness	0.007**	0.002*	0.001	0.003**	0.001*	0.000	0.003	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Conscientiousness	−0.008**	−0.003*	−0.003*	−0.005***	−0.002**	−0.000	−0.003	−0.001	−0.001
	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.003)	(0.002)	(0.001)
Extraversion	−0.001	−0.002	−0.000	−0.002*	−0.002**	−0.000	0.001	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Agreeableness	0.003	0.003	0.002	0.001	0.001	0.000	0.001	0.001	0.001
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)
Neuroticism	−0.004	−0.003	−0.001	−0.001	−0.000	0.000	−0.003	−0.002	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)
Risk indicator	0.009	0.004	0.002	0.008**	0.003**	0.001	−0.003	−0.002	−0.001
	(0.007)	(0.005)	(0.003)	(0.004)	(0.002)	(0.001)	(0.005)	(0.003)	(0.001)
Covariates									
Set 1	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Set 2	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1573	1573	1573	1555	1555	1426	1562	1562	1562

Note: The table shows marginal effects from probit estimation, evaluated at sample mean. The outcome variable, measured in 2012, captures the migration that occurred between 2007 and 2012. The *risk* indicator, measured in 2007, denotes a dummy variable for values greater than 5 on a scale from 0 to 10. *Set 1* represents covariates of age, age squared, female and Ukrainian language, while *Set 2* refers to covariates of married, number of children, education level, employed, and log of net household income. The covariates are measured in 2007. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Robustness checks and extensions

A potential concern is that most of the moves observed in the data occur before risk preferences were first measured in the 2007 wave and that our results might possibly be subject to a reverse causality problem. As stated by Jaeger et al. (2010), successful migration could make individuals apt to rate themselves as more risk loving, which would yield an upward bias in the risk estimates from the regression of rural-to-city migration. To check the relevance of this concern, we first estimate models similar to those of Table 5, restricting the dependent variable to represent moves between 2007 and 2012, i.e., after risk attitudes were measured in 2007. More precisely, we estimate a regression the same as Eq. (1) in which the dependent variable is, however, limited to the movements between 2007 and 2012 and the risk indicator is measured in 2007. This way we clearly avoid any reverse causality issue. Given that the number of moves is very limited over the period 2007 to 2012, the results of Table 6 are encouraging. They show similar point estimates and statistical significance as in Table 5 regarding rural-to-city migration, as long as we only condition on the pre-determined covariates. For all specifications with respect to rural-to-town migration and when we condition on the whole sets of covariates in all specifications there is too little variation in the data to get meaningful results.

As a second and more direct check of reverse causality, exploiting the panel feature of the ULMS, we construct a variable representing the change in the risk index between 2007 and 2012. This change in the risk measure is regressed on a migration dummy for moves between 2007 and 2012, as formally presented in Eq. (3):

$$\Delta Risk_i = \gamma_0 + \gamma_1 Y_{i,2012} + X'_{i,2007}\gamma_2 + \nu_{i,2012} \tag{3}$$

where $\Delta Risk_i$ denotes the change in the risk index (on the scale of 0–10) between 2007 and 2012. $Y_{i,2012}$ represents the migration that occurs between 2007 and 2012. The covariates denoted by the vector X are measured in 2007.

Similarly, in a separate regression, we use the risk index in 2012 as the dependent variable (on the scale of 0–10), and investigate the impact of internal migration between 2007 and 2012, conditioning on the risk index measured in 2007 –before the move occurred. For this purpose, we estimate the following regression equation:

$$Risk_{i,2012} = \theta_0 + \theta_1 Risk_{i,2007} + \theta_2 Y_{i,2012} + X'_{i,2007}\theta_3 + \vartheta_{2012} \tag{4}$$

(*footnote continued*)
urban setting. This nexus exists because some personality traits and risk preferences influence the perceived costs and the assessment of potential benefits of migration. This implies that this nexus should also be observable if we look at other types of migratory moves, for example from town to city and from city to town, moves that we can readily calculate. Table B.2 in the online appendix shows the marginal effects of probit regressions with the probability of city-to-town and town-to-city moves as the dependent variable. The results of town-to-city moves strike us as particularly relevant since they deal with an individual's decision to migrate from a smaller to a larger entity, similar to the decision to migrate from a rural to an urban setting. The results strike us as encouraging since they show openness to new experiences, conscientiousness and the willingness to take risks in general as highly significant determinants of the decision to migrate from town to city. The marginal effects on these variables also have the same signs as in our principal results regarding rural to city migration. The only deviation from our principal results is the significance of neuroticism, which has a positive impact on the town-to-city migration decision. Overall we can state, though, that personality traits and the willingness to take risk are important determinants of spatial mobility in general and not only of moves from rural to urban areas.

Table 7
Reverse causality check for risk: the impact of migration on the risk measure.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(a) **Dependent variable: Change in risk index btw. 2007-12**									
(i) Rural-urban migration btw. 2007–2012	0.084	0.058	0.069						
	(0.204)	(0.207)	(0.206)						
(ii) Rural-city migration btw. 2007–2012				−0.033	−0.079	−0.022			
				(0.437)	(0.438)	(0.436)			
(iii) Rural-town migration btw. 2007–2012							0.150	0.131	0.118
							(0.198)	(0.250)	(0.205)
Observations	1520	1520	1520	1504	1504	1504	1511	1511	1511
(b) **Dependent variable: Risk index in 2012**									
(i) Rural-urban migration btw. 2007–2012	0.133	−0.017	−0.035						
	(0.188)	(0.187)	(0.188)						
(ii) Rural-city migration btw. 2007–2012				0.071	−0.110	−0.128			
				(0.392)	(0.393)	(0.394)			
(iii) Rural-town migration btw. 2007–2012							0.169	0.034	0.016
							(0.192)	(0.224)	(0.186)
Risk index 2007	0.238***	0.201***	0.198***	0.237***	0.200***	0.197***	0.241***	0.203***	0.200***
	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.026)	(0.024)	(0.027)
Covariates									
Set 1	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Set 2	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1432	1432	1432	1416	1416	1416	1423	1423	1423

Note: Rows (i), (ii) and (iii) display *OLS* estimation results from separate regressions, based on a balanced panel sample of 2007 and 2012. In **panel (a)** the outcome variable is the change in the risk index between 2007 and 2012, which is regressed on (one of the three) migration variable measured in 2012, capturing the moves between 2007 and 2012. In **panel (b)** the outcome variable refers to the risk index measured in 2012, which is regressed on the migration variable measured in 2012 and the risk index measured in 2007. The *risk index* is measured on a scale of 0 to 10. The top and bottom panel regressions also condition on two sets of controls variables. While *Set 1* represents covariates of age, age squared, female and Ukrainian language, *Set 2* refers to covariates of married, number of children and education level, employed, and log of net household income. The covariates are measured in 2007. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

where $Risk_{i,2012}$ and $Risk_{i,2007}$ represent the risk index measured in 2012 and 2007, respectively. Other variables in the regression are the same as those described in Eq. (3).

The results are provided in Table 7. The statistically insignificant coefficient estimates in the table reveal that internal migration between 2007 and 2012 do neither affect the observed change in the risk index over the period nor the level of risk attitudes in 2012 once we control for the risk index in 2007. We therefore conclude that reverse causality does not bias our results concerning the impact of risk attitudes on migration. This evidence is in line with the results of earlier works of Gibson et al. (2016) and Jaeger et al. (2010), who also found no impact of migration on risk preferences.

We also investigate whether non-cognitive skills and risk preferences contribute jointly to the explanation of the migration behavior by calculating the Akaike's information criterion (AIC), a goodness-of-fit measure applied to non-linear models. Given two models are estimated with the same data, the model with the smaller value of the information criterion is considered to show a better fit.[23] Each row in Table 8 shows, besides the pre-determined characteristics (i.e., age, age squared, gender and language), which of the two sets of regressors –Big Five measures, risk measures– are separately or together included in the regression analysis. An inspection of Table 8 shows that the Big Five factors have larger explanatory power, improving the goodness-of-fit measures more than the risk factor. In particular, the AIC statistic is lower in the model that only includes non-cognitive skills than the model with only the risk indicator. As for rural-to-city migration, where the willingness to take risk is consistently estimated as a significant positive determinant of the migration probability, the explanatory power is maximized, i.e., the AIC is smallest, when both non-cognitive skills and risk attitudes are included in the regression.[24] For rural-to-town migration, we also have a better fit of the data when both personality traits and risk preferences are included. These findings are consistent with the evidence by Becker et al. (2012) who show very low correlations between the Big Five and risk preferences and their complementarity in explaining life outcomes in Germany.

An alternative method to estimate the impact of personality traits and risk preferences on the migration propensity might be through multinomial logit estimation. This time the dependent variable comprises a categorical variable with three possible outcomes: (1) rural stayers (as the reference category), (2) rural-to-town movers, and (3) rural-to-city movers. The regression results, both the coefficient estimates and the marginal effects are displayed in Table A.4 in the appendix. The significance of the personality traits and the risk attitude in explaining the migration propensity is very much in line with our findings from the probit model

[23] The AIC is a measure for comparing non-linear models that are estimated with maximum likelihood. AIC is defined as: AIC = −2*ln(likelihood) + 2*k, where k = number of parameters estimated.

[24] There is indeed a slight difference between the two models which only includes non-cognitive skills and which jointly estimates non-cognitive skills and risk preferences. This is due to the relatively smaller role of the risk measure in improving the goodness-of-fit measures.

Table 8
Complementarity between the Big Five and risk in explaining the migration propensity.

	ll(null)	ll(model)	df	AIC	Pseudo R2
			Rural-to-urban migration		
Risk	−780.20	−706.85	6	1425.70	0.094
Big Five	−780.20	−685.15	10	1390.31	0.122
Risk and Big Five	−780.20	−685.05	11	1392.10	0.122
			Rural-to-city migration		
Risk	−455.13	−419.52	6	851.04	0.078
Big Five	−455.13	−402.61	10	825.21	0.115
Risk and Big Five	−455.13	−401.27	11	824.53	0.118
			Rural-to-town migration		
Risk	−442.36	−388.87	6	789.73	0.121
Big Five	−442.36	−383.38	10	786.76	0.133
Risk and Big Five	−442.36	−380.43	11	782.87	0.140

Note: AIC refers to the Akaike's information criterion. The AIC is a goodness-of-fit measure calculated after the estimation of probit models. The model with the smaller value of the information criterion is considered to be better. All specifications include individual-level controls of age, age squared, female, and Ukrainian language. The number of observartions varies depending on the outcome variable: rural-to-urban migration (6114), rural-to-city migration (6030), and rural-to-town migration (6027)

estimation. Compared with the results presented in the fifth and eighth columns of Tables 3 and 5, where we only control for the set of predetermined covariates, the size and sign of the marginal effects estimates are very similar and nearly always statistically significant. Only the marginal effect on openness is not significant but has the same sign and magnitude as the marginal effect estimated with probit. We are thus pretty confident that the estimated marginal effects of certain personality traits and of risk attitudes are not determined by the functional form assumptions that the probit model relies on.

We also need to raise the issue of attrition in our data, which could bias the estimation results. Of concern is the high number of dropouts from the sample over the panel period. In the original rural-to-urban sample, individuals who are surveyed in 2004 but attrite in 2007 (and onwards) account for 25% of the 2004 panel. The attrition rate goes up to 30% for those who are observed in 2004 and 2007 but only attrite in 2012. While we cannot directly test whether attrition is correlated with non-cognitive skills, we can check to which extent the decision to migrate might be affected by attrition. We, therefore, run two separate regressions of spatial mobility on an attrition dummy, besides the demographic and socio-economic characteristics described in Table 6. Relying on the 2004 panel, the first model checks whether attrition in 2007 matters for migration by including a dummy which takes the value of 1 if the respondent potentially moves between 2003 and 2004 but attrites in 2007. The results of the first model are shown in the upper panel of Table A.5 in the appendix, and the bottom panel presents the results of the second model. In this model, the attrition dummy takes the value of 1 if the respondent potentially moves between 2004 and 2007 but attrites in 2012. As seen in Table A.5, while attrition in 2007 matters for predicting the migration outcome (panel A), attrition in 2012 does not seem to be an issue as the attrition dummy is statistically insignificant in every specification (panel B).

How important attrition is for predicting the decision to migrate can also be seen by reporting the distribution of characteristics of attriters and non-attriters. We present the summary statistics of the characteristics of non-attriters and attriters in the online appendix, in Tables B.3 and B.4.[25] There are stark differences between non-attriters and attriters as far as age, marital status, number of children and employment status are concerned: non-attriters are younger, are more females, have a higher incidence of marriage, number of children and a far higher rate of employment. Turning back to Table 3, we can see that apart from age none of these factors have a statistically significant impact on migration in any of the specifications. In contrast, Ukrainian ethnicity, educational attainment and household income, characteristics that have dominant predictive power on any type of rural-to-urban migration, exhibit no statistically discernible differences between non-attriters and attriters.

Even though we find only a weak association between attrition and migration, attrition can bias our results if it is correlated with both personality traits and the migration behavior. To determine the direction of the bias is, however, quite difficult, since one needs to assess how attrition is correlated with each of the personality traits. For example, if people who are more open to new experience are more likely to attrite, and if attrition is also positively correlated with the propensity to migrate, then we would expect an upward bias. On the other hand, if attrition is negatively correlated with the trait but positively correlated with the migration attitude, then the bias would be negative.

Finally, given the large international migratory flows from Ukraine in the reported period, an additional concern could be that this large international migration biases our results. While the stock of Ukrainian international migrants is indeed large, we do not think that international migration strongly biases our results. A study by the International Organization for Migration on Ukraine states that the vast majority of international migrants departs from cities, while we study rural to urban internal migration (IOM, 2016). Since international migration entails costs that are substantially larger than the costs associated with internal migration it also seems reasonable to assume that observable characteristics, including risk preferences and non-cognitive skills, are different across the two groups. However, we do not have international migrants in our data set and cannot validate the assumption of a negligible overlap of the two groups.

[25] The online appendix is available at http://ftp.iza.org/dp10982_app.pdf.

6. Discussion and conclusions

Using rich panel data of the Ukrainian Longitudinal Monitoring Survey we analyze the link between non-cognitive skills and risk preferences and rural-to-urban migration in Ukraine. To this purpose we map 24 facets of non-cognitive skills into the Big Five personality traits, i.e., openness to new experiences, conscientiousness, extraversion, agreeableness and neuroticism. Estimating probit models, we analyze the importance of these Big Five personality traits and of general risk attitudes for internal migration behavior.

Our results show that four of the Big Five traits, namely openness to new experiences, conscientiousness and agreeableness are consistently correlated with rural-to-urban migration. These results are driven both by rural-to-city and by rural-to-town migration. While openness to new experiences impacts positively on the migration decision, the other two significant personality traits lower the willingness to migrate. Our risk measure is, however, ambiguous, since persons expressing a greater willingness to take risks have a higher propensity to move from rural areas to cities while we establish a negative correlation when it comes to moves to towns.

The estimated effects of a one standard deviation increase in a significant personality trait or in our risk measure amount to between 0.3 and 0.8 percentage points regarding moving from a rural area to a city, and between 0.4 and 0.9 percentage points as far as moves from a rural area to a town are concerned.The size of these effects are substantial in that the unconditional rural-to-city and the rural-to-town migration probabilities both amount to 1.5% .

We argue that the link between non-cognitive skills and risk preferences and migration should work through the channel of psychic costs of migration and/or through the channel of expected benefits in the destination. It is reasonable to expect that individuals who, for example, are open to new experiences and willing to take risks perceive these costs lower while assessing the potential gains more positively than persons who do not exhibit these traits. On the other hand, a skill such as conscientiousness described by a high valuation of persistence and predictability might lead people to consider moving as relatively costly and to regard potential future gains arising from migration with more skepticism than persons who lack conscientiousness. Therefore, openness to new experiences and risk willingness are expected to be positively, conscientiousness negatively linked to the decision to migrate. However, the data at our disposal do not allow us to distinguish between these two channels.

Reverse causality tests allow us to conclude that a causal interpretation of the link between risk attitudes and migration has some validity, i.e., risk preferences are determinants of internal migration in Ukraine, whilst internal migration does not seem to influence these preferences. We also perform a robustness check for non-cognitive skills that demonstrates that the assumption of the time-invariant nature of these skills is reasonable. We also show that personality traits and risk preferences are complementary in explaining rural-to-urban migration. This tells us that cross section or pooled data regressions that do not include personality traits when estimating the impact of risk attitudes on life outcomes might suffer from an omitted variables bias.

In the final analysis, it is at any rate striking that non-cognitive skills are very consistent predictors of rural-to-urban migration. We take this as an important contribution to basic research on the nexus of non-cognitive skills and internal migration. However, we should also ask whether we could draw some policy conclusions from our results. Clearly, if rural to urban migration is deemed to be growth enhancing and if non-cognitive skills are formed during childhood and malleable during adolescence (see, e.g., Almlund et al., 2011), there might be some beneficial role for educational policy that contributes to shaping non-cognitive skills and hence migration flows.[26] There are at least two caveats, though, when one wants to formulate educational policy meant to influence non-cognitive skills. First, and foremost, formation of these skills takes place predominantly in the family and the state has little leeway in shaping them unless early childhood programs furthering non-cognitive skills are an integral and widespread part of the educational system. In low middle income countries like Ukraine implementing such early childhood programs on a country-wide scale seems beyond the financial and organizational possibilities of governments. However, even if feasible, these programs might be hard to implement especially in rural areas, where the population of interest lives. Second, assuming the feasibility of such educational policy, one needs to be careful when implementing it. It certainly makes sense to further openness to new experiences in pupils since this measure will not only positively affect the decision to migrate, but will beneficially impact on future labor market and general life outcomes across many other dimensions. Developing measures, on the other hand, that produce less conscientious and less agreeable individuals would be very counterproductive since conscientiousness and agreeableness, whilst lowering the propensity to migrate, boost many positive future labor market and general life outcomes. Therefore a selective fine-tuning of measures would be required if such educational policy were to have the desired impact. This would require resources that are beyond the scope of governments in low middle income countries. The policy relevance of our results strikes us, therefore, as rather limited, which leads us to stress once more our contribution to basic research in an important understudied area.

Acknowledgement

We would like to thank Holger Bonin, Thomas Dohmen, Benjamin Elsner, Robert Grundke, Olga Kupets, David McKenzie, Chiara Monfardini, Alexander Muravyev, Mark Schaffer and Anzelika Zaiceva for helpful comments and suggestions. We also thank seminar participants of IZA, of the University of Bologna, IOS-Regensburg, the University of Münster and participants of the EACES Conference in Regensburg in 2016, the Applied Economics Conference 2017, the International Panel Data Conference 2017, the 2017 ASSA meetings in Chicago, and the 2017 EALE Conference in St. Gallen for helpful comments.The comments and suggestions of two anonymous referees have helped us to improve the paper considerably.The usual caveat applies. Lehmann is grateful to the Leibniz

[26] Policies that further non-cognitive skills enhance individuals' mobility in general across many dimensions and are hence beneficial to economic development. Here we exclusively focus on their impact on internal migration.

Institute of East and Southeast European Studies for the generous support given to him when he visited the institute in August 2017 as well as for the partial support provided by the Russian Academic Excellence Project '5-100' within the framework of the HSE University Basic Research Program.

Appendix

Table A.1
Summary statistics of 2004 and 2007.

2004	Urban sample			Rural stayers			Movers into urban		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Age	3800	43,20	16,69	1843	41,99	13,55	75	40,17	13,64
Female	3800	0,59	0,49	1843	0,62	0,49	75	0,56	0,50
Ukranian language	3799	0,36	0,48	1843	0,69	0,46	75	0,13	0,34
Married	3782	0,60	0,49	1836	0,72	0,45	74	0,73	0,45
Number of children	3799	1,27	0,98	1842	1,67	1,09	75	1,28	0,97
Education level	3797	2,72	1,02	1842	2,47	0,95	75	2,83	0,78
Employed	3800	0,51	0,50	1843	0,49	0,50	75	0,60	0,49
Household income	3639	866,30	741,70	1762	625,29	565,80	74	847,43	437,99

2007	Urban sample			Rural stayers			Movers into urban		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Age	3606	43,70	16,91	1851	44,71	13,87	49	40,20	13,94
Female	3606	0,58	0,49	1851	0,62	0,49	49	0,49	0,51
Ukranian language	3595	0,38	0,49	1840	0,67	0,47	49	0,35	0,48
Married	3603	0,62	0,48	1850	0,73	0,44	49	0,69	0,47
Number of children	3603	1,22	0,96	1850	1,70	1,06	49	1,53	1,12
Education level	3585	2,98	0,82	1840	2,77	0,80	49	2,84	0,75
Employed	3606	0,53	0,50	1851	0,51	0,50	49	0,69	0,47
Household income	3438	2452,01	1717,34	1775	1829,06	1288,00	49	2082,53	1260,03
Risk indicator	3533	0,26	0,44	1779	0,19	0,40	49	0,16	0,37
Risk index	3533	3,77	2,90	1779	3,17	2,83	49	2,35	2,69

Source: Authors' tabulations from the 2004 and 2007 waves of the ULMS

Table A.2
OLS estimation: effects of the Big Five and risk on migration.

	(1) rural-urban	(2) rural-urban	(3) rural-urban	(4) rural-city	(5) rural-city	(6) rural-city	(7) rural-town	(8) rural-town	(9) rural-town
Age	−0.002**	−0.002*	−0.002*	−0.002***	−0.002***	−0.002***	−0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age squared	0.001	0.001	0.001	0.002**	0.002**	0.002**	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	−0.008**	0.003	0.002	−0.004	0.002	0.003	−0.005*	0.001	−0.000
	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Ukrainian language	−0.046***	−0.049***	−0.048***	−0.016***	−0.018***	−0.018***	−0.032***	−0.033***	−0.032***
	(0.005)	(0.006)	(0.006)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Risk indicator	−0.004		−0.002	0.005**		0.007**	−0.010***		−0.009***
	(0.005)		(0.005)	(0.003)		(0.004)	(0.003)		(0.003)
Openness		0.004**	0.004**		0.002**	0.002**		0.002*	0.002*
		(0.002)	(0.002)		(0.002)	(0.002)		(0.001)	(0.001)
Conscientiousness		−0.011***	−0.011***		−0.008***	−0.008***		−0.004***	−0.004***
		(0.003)	(0.003)		(0.002)	(0.002)		(0.001)	(0.001)
Extraversion		−0.003	−0.002		−0.003**	−0.004**		0.001	0.001
		(0.002)	(0.002)		(0.002)	(0.002)		(0.001)	(0.001)
Agreeableness		−0.009***	−0.008***		−0.004*	−0.004*		−0.005***	−0.005***
		(0.003)	(0.003)		(0.002)	(0.002)		(0.002)	(0.002)
Neuroticism		−0.005**	−0.005**		−0.002	−0.002		−0.004**	−0.003**
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
Constant	0.112***	0.108***	0.109***	0.071***	0.078***	0.076***	0.044***	0.033***	0.036***
	(0.017)	(0.020)	(0.020)	(0.013)	(0.017)	(0.017)	(0.011)	(0.012)	(0.012)
Observations	7656	6153	6114	7548	6068	6030	7547	6066	6027
Adjusted R-squared	0.021	0.031	0.031	0.010	0.017	0.018	0.017	0.019	0.020

Note: The table shows the OLS estimation results. The Big Five factors, risk measure and the (set 1) controls are considered the same as those described in Table 5. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3
Effects of the Big Five and risk on migration conditional on regional controls.

	(1) rural-urban	(2) rural-urban	(3) rural-urban	(4) rural-city	(5) rural-city	(6) rural-city	(7) rural-town	(8) rural-town	(9) rural-town
Openness	0.003*	0.003*	0.003*	0.002**	0.002**	0.002**	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Conscientiousness	−0.008***	−0.008***	−0.007***	−0.005***	−0.005***	−0.004***	−0.002**	−0.002**	−0.002*
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Extraversion	−0.001	−0.002	−0.002	−0.002**	−0.002**	−0.002**	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agreeableness	−0.005***	−0.005**	−0.003	−0.002	−0.002	−0.001	−0.003***	−0.003***	−0.002**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neuroticism	−0.003	−0.003	−0.001	−0.001	−0.001	−0.000	−0.002*	−0.002	−0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Risk indicator	−0.001	−0.001	0.002	0.005**	0.005**	0.006**	−0.005***	−0.004***	−0.003*
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Regional covariates									
Unemployment rate		−0.003***			−0.001**			−0.001***	
		(0.001)			(0.000)			(0.000)	
Log of GDP			0.016***			0.007***			0.006***
			(0.002)			(0.001)			(0.001)
Observations	6114	6114	6114	6030	6030	6030	6027	6027	6027

Note: The table shows marginal effects from probit estimation, evaluated at sample means. The Big Five factors –openness, conscientiousness, extraversion, agreeableness, neuroticism– are standardized averages with a mean of 0 and standard deviation of 1. The *risk indicator* is a dummy variable for values greater than 5 on a 11-point scale. Regional controls include *unemployment rate* and *log of GDP* at *oblast* level. All specifications also include individual-level controls of age, age squared, female and Ukrainian language, as well as year fixed effects. The covariates are lagged variables, i.e., the values are taken from the previous wave. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4
Multinomial logit regression results.

	Without risk		With risk	
	Town	City	Town	City
	(1)	(2)	(3)	(4)
Coefficient estimates				
Openness	0.135	0.143	0.107	0.132
	(0.117)	(0.141)	(0.115)	(0.141)
Conscientiousness	− 0. 276**	− 0. 550***	− 0. 266**	− 0. 567***
	(0.109)	(0.147)	(0.111)	(0.148)
Extraversion	0.0755	− 0. 209*	0.123	− 0. 237**
	(0.101)	(0.108)	(0.102)	(0.108)
Agreeableness	− 0. 383***	−0.256	− 0. 379***	−0.244
	(0.129)	(0.161)	(0.129)	(0.162)
Neuroticism	− 0. 270**	−0.159	− 0. 244*	−0.172
	(0.132)	(0.154)	(0.133)	(0.157)
Risk indicator			− 0. 928**	0.491**
			(0.399)	(0.250)
Marginal effects				
Openness	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Conscientiousness	− 0. 002**	− 0. 004***	− 0. 002**	− 0. 005***
	(0.001)	(0.001)	(0.001)	(0.001)
Extraversion	0.000	− 0. 002*	0.001	− 0. 002**
	(0.001)	(0.001)	(0.001)	(0.001)
Agreeableness	− 0. 002***	−0.002	− 0. 002***	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Neuroticism	− 0. 002**	−0.001	− 0. 001*	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Risk indicator			− 0. 004***	0.005*
			(0.001)	(0.003)
Observations	6153		6114	

Note: All specifications include individual-level controls of age, age squared, female, and Ukrainian language. Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5
Attrition check

	(1) rural-urban	(2) rural-urban	(3) rural-city	(4) rural-city	(5) rural-town	(6) rural-town
			A. **Attrition in 2007**			
Attrition dummy	0.016***	0.017***	0.009***	0.007**	0.007**	0.007**
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.001	0.001	−0.000	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Age squared	−0.001	−0.001	−0.000	0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	−0.004	−0.003	−0.000	0.001	−0.003	−0.002
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Ukrainian language	−0.056***	−0.055***	−0.024***	−0.019***	−0.030***	−0.026***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
Married		0.008		0.001		0.007*
		(0.007)		(0.004)		(0.004)
Number of children		−0.008**		−0.006***		−0.001
		(0.003)		(0.002)		(0.001)
Employed		−0.003		−0.000		−0.001
		(0.006)		(0.003)		(0.003)
Log of household income		0.010***		0.004		0.005***
		(0.004)		(0.002)		(0.002)
Education: Secondary		0.000		0.012**		−0.010**
		(0.007)		(0.005)		(0.004)
Education: Vocational		0.009		0.006*		0.001
		(0.007)		(0.003)		(0.005)
Education: Higher		−0.001		0.008		−0.008*
		(0.009)		(0.006)		(0.005)
Observations	3366	3066	3293	2993	3306	3009
			B. **Attrition in 2012**			
Attrition dummy	−0.000	−0.003	−0.000	−0.003	−0.000	0.000
	(0.005)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Age	0.000	0.001	−0.000	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Age squared	−0.001	−0.001	−0.000	−0.000	−0.001	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Female	−0.010***	−0.009**	−0.005*	−0.005*	−0.004**	−0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Ukrainian language	−0.037***	−0.033***	−0.011***	−0.008***	−0.020***	−0.018***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
Married		−0.004		−0.006*		0.002
		(0.005)		(0.003)		(0.002)
Number of children		−0.005*		−0.004*		−0.001
		(0.003)		(0.002)		(0.001)
Employed		−0.004		−0.004		0.000
		(0.004)		(0.003)		(0.002)
Log of household income		0.012***		0.007***		0.003***
		(0.003)		(0.002)		(0.001)
Education: Secondary		−0.003		0.006*		−0.006**
		(0.005)		(0.003)		(0.003)
Education: Vocational		0.010*		0.009***		0.001
		(0.006)		(0.003)		(0.003)
Education: Higher		−0.002		0.005		−0.005
		(0.006)		(0.004)		(0.003)
Observations	5092	4722	5015	4645	5022	4656

Note: The table shows marginal effects from probit estimation, evaluated at sample mean. The covariates are considered the same as those described in Table 3. The regressions additionally include an attrition dummy. The upper panel of the table shows the results of a regression estimation for 2003–2004. The *attrition dummy* takes the value of 1 if the respondent surveyed in 2004 is not present in the 2007 panel, and 0 if she/he is present in both survey years. The bottom panel of the table shows the estimation results for 2004 and 2007 periods. The *attrition dummy* takes the value of 1 if the respondent is in the panel until 2007 but only attrite in 2012, and 0 otherwise. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jce.2019.09.001

References

Almlund, M., Duckworth, A.L., Heckman, J., Kautz, T., 2011. Personality psychology and economics. Handbook of the Economics of Education. 4. Elsevier, pp. 1–181.
Bauernschuster, S., Falck, O., Heblich, S., Suedekum, J., Lameli, A., 2014. Why are educated and risk-loving persons more mobile across regions? J. Econ. Behav. Organ. 98, 56–69.
Becker, A., Deckers, T., Dohmen, T.J., Falk, A., Kosse, F., 2012. The relationship between economic preferences and psychological personality measures. Annu. Rev. Econ. 4 (4), 453–478.
Borghans, L., Duckworth, A.L., Heckman, J.J., Ter Weel, B., 2008. The economics and psychology of personality traits. J. Hum. Resour. 43 (4), 972–1059.
Borghans, L., Ter Weel, B., Weinberg, B.A., 2008. Interpersonal styles and labor market outcomes. J. Hum. Resour. 43 (4), 815–858.
Brück, T., Danzer, A.M., Muravyev, A., Weisshaar, N., 2010. Poverty during transition: household survey evidence from ukraine. J. Compar. Econ. 38 (2), 123–145.
Bütikofer, A., Peri, G., 2016. The Role of Cognitive and Noncognitive Skills in Selecting into Migration.
Caliendo, M., Cobb-Clark, D. A., Hennecke, J., Uhlendorff, A., 2016. Job Search, Locus of Control, and Internal Migration.
Canache, D., Hayes, M., Mondak, J.J., Wals, S.C., 2013. Openness, extraversion and the intention to emigrate. J. Res. Personality 47 (4), 351–355.
Danzer, A.M., Dietz, B., 2014. Labour migration from eastern Europe and the EU's quest for talents. JCMS 52 (2), 183–199.
Gibson, J., McKenzie, D., Rohorua, H., Stillman, S., 2016. The Long-term Impact of International Migration on Economic Decision-Making.
Gill, D., Prowse, V., 2016. Cognitive ability, character skills, and learning to play equilibrium: a level-k analysis. J. Polit. Econ. 124 (6), 1619–1676.
Goldberg, L.R., 1990. An alternative" description of personality": the big-five factor structure. J. Personality Soc. Psychol. 59 (6), 1216.
Groves, M.O., 2005. How important is your personality? labor market returns to personality for women in the US and UK. J. Econ. Psychol. 26 (6), 827–841.
Harris, J.R., Todaro, M.P., 1970. Migration, unemployment and development: a two-sector analysis. Am. Econ. Rev. 60 (1), 126–142.
Heineck, G., Anger, S., 2010. The returns to cognitive abilities and personality traits in germany. Labour Econ. 17 (3), 535–546.
IOM, 2016. Migration in ukraine. facts and figures. Int. Organ. Migr.
Jaeger, D.A., Dohmen, T., Falk, A., Huffman, D., Sunde, U., Bonin, H., 2010. Direct evidence on risk attitudes and migration. Rev. Econ. Stat. 92 (3), 684–689.
John, O.P., Srivastava, S., 1999. The big five trait taxonomy: history, measurement, and theoretical perspectives. HandbookPersonality 2 (1999), 102–138.
Jokela, M., 2009. Personality predicts migration within and between us states. J. Res. Personality 43 (1), 79–83.
Jokela, M., Elovainio, M., Kivimäki, M., Keltikangas-Järvinen, L., 2008. Temperament and migration patterns in finland. Psychol. Sci. 19 (9), 831–837.
Kautz, T., Heckman, J.J., Diris, R., Ter Weel, B., Borghans, L., 2014. Fostering and Measuring Skills: Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success. Technical Report. National Bureau of Economic Research.
Koettl, J., Kupets, O., Olefir, A., Santos, I., 2014. In search of opportunities? the barriers to more efficient internal labor mobility in Ukraine. IZA J. Labor Dev. 3 (1), 21.
Kupets, O., 2014. Interregional migration in Ukraine: spatial, economic and social factors. Demogr. Soc. Econ. 2, 22.
Lang, F.R., John, D., Lüdtke, O., Schupp, J., Wagner, G.G., 2011. Short assessment of the big five: robust across survey methods except telephone interviewing. Behav. Res. Methods 43 (2), 548–567.
Lehmann, H., Muravyev, A., Zimmermann, K.F., 2012. The ukrainian longitudinal monitoring survey: towards a better understanding of labor markets in transition. IZA J. Labor Dev. 1 (1), 1.
Paulauskaite, Š.L., Endriulaitienė, E.A., et al., 2010. Big five personality traits linked with migratory intentions in lithuanian student sample. Tarptautinis psichologijos žurnalas: Biopsichosocialinis požiūris (7), 41–58.
Pierre, G., Sanchez Puerta, M. L., Valerio, A., Rajadel, T., 2014. Step skills measurement surveys: innovative tools for assessing skills.
Pissarides, C.A., 1994. Search unemployment with on-the-job search. Rev. Econ. Stud. 61 (3), 457–475.
Silventoinen, K., Hammar, N., Hedlund, E., Koskenvuo, M., Ronnemaa, T., Kaprio, J., 2008. Selective international migration by social position, health behaviour and personality. Eur. J. Public Health 18 (2), 150–155.
Sjaastad, L., 1962. The costs and returns of human migration. J. Polit. Econ. 70 (5 Pt 2), 80–93.
Weel, B.t., 2008. The noncognitive determinants of labor market and behavioral outcomes: introduction to the symposium. J. Hum. Resour. 43 (4), 729–737.