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Labor-market exposure as a determinant of attitudes toward immigration ☆

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A B S T R A C T

This paper re-examines the role of labor-market competition as a determinant of attitudes toward immigration. We claim two main contributions. First, we use more sophisticated measures of the degree of exposure to competition from immigrants than previously done. In addition to education, we focus on the protection derived from (self-assessed) investments in job-specific human capital and from specialization in occupations that are (objectively) intensive in communication tasks. Second, we explicitly account for the potential endogeneity arising from job search. Methodologically, we estimate by instrumental variables, an econometric model that allows for heterogeneity at the individual, regional and country level. Drawing on the 2004–2005 European Social Survey, we obtain the following main results. First, natives that dislike immigrants tend to work in low-immigration jobs, biasing OLS estimates. Second, working in jobs that require high levels of specific human capital leads to relatively more pro-immigration attitudes, although this effect is only found for respondents with more than 12 years of schooling. Third, the degree of manual (communicational) intensity of workers' occupations has a negative (positive) effect on their pro-immigration views. This effect is the most significant, both in a statistical and in a quantitative sense, and is distinct from the protection from immigrant competition provided by formal education. Overall our results suggest a large role for skill-based labor market competition in determining individual attitudes toward immigration.

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1. Introduction

Several European countries have experienced a rapid increase in immigration over the course of the last decade. Immigration poses important challenges to Europe. Will European societies be able to integrate increasing immigrant flows? Will European citizens continue to tolerate growing levels of immigration or will they push instead for a tightening of immigration policies? To a very large extent the answer to these questions depends on voters' own perceptions of the economic and cultural effects of immigration. But what are the determinants of these perceptions? Fueled by these concerns, economic research on migration has of late drawn increasing attention to the study of native attitudes toward immigrants.

Most studies in economics focus on the role of competition in the labor market as a crucial determinant of attitudes toward immigration.[1] Usually the degree of competition between native and immigrant workers is measured in terms of schooling levels. Under the assumption that immigrants are, on average, less educated than natives, it is expected that low-educated natives oppose immigration to avoid depressing their wages. In contrast, being less exposed to competition from immigrants, highly educated natives are expected to be relatively more pro-immigrant. Empirical studies have consistently found a positive association between respondents' educational attainment and pro-immigration views, which has been typically interpreted as evidence that labor-market competition is an important determinant of attitudes toward immigration. However, it must be noted that these correlations do not constitute unequivocal evidence in favor of the labor market exposure hypothesis. As argued by several authors across the social sciences, the positive effect of education on pro-immigration attitudes could be entirely due to values and predispositions associated to schooling, such as tolerance, openmindedness or political correctness, rather than labor market competition per se.[2]

This paper re-examines the role of labor-market competition as a determinant of attitudes toward immigration using individual-level data for a large number of European countries. Our main contribution

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[1] For a review see Mayda (2006).

[2] See Jackman and Muha (1984), Bobo and Licari (1989), Burns and Gimpel (2000), Kingston et al. (2003), Hainmueller and Hiscox (2007), Côté and Erickson (2009), among several others.

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is the use of more sophisticated measures of exposure to immigration in the labor market than typically available. Besides education, we consider two further measures of exposure that are directly linked to the tasks workers perform at their jobs. From an empirical point of view, an attractive feature of these new skill measures is their large variation across jobs and occupations.

Our first new measure of labor-market exposure is a self-assessed measure of job-specific human capital. Workers acquire job-specific skills at their firms via formal training, informal instruction or learning-by-doing. Investing in job-specific skills makes workers less replaceable, regardless of their level of education (Becker, 1993 [1964]; Lazear, 1995). Job-specific human capital thus provides protection against competition from other workers, native and immigrant alike.

Our second measure of labor market exposure is based on *objective* characteristics of respondents' occupations and is motivated by recent work studying how native workers respond to recent immigration. Using US data, Peri and Sparber (2009) show that when immigrants arrive into an economy, native workers mitigate the wage effects of immigration by shifting toward occupations for which they have a comparative advantage. Specifically, immigration induces native workers to shun manual jobs and specialize in communication-intensive occupations.[3] Natives' comparative advantage in such occupations stems from the possession of those skills that immigrants typically lack, in particular, language and other cultural country-specific skills. We hypothesize that native workers employed in occupations that are intensive in manual tasks (communicational tasks) will be more (less) exposed to immigrants' competition and hence less (more) likely to display pro-immigration attitudes.[4]

Following Mayda (2006), we use individual-level data from many countries as a key source of identification. Specifically, we draw on the 2004–2005 European Social Survey.[5] The survey contains several questions regarding opinions on immigration. The data also contain a rich set of individual characteristics, including education, job descriptors, occupation, region of residence within the country and a number of questions on individual values. We also use the US Occupational Network Online Dataset (O*NET) to build measures of the intensity of manual (and interactive) tasks by occupation, following the lead of Autor et al. (2002).

Methodologically, we estimate an econometric model that allows for heterogeneity at the individual, regional, and country level. The dependent variable is a measure of the respondent's views toward immigration and we consider three dimensions of skills: formal education, required job-learning time at the current job net of education (that is, job-specific human capital) and manual/communication-intensity of the current occupation. Each of these dimensions captures a different level of skills (individual, job and occupation) and measures a distinct source of protection from immigrant competition in the labor market. Another important contribution of our study is our treatment of individual heterogeneity. Our analysis explicitly accounts for heterogeneity among natives in their views toward immigration and for potential self-selection into low-immigration jobs. Individual observable heterogeneity is addressed by estimating specifications that include a vector of controls for ideological and attitudinal variation, while self-selection is addressed by using an instrumental-variable approach. Specifically, we use the *regional* availability of low-exposure jobs as an instrument for actual *individual* exposure in the current job, in the spirit of Dustmann and Preston (2001).[6]

Overall our results suggest a larger role for labor market competition as a determinant of individual attitudes toward immigration than previously found. More specifically, we report the following three main findings. First, the limited role for labor market competition (when compared to welfare considerations and non-economic factors) found in earlier studies may have been due to a combination of poor skill indicators and endogeneity problems. Our estimates suggest that individuals with above-average dislike for immigrants tend to work in low-immigration jobs, biasing down OLS estimates of the effects of job protection on attitudes toward immigration. Second, our instrumental-variables estimates show that working in jobs that require high levels of specific human capital increases pro-immigrant attitudes, although this effect seems to operate only at high levels of formal education (employees with more than 12 years of schooling). Third, we find that the degree of manual intensity of workers' occupation is strongly and negatively associated with pro-immigration views. Among our determinants of exposure to immigration, manual intensity in one's current occupation plays the most important role in explaining attitudes toward immigrants.

The paper is organized as follows. Section 2 situates this paper in the context of the previous literature. Section 3 presents the data sources, definitions of variables and descriptive statistics. Section 4 introduces our estimation method and explains how we deal with endogeneity. The main findings are presented in Section 5. Sensitivity analyses are reported in Section 6. Section 7 concludes.

2. Previous literature

Our paper is part of a large and growing body of literature analyzing the determinants of attitudes toward immigration. We can classify the work that is more directly related to our analysis in four main groups.

First, several authors have attempted to quantify the contribution of labor market considerations relative to welfare state considerations and to non-economic factors in explaining attitudes toward immigration. Using factor analysis, Dustmann and Preston (2005) analyze the determinants of immigration attitudes using the 2002 European Social Survey. With a similar methodology, Dustmann and Preston (2007) use data for Great Britain. To identify the role of labor market concerns they employ survey questions on fear of job loss, ease of finding a job, and expected future earnings. The results are similar in both cases. They find that subjective labor market concerns are a significant determinant of attitudes toward immigration. However, fiscal considerations and cultural and racial concerns seem to play a larger role. We note that their labor market variables are not directly related to exposure to competition from immigrants.

Secondly, our paper is closely related to the large empirical literature examining the relationship between individual education levels and attitudes toward immigration. The common finding across all papers listed below is that more educated individuals are more pro-immigration, a finding that is typically interpreted as evidence in favor of the labor-market competition hypothesis. Among the early studies, Espenshade and Hempstead (1996) and Scheve and Slaughter (2001) use data for the US, while Dustmann and Preston (2001, 2005) study the UK. More recently, Mayda (2006) and O'Rourke and Sinnott (2006) have employed individual-level data

[3] Amuedo-Dorantes and De la Rica (2009) conduct a similar study using data for Spain and focus on gender differences.

[4] Supply constraints or job searching costs may limit the number of native workers that can shift from manual to communication-intensive occupations.

[5] Card, Dustmann and Preston (2005) provide a detailed overview of the immigration module in the 2002 European Social Survey. The 2004–2005 survey does not include all the attitudinal questions on immigration that appeared in the 2002 round, but adds crucial information on respondents' job-specific human capital.

[6] Endogeneity concerns of the type addressed in this study are also at the heart of the analysis of Dustmann and Preston (2001). These authors are interested in the effects of ethnic concentration at the local level on individual attitudes toward immigration. To that effect they build an instrument for local ethnic concentration using regional data.

covering several (mostly rich) countries. Mayda (2006) shows that education is more strongly associated to pro-immigration attitudes in countries with higher GDP per capita. She provides a labor-market interpretation for her finding, which is consistent with the factors proportion model. O'Rourke and Sinnott (2006) find a similar result. They also find that non-economic considerations play a larger role than labor market concerns. Facchini and Mayda (2009) study empirically the joint relationship between individual income and education and attitudes toward immigration. They find that in countries with relatively unskilled immigration, individual income is negatively correlated with pro-immigration preferences, while education has a positive effect. They propose a model with endogenous income redistribution that can rationalize this pattern.[7]

In addressing endogeneity in the analysis of attitudes toward immigration our paper connects to the work of Dustmann and Preston (2001) on the effects of ethnic residential concentration at the local level. These authors argue that the location choices of immigrants (and natives) are likely to depend on unobserved determinants of individual attitudes. They propose an instrumental variables approach, where *region*-level ethnic composition is used as an instrument for *local* ethnic composition. Controlling for endogeneity, they find that high local ethnic concentration leads to worse attitudes toward immigration among natives. Their results suggest that ignoring the endogeneity problem leads to underestimating the effect, since it appears that natives that dislike immigrants tend to locate in low-immigration localities.

3. Data

3.1. Sources and definitions

Our main data source is the second round of the European Social Survey (ESS, 2004–2005). It contains information on over 47,000 individuals from 25 countries.[8] In turn each country is subdivided into regional units. We restrict our sample to currently employed individuals in age bracket 18–64 who are citizens in the respective country of residence in 2004. As will become clear later, within-country regional variation will be central to our identification strategy. As a result, we need to drop those countries that are not subdivided into regional units, as well as those with missing data for our main variables. Our resulting sample covers over 16,000 individual observations from the following 19 countries: Austria, Switzerland, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Great Britain, Hungary, Ireland, the Netherlands, Norway, Poland, Portugal, Sweden, Slovakia and Slovenia (see Table 1).

In line with the existing literature, our dependent variable measures respondents' desired levels of immigration in their countries. The ESS contains three related questions, referring to immigrants from different ethnicities.[9] In each question, the respondent is asked about his or her desired immigration level. There are four possible responses: allow many more to come into the country, allow some, allow a few, or allow none. We re-scale each variable so that higher values mean higher support for immigration: 25 (none), 50 (a few), 75 (some), and 100 (many). Our main dependent variable is a pro-immigration index built by averaging the scores in these three questions. We will also examine the robustness of our results to alternative dependent variables based on each of the three attitudinal questions separately. In addition we also present results based on a dichotomous dependent variable.

An important variable in our analysis is the specific human capital required by the respondent's job. The question is subjective in nature yet the wording of the question has been chosen to minimize self-reporting bias. Specifically, the ESS asks respondents: "*If someone with the right education and qualifications replaced you in your job, how long would it take for them to learn to do the job reasonably well?*" Note also that the question clearly differentiates between general (education and qualifications) and job-specific human capital. The original question allows for eight possible answers, detailing intervals of time expressed in days, weeks, months or years. Based on this information we create a numerical variable expressed in months that can be used in a regression framework. We shall denote our variable by SHK (specific human capital). Interestingly, the correlation coefficients between specific human capital and the rest of the skill measures used in this study are very low: the correlation with years of education is 0.14.[10]

By the subjective nature of the question on specific human capital, one may be concerned about the comparability of this measure across countries. For instance, if differences in social norms across countries affected workers' self-reporting, two individuals performing the exact same occupation in two different countries could report substantially different job learning times.[11] In order to address this concern we have compared the occupational rankings by job-learning time across the countries in our sample. The correlation coefficients across the country rankings are very high (around 0.8 on average). This suggests that there is a strong consistency in workers' perceptions of the specific human capital required in their jobs across the countries in our sample. Further details on the consistency of the SHK indicator across countries can be found in Appendix 4.

Additionally, we measure workers' degree of exposure/protection to labor market competition from immigrants by considering the task-content of their occupations. Unlike the job-specific human capital measure just described, these measures are based on objective assessments of the tasks performed by workers in each occupation.[12] Following Peri and Sparber (2009), we build measures of manual and communication skills using the O*NET dataset, which provides very detailed information of the task-content of occupations in the US. The O*NET covers 449 detailed occupations and provides 277 descriptors for each occupation. Each descriptor consists of a score ranging from 0 to 1 for each dimension of skill or ability considered. These scores are collected by occupation analysts and are constantly updated by ongoing surveys of each occupation's worker population and external occupation experts.[13] We proceeded as follows: first, we used exploratory factor analysis to identify our skill dimensions of interest out of the 277 descriptors available in the dataset. Informed by this analysis, we constructed two different measures. The first measure is an index that tells us how important *manual dexterity and physical skills* are in each occupation. For each occupation of the dataset, this index simply averages the scores rating the task-importance and the mean observed abilities of 7 different skills previously identified (by factor analysis) as part of the same skill dimension: visualization, arm-hand steadiness, manual dexterity, finger dexterity, control precision, wrist-finger speed and visual color discrimination. The second measure captures, in turn, how intensive in

[7] Another theoretical model analyzing the determination of attitudes toward immigration in the presence of an endogenously determined welfare state is Ortega (2010), which builds on the dynamic political-economy model by Ortega (2005).

[8] The second round of the ESS was carried out between 2004 and 2005. We use this dataset because it includes information on job-learning time. Although Italy took part in this round of the ESS, the questionnaire implemented by the Italian team did not include the question on job-learning time. For more details see http://www.europeansocialsurvey.org/.

[9] The specific questions posed to the respondents can be found in the Appendix.

[10] The correlation with the measures of manual intensity and communicational intensity, defined below, is also very low: −0.013 and 0.16, respectively.

[11] We thank an anonymous referee for pointing this out.

[12] The literature on the task-content of occupations was pioneered by Autor et al. (2002, 2006). Current work on job polarization also builds heavily on this type of data, as in Autor and Dorn (2011).

[13] For more details see http://online.onetcenter.org/.

Table 1
Descriptive statistics.

Country	Obs	Fraction Pro-immigration	Pro-immig. index	Years of education	Job-learning time (SHK) in months	Manual intensity index	Comm. intensity index	Age	Fraction female	Fraction with children	Fraction rural	Fraction mother foreign-born
Portugal	786	0.42	54.9	9.4	3.9	0.52	0.45	39.7	1.53	0.54	0.25	0.02
Hungary	613	0.43	52.4	12.3	11.3	0.56	0.46	41.0	1.51	0.60	0.32	0.03
Estonia	751	0.53	57.1	13.5	5.1	0.55	0.45	41.7	1.56	0.58	0.32	0.16
Czech Rep.	1067	0.58	60.1	12.9	6.5	0.59	0.44	43.0	1.45	0.51	0.26	0.06
Finland	1005	0.61	62.7	13.7	11.2	0.53	0.51	43.5	1.49	0.49	0.41	0.01
Great Britain	842	0.64	63.4	12.8	11.7	0.51	0.52	41.5	1.49	0.47	0.21	0.11
Spain	699	0.65	68.1	13.1	8.2	0.51	0.49	39.9	1.39	0.50	0.42	0.02
Austria	910	0.67	65.4	12.8	6.8	0.50	0.50	41.0	1.48	0.53	0.43	0.07
Germany	1130	0.69	65.0	14.1	8.7	0.52	0.51	43.4	1.45	0.47	0.29	0.07
Slovenia	598	0.70	66.3	12.4	13.2	0.58	0.46	39.9	1.47	0.67	0.52	0.13
Netherlands	832	0.70	65.4	13.5	10.5	0.48	0.56	43.1	1.46	0.41	0.42	0.10
France	818	0.71	66.0	12.8	13.3	0.51	0.52	41.4	1.51	0.53	0.35	0.11
Denmark	771	0.78	67.4	14.4	9.6	0.52	0.54	43.7	1.49	0.51	0.27	0.05
Slovakia	633	0.78	69.9	12.9	7.0	0.57	0.46	40.2	1.41	0.66	0.43	0.04
Ireland	989	0.79	71.2	13.4	8.0	0.53	0.50	41.5	1.48	0.51	0.45	0.02
Poland	687	0.80	70.5	12.9	9.0	0.58	0.44	39.1	1.44	0.66	0.37	0.02
Norway	1001	0.82	70.1	13.9	9.6	0.51	0.52	43.8	1.44	0.52	0.43	0.06
Switzerland	947	0.84	71.6	10.9	7.1	0.52	0.54	43.2	1.47	0.36	0.63	0.14
Sweden	1029	0.90	79.1	13.1	8.8	0.54	0.51	43.5	1.45	0.51	0.32	0.11
Total	*16,108*	*0.70*	*66.3*	*13.0*	*8.9*	*0.53*	*0.5*	*41.6*	*0.50*	*0.51*	*0.36*	0.07

Notes: The pro-immigration index is our main dependent variable. It is an average of the three questions on the desired immigration level and ranges between 25 and 100. The fraction of pro-immigration individuals is the fraction in each country that supports allowing many or some immigrants to come into the country. Our sample excludes the following countries. Italy and Romania are not included because they lack information on job-specific human capital. We exclude Iceland and Luxembourg for being one-region countries. The Eurostat has no regional Census data on the foreign-born population for year 2001 for Belgium, Greece, Turkey and Ukraine so we also exclude them. The countries in the table have been sorted from less to more pro-immigration (based on the fraction of individuals in each country reporting that they want more immigration). See appendix for detailed definitions of all variables. Source: ESS 2004–2005.

communication tasks a particular occupation is. This is done by averaging the task-importance and the mean observed ability scores of the following 6 skills: oral comprehension, oral expression, written comprehension, written expression, speech recognition, and speech clarity. These two indices are then matched to ISCO-88 occupations (4 digits).[14] Further details on the construction and merging of O*NET scores can be found in Appendix 2.

In the O*NET dataset the two indices of manual and communication intensities are strongly negatively correlated, with a coefficient of correlation equal to −0.54. In the ESS data the correlation goes up to −0.63. This high correlation implies that, effectively, there is an important overlap in the information contained in both variables. In this sense, we view both of these indices as measures of the relative communication-manual intensity in each occupation. Given their high (negative) correlation we shall only include them one at a time in our regressions to avoid issues of high collinearity.

Implicitly, by relying on the O*NET dataset, we are assuming that the task-content of occupations in the US and in our sample of European countries is similar in relation to these two basic skill dimensions.[15] While this is a strong assumption, data limitations prevent us from observing the task-content of occupations in each country.[16] As we shall argue later, the inclusion of country-fixed effects in our regression models alleviates this problem. In other words, our source of identification will be within-country variation at the regional and individual levels.

Finally, an important control variable in our regression models is the fraction of immigrants in one's region of residence. These data have been obtained from the 2000/2001 national Censuses assembled by the Eurostat and subsequently matched to the ESS data.

3.2. Descriptive statistics

As can be seen in Table 1, the mean pro-immigration index in our sample is 66.3 and 70% of the individuals in the sample are pro-immigration, defined as reporting that we should allow some or many immigrants to come to live in the country.[17] However, it is interesting to note that there is substantial variation across countries. While 42% of Portuguese are pro-immigration, the corresponding figure is 90% for the Swedes (column 2).[18]

Let us now turn to the main explanatory variables. As shown in column 4, the mean value of education across all countries is 13 years, with substantial cross-country variation. The mean value across all countries for specific human capital (SHK), measured as the amount of time needed for someone with the right qualifications to learn to do the job, is 8.9 months (Table 1, column 5), ranging from 3.9 months for the average worker in Portugal to 13.3 in France.

The other key variables in our analysis are the indices of manual-dexterity skills and communication skills by occupation. By construction, these indices take values between zero and one. As seen in Table 1 (column 6), the mean value for the manual-dexterity skills index ranges from 0.48 in the Netherlands to 0.58 in Poland and 0.59 in the Czech Republic. The next column reports the country means for the index of communication skills, which ranges from 0.44 in the Czech Republic and in Poland to 0.56 in the Netherlands. Observe that the top of the ranking by communication skills coincides with the bottom by manual skills, and vice versa, consistent with the strong negative correlation between the two variables reported earlier. Table 1 also

[14] The authors are grateful to Jane Elliott and Vania Gerova (Centre for Longitudinal Studies, Institute of Education, University of London) for making their occupational crosswalk publicly available,. See further details in Appendix 2.

[15] Unfortunately, the analog of the O*NET for European countries does not exist. Germany and the UK have occupation surveys that provide information on the task-content of occupations but these data are not directly comparable to the O*NET. Nevertheless Spitz-Oener (2006) analyzes the German Qualification and Career Survey and concludes that the changes in the task-content of occupations experienced by the US in the last two decades can also be observed in the German data, suggesting some similarity between the task-occupation mapping in the two countries. Felstead et al. (2007) analyze the British Skill Surveys, which are analogous to the German survey.

[16] Among others, Goos et al. (2009) and D'Amuri and Peri (2011) also impose the O*NET task-content on occupational data for European countries.

[17] When asked about immigration from a different ethnic group as the current majority in the population or immigration from poor countries outside Europe the fraction of pro-immigration individuals falls to 53% and 50%, respectively.

[18] The countries in Table 1 have been ranked by the fraction of pro-immigration individuals in each country.

Table 2
The top 10 occupations according to average years of education, average job-specific human capital (job-learning time), average manual-dexterity scores and average communicational intensity scores.
Source: ESS 2004–2005 and O*NET.

Education (in years)	*Mean*	Job-specific human capital (in months)	*Mean*
Physicists, Chemists and related professionals	20.8	Riggers and cable splicers	73
Medical Doctors	19.4	Photographic-products machine operators	42.6
Biologists, botanists, zoologists and related	18.7	Farming and forestry advisers-technicians	39.6
Higher education teaching professionals	18.4	Tobacco preparers and tobacco products makers	38.6
Judges	17.8	Aircraft engine mechanics and fitters	38.4
Veterinarians	17.6	Wood processing and paper-making plant operators	36.6
Lawyers	17.6	Physical, mathematical and engineering science professors	34.5
Dentists	17.4	General managers of small enterprises	31.9
Psychologists	17.4	Upholsterers and related workers	27.6
Mathematicians and related professionals	17.1	Production and operations managers in agriculture, hunting, forestry and fishing	26.5
Manual-dexterity and physical skills	*Score*	Communicational skills	
Building and related electricians	0.971	Legislators and senior government officials	0.95
Jewelry and precision metal workers	0.966	Personnel and industrial relations managers	0.93
Metal wheel-grinders, polishers and tool sharpeners	0.938	Medical doctors	0.903
Pelt dressers, tanners, fell mongers and shoemakers	0.929	Production and operations managers in construction	0.898
Musical instrument makers and tuners	0.926	Legal professionals	0.896
Dentists	0.924	Psychologists	0.892
Aircraft engine mechanics and filters	0.923	Advertising and public relations managers	0.889
Aircraft pilots and related associate professionals	0.918	Production and operations managers not elsewhere classified	0.886
Assemblers	0.917	College, university and higher education teaching professionals	0.875
Miners, shot-firers, stone cutters and carvers	0.914	Veterinarians	0.861

Notes: Average years of education in occupation and average job-learning time in occupations calculated using ISCO-88 4-digit coding. Average communication intensity and manual intensity scores calculated using crosswalk from US 2000 Census-Occupations into ISCO-88 4-digit coding.

reports a number of individual-level variables that we will use to control for observable individual heterogeneity in immigration views. These variables are age, gender, and dummy variables for the presence of children in the house, for living in a rural area, and for having a foreign-born mother. Although not shown in the Table, some of our specifications will also control for several attitudinal variables regarding respondents' individual values on ideology, religiosity, and so on.

To provide some insight into what is captured by our measures of manual-dexterity and communication skills, we next compare the samples of individuals currently employed in manual-intensive occupations (75 percentile) to those in communication-intensive occupations (75 percentile). We find that, on average, workers employed in occupations intensive in manual-dexterity skills have 2.6 fewer years of education, and 77 fewer days of job-learning time. Furthermore, Table 2 reports the top 10 occupations ranked, respectively, by their average years of schooling, average job-specific human capital (job-learning time), average manual intensity scores and average communicational intensity scores. These rankings illustrate well the different skill dimensions captured by our indicators. Note, for instance, that the top occupations in terms of manual dexterity intensity include both examples that require high levels of formal education (e.g. dentists and aircraft pilots) as well as examples only requiring a few years of education (e.g. miners, assemblers, and building electricians). Similarly, in the top jobs ranked according to job-learning time we find both high-education (e.g. physical, mathematical and engineering science professors) as well as low-education examples (e.g. riggers and cable splicers). Only the comparison between the top education and top communicational intensity occupations suggests a high degree of correlation between both dimensions, which is indeed the case (0.47).

4. Estimation

4.1. Econometric model

We estimate linear regression models.[19] Our dependent variable $IM_{i,r,c}$ is the average response of individual *i* living in region *r* and country *c* to the three questions on the desired level of immigration, with higher values associated to higher desired levels of immigration. Our model attempts to explain individual variation in this variable employing several models of the form:

$$IM_{irc} = \alpha_c + \beta_1 Edu_{irc} + \beta_2 SHK_{irc} + \beta_3 Manual_{irc} + \delta FB_{rc} + X'_{irc}\lambda + v_{irc} \quad (1)$$

where the right-hand side contains country-specific intercepts, years of education, job-specific human capital (SHK), manual (or communication) intensity, the share of foreign-born in the respondent's region of residence, and a set of individual controls.[20] The vector of controls always includes age, age squared, gender, and dummies for the presence of children in the household, living in a rural area, and having a foreign-born mother. Occasionally, we will also introduce a set of additional controls for individual values that may be relevant to account for the respondent's views on immigration (ideology, religiosity, happiness, trust, and social capital).[21] Finally, we allow the error term to be correlated across individuals living in the same region.

We note that by virtue of including country fixed effects in the regression model, identification is based on individual variation within countries. In other words, even if there are country differences in, say, social norms or institutions affecting self-assessments of job-learning time, those differences will be at least partially absorbed by the country fixed effects. We also note that including the regional foreign-born share in the vector of controls is potentially important.[22] In its absence, our estimates might suffer from omitted-variable bias. It is easy to imagine that living in a region with high immigrant density affects one's views toward immigration in a manner unobserved by the econometrician. At the same time regional immigration levels may possibly influence the respondent's occupational choices, as

[19] Using linear regression models simplifies the assessment of our instrumental variables strategy.

[20] In principle it would be possible to include region-specific intercepts. We shall do so in one of our OLS specifications. However, given the definition of our instrument, only country-specific intercepts can be included in our instrumental-variables specifications.

[21] We are aware that some of these attitudinal variables may be endogenous. To evaluate this concern we will estimate all our main specifications with and without the vector of attitudes.

[22] We thank an anonymous referee for pointing this out.

demonstrated by Peri and Sparber (2009) using US data. It is thus crucial to control explicitly for the regional foreign-born share.

As argued above, together with general skills, job-specific human capital should provide protection against labor-market competition from immigrants, while manual-dexterity skills should increase exposure to competition. Hence we expect the coefficient on years of education and on job-specific human capital to be positive, and the coefficient for manual-dexterity intensity to be negative. In some specifications we will replace manual-dexterity intensity with communication intensity. Naturally, in that case we will expect a positive coefficient since communication intensive occupations should be more protected from immigrant competition.[23]

The literature on comparative advantage between natives and immigrant groups focuses on low-education individuals (Peri and Sparber, 2009; Amuedo-Dorantes and De la Rica, 2009). In order to better compare our results to those studies, as well as to investigate possible interactions between our new skill measures and education, we will also estimate our main models on two subsamples of similar size: one comprising individuals with more than 12 years of schooling and the other comprising individuals with less than 13.

4.2. Endogeneity

We are concerned that individuals that particularly dislike immigration may search more intensively for jobs and occupations with few immigrants. These jobs and occupations will tend to display a high degree of protection from competition from immigrants. As a result, OLS estimates of our coefficients of interest are likely to be biased.

Our strategy to deal with this endogeneity problem is to use instrumental variables. Specifically, we postulate that individuals living in a region where there is a high availability of highly protected jobs are more likely to end up in one of these jobs than a comparable individual in a region where low-exposure jobs are scarce. Thus we propose to use a skill-based measure of the *regional* availability of protected jobs as an instrument for the degree of protection in an *individual*'s current job. For instance, we instrument the degree of specific human capital in an individual's job by the average specific human capital among all workers in his or her region of residence. Our identifying assumption is that natives do not sort into regions (or countries) based on their views on immigration.[24] Similarly, and in line with the literature, we also assume that educational attainment is not determined by one's views over immigration.

Let us now examine the relevance of our instrument. Table 3 reports the results of the first-stage regressions. In column 1 the dependent variable is SHK, our measure of job-specific human capital. The right-hand side of the regression contains country-specific dummies, a series of controls (not shown in the Table) that include years of education, and the average regional values of SHK and manual-dexterity intensity.[25] The point estimate associated to the average SHK is 0.93 and the F test of the excluded instruments is 632.1, which allows us to reject the null of weak instruments. Hence, our instrument is highly relevant: individuals residing in a region with a large availability of jobs requiring high specific human capital are more likely to end up in such jobs, provided that they have the right education level. Column 3 reports an analogous regression where average manual-dexterity intensity in the region has been replaced by the average communication intensity, delivering similarly strong results. Columns 2 and 3 report the first-stage regressions where the dependent variables are, in turn, our measures of manual-dexterity intensity and communication intensity. As expected, each one is strongly predicted by the respective regional average. In addition, the values of the F-statistics imply that we can clearly reject the null hypothesis of weak instruments in both instances.

Table 3
First-stage regressions.
Source: ESS 2004–2005.

Dep. var.	(1)	(2)	(3)	(4)
	SHK	Manual	SHK	Comm.
Average SHK region	0.935***	0.00116*	0.956***	−0.000151
	[0.0252]	[0.000607]	[0.0250]	[0.000828]
Average manual region	4.542***	0.729***		
	[1.423]	[0.0337]		
Average comm. region			−4.850***	0.589***
			[1.213]	[0.0428]
Observations	12,637	12,364	12,637	12,364
R-squared	0.106	0.206	0.106	0.327
F excluded instruments	632.1	235.5	537.1	97.7

Notes: The dependent variables are specific human capital (SHK), a measure of the communication-intensity in the current occupation (Comm.), and a measure of the manual intensity of the current occupation (Manual). The main explanatory variables are the regional averages of these variables in the individual's region of residence. All regressions include a constant, country fixed effects, years of education, controls for age, age squared, and dummy variables for having children, as well as controls for individual values (ideology, religiosity, happiness, trust and social capital). These regressions have been estimated using only regions with more than 25 observations. Standard errors clustered by region and robust to heteroskedasticity. In total, 167 regional clusters have more than 25 individual observations (out of a total of 216 regions in our sample).
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

5. Main results

This section presents our estimates of the regression model in Eq. (1). We start by estimating a model where job-specific human capital and years of education are the measures of exposure to immigration that are included. Next, we consider a model based on education and manual (communication) intensity as measures of exposure. Finally, we estimate our main model, where education, specific human capital and manual (communication) intensity are all simultaneously included. In all models we include country fixed effects and the set of individual controls described earlier.

5.1. Job-specific human capital

We are interested in testing the following hypothesis. Individuals employed in jobs characterized by high requirements of specific human capital hold more favorable views on immigration. This is because job-specific skills protect insider native workers from outside competition. We estimate the regression model described in Eq. (1), where the measures of exposure to immigration are years of education and specific human capital.

Table 4 presents both OLS (columns 1–4) and IV estimates (columns 5–8). As a benchmark, column 1 reports the OLS estimate of a regression where attitudes toward immigration are solely a function of years of education and individual controls. As expected, the education coefficient is positive and significant. The following columns include the main explanatory variable, job-specific human capital. The

[23] Given the high (negative) correlation between communicational and manual intensity, we only include them separately.

[24] Geographic worker mobility in Europe remains low, compared to the US. Nickell (1997) reports that while about 3% of American households change their region of residence in a given year the analogous figure is closer to 1% in the UK, Germany and France, and even lower in southern European countries. Using data for Spain, Gonzalez and Ortega (2010) show that immigration does not seem to affect, in general, the size of sectors and industries at the regional level. Farré et al. (2011) show that one important exception is the unskilled-intensive sector of household services.

[25] Standard errors are heteroskedasticity-robust and have been clustered at the region level. These regressions have been estimated using only regions for which we have at least 25 individual observations.

Table 4
Job-specific human capital (SHK).
Source: ESS 2004–2005.

Estimation sample	1	2	3	4	5	6	7	8
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
	All	All	All	All	All	All	High edu > 12 years	Low edu < 13 years
Years edu	1.237***	1.255***	1.096***	1.097***	1.214***	1.054***	0.995***	0.625***
	[0.0601]	[0.0633]	[0.0596]	[0.0560]	[0.0924]	[0.0894]	[0.130]	[0.191]
shk_months		−0.000460	0.00285	0.00153	0.0676	0.0740	0.228*	−0.0600
		[0.0129]	[0.0126]	[0.0126]	[0.117]	[0.114]	[0.131]	[0.158]
Obs	16,091	13,273	13,179	13,179	13,273	13,179	6719	6460
R-squared	0.155	0.158	0.203	0.231	0.156	0.201	0.150	0.160
Fixed effects	Country	Country	Region	Country	Country	Country	Country	Country
Ind. values	No	No	Yes	Yes	No	Yes	Yes	Yes

Notes: Dependent variable is the pro-immigration index, taking values between 25 and 100. It is an average of the three questions on the desired immigration level. SHK stands for specific human capital (job-learning time in months).
All regressions are weighted using the ESS-provided design weights and include a constant and controls for age, age squared, the regional foreign-born share, and dummy variables for having children, living in a rural area, and having a foreign-born mother. Specifications with controls for individual values include ideology, religiosity, happiness, trust and social capital. Standard errors, in brackets, clustered by region and robust to heteroskedasticity.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

OLS estimates are positive but small and we cannot reject a value of zero (columns 2–3). Column 4 includes region fixed effects, which hardly affect the estimates obtained in column 3.

Columns 5 through 8 present our IV estimates. Column 5 shows that the IV estimates of the SHK coefficient are larger than the OLS, although we still cannot reject the zero value. Column 6 adds the vector of attitudinal variables. Note that these additional controls reduce the effect of education by roughly 13% but do not seem to affect our estimate for job-specific human capital. Yet again, we cannot reject the null hypothesis that the estimated impact of SHK on pro-immigration attitudes is different from zero.

Models 1 through 6 assume that the impact of SHK on pro-immigration views is the same for different educational levels. We now relax that assumption by splitting the sample in two large educational groups: those with more than 12 years of schooling (column 7) and those with less than 13 years (column 8). Each of these two large educational groups accounts roughly for one half of the total sample size. Such splitting still allows for within-group variation in years of schooling. Column 7 reveals a large coefficient for SHK among respondents with more than 12 years of schooling at the 90% level. In contrast, for respondents with less than 13 years of education we find a negative, close to zero and non-significant effect of SHK on pro-immigration views (column 8).

In sum, our estimates suggest that SHK may play a significant role in determining attitudes toward immigration, but only for respondents with at least 12 years of schooling (we discuss the magnitude of the estimates for all the skill measures in Section 6.1).

5.2. Communicational and manual-dexterity skills

We have argued that job-specific human capital should provide protection toward all outsiders to the job, natives and immigrants alike. Here we try to be more specific and focus on a characteristic that only offers protection toward recent immigrants, but not toward natives or immigrants that are already fully assimilated. Building on Peri and Sparber (2009), we hypothesize that individuals employed in manual-intensive occupations will be relatively less pro-immigration because they are more exposed to competition with non-natives. Conversely, individuals employed in occupations that are intensive in communicational tasks are expected to be relative more pro-immigration since communication skills protect them from competition.

The top panel in Table 5 presents the results from estimating a version of Eq. (1) that includes measures of manual skill intensity and years of education but excludes specific human capital. Columns 1–4 report OLS estimates. Compared to column 1, when we introduce our index of manual intensity, the coefficient on years of education falls but remains highly significant. In turn, the OLS point estimate associated to manual skills is negative and highly significant, with values roughly between −6 and −5. Columns 5 and 6 present our IV estimates. As was the case for job-specific human capital (Table 4), IV estimates are substantially higher (in absolute value) than OLS estimates, with a value of −23.76 in column 5. We also note that accounting for potential endogeneity reduces the effect of education substantially, although it remains significant. Column 6 shows that controlling for individual values reduces the effect of education even further but does not affect our estimate of the effect of manual-dexterity skills. Finally, columns 7 and 8 present the results of splitting the sample in two educational groups. The effect of manual intensity is of similar strength in both subsamples.

Moving down to Panel B, we consider an analogous set of models where manual skill intensity has been replaced by communication intensity. The results largely confirm the findings in the previous paragraph. Respondents in occupations requiring high levels of communicational intensity are significantly more pro-immigration than observationally equivalent individuals employed in occupations less intensive in communication. Turning directly to the IV estimates (columns 5 and 6), we find highly significant coefficients for communication intensity with point estimates between 18 and 19. It is worth noting that the point estimates for years of education are now lower than in Panel A and that the effect of communication intensity is somewhat larger for the high education subsample (24.4) than it is for the low (16.4). We also note that the coefficient on years of education is less precisely estimated than in the previous panel. This is due to the fact that communication intensity is more correlated with education than manual intensity. Respectively, the correlation coefficients are 0.47 and −0.26. As a result, it seems that our indicator of relative manual intensity is more useful in separately identifying the effect of education from that of communication/manual skills.[26]

[26] When both manual and communication intensities are included jointly as regressors the former tends to be more highly significant. However, we suspect that multicollinearity problems arise due to the high (negative) correlation between the two variables.

Table 5
Communication and manual intensity in current occupation.
Source: ESS 2004–2005.

Specification estimation sample	1	2	3	4	5	6	7	8
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
	All	All	All	All	All	All	High edu	Low edu
Panel A: manual intensity								
Years edu	1.237***	1.144***	0.992***	1.006***	0.844***	0.655***	0.759***	0.203
	[0.0601]	[0.0587]	[0.0538]	[0.0506]	[0.126]	[0.118]	[0.160]	[0.181]
Manual		−5.835***	−5.809***	−5.381***	−23.76***	−26.35***	−27.97***	−26.21***
		[0.911]	[0.891]	[0.884]	[7.322]	[6.908]	[9.404]	[9.119]
Obs.	16,091	15,699	15,565	15,565	15,699	15,565	7789	7776
R-squared	0.155	0.160	0.205	0.229	0.127	0.162	0.131	0.121
Panel b: communication intensity								
Years edu	1.237***	0.969***	0.838***	0.852***	0.610**	0.435*	0.335	0.157
	[0.0601]	[0.0639]	[0.0599]	[0.0565]	[0.283]	[0.264]	[0.374]	[0.265]
Comm.		7.829***	7.308***	7.035***	18.16**	19.08**	24.41**	16.36*
		[0.851]	[0.867]	[0.861]	[8.223]	[7.733]	[10.74]	[9.037]
Obs.	16,091	15,699	15,565	15,565	15,699	15,565	7789	7776
R-squared	0.155	0.163	0.208	0.232	0.151	0.192	0.154	0.156

Notes: Dependent variable is the pro-immigration index, taking values between 25 and 100. It is an average of the three questions on desired change in immigration level. High education is more than 12 years; low education is less than 13.
All regressions are weighted using design weights and include a constant and controls for age, age squared, the regional foreign-born share, and dummy variables for having children, living in a rural area, and having a foreign-born mother. Specifications with controls for individual values include ideology, religiosity, happiness, trust and social capital. Standard errors, in brackets, clustered by region and robust to heteroskedasticity.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

5.3. All measures of exposure simultaneously

In this section we estimate regression model (1) including all our measures of exposure to competition from immigrants. Specifically, our explanatory variables are years of education, specific human capital and manual (communication) intensity. In addition all specifications feature country fixed effects and a series of individual controls.

Table 6 reports our findings. Column 1 reports OLS estimates for a specification including formal education, job-specific human capital

Table 6
Education, Job-specific human capital, and manual-communication intensity.
Source: ESS 2004–2005.

Estimation sample	1	2	3	4	5	6	7	8
	OLS	IV	IV	IV	IV	IV	IV	IV
	All	All	All	High edu (>12 years)	Low edu (<13 years)	All	All	All
Years edu	0.980***	0.658***	0.449***	0.478**	0.0613	0.118	−0.0454	0.399**
	[0.0604]	[0.184]	[0.170]	[0.224]	[0.251]	[0.303]	[0.288]	[0.157]
SHK	0.00225	0.0972	0.104	0.241*	−0.0173	0.0388	0.0580	0.120
	[0.0128]	[0.119]	[0.115]	[0.126]	[0.165]	[0.117]	[0.114]	[0.111]
Manual	−6.283***	−28.98***	−32.18***	−33.01***	−32.52***			−34.37***
	[0.932]	[8.450]	[7.851]	[11.13]	[10.32]			[7.238]
Comm.						26.55***	30.81***	
						[7.988]	[7.681]	
FB share	11.09**	3.349	4.669	11.02**	−5.432	7.032		
	[4.854]	[5.145]	[4.662]	[5.200]	[6.671]	[4.723]		
Female	−1.445***	−2.839***	−3.695***	−2.464**	−4.967***	−2.377***	−2.566***	−3.838***
	[0.417]	[1.034]	[0.955]	[1.125]	[1.558]	[0.788]	[0.772]	[0.891]
Rural	−2.011***	−1.196***	−1.213***	−1.299**	−1.247**	−1.245***	−1.125**	−1.172***
	[0.383]	[0.460]	[0.456]	[0.628]	[0.589]	[0.483]	[0.461]	[0.427]
FB mother	2.755***	3.497***	3.397***	2.561***	4.340***	3.547***	3.927***	3.643***
	[0.681]	[0.773]	[0.767]	[0.980]	[1.132]	[0.807]	[0.775]	[0.728]
Obs.	12,893	12,983	12,893	6583	6310	12,893	14,143	14,143
R-squared	0.209	0.111	0.139	0.072	0.108	0.169	0.147	0.130
Fixed effects	Country	Country	Country	Country	Country	Country	Country	Country
Ind. values	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the pro-immigration index, taking values between 25 and 100. All regressions are weighted using the ESS design weights and include a constant and controls for age, age squared, and a dummy variable for having children (not shown). Specifications with controls for individual values include ideology, religiosity, happiness, trust and social capital.
Standard errors, in brackets, clustered by region and robust to heteroskedasticity.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

and the manual-dexterity intensity of the occupation. Column 2 estimates the same specification by instrumental variables. Column 3 adds our vector of individual values. Across this specifications, the coefficient on years of education falls from 0.98 (column 1) to 0.45 (column 3). Controlling for individual values alone reduces the effect of formal education by 32% (see columns 2 and 3). This is consistent with the interpretation that formal education is a vehicle for the transmission of values and ideologies that are associated with pro-immigration views.

Regarding job-specific human capital, the coefficient is very small and non-significant in OLS regressions. SHK increases considerably in size in the IV estimates but it only reaches statistical significance at the 90% level when the sample is restricted to respondents with more than 12 years of education (column 4). We note that this effect of SHK for the highly educated is roughly six times larger than that of years of schooling, when both are measured in the same time units.[27]

Across these specifications, the main finding is the very strong negative effect of manual-dexterity intensity. The estimates in columns 4–6 clearly show that workers employed in occupations that require high levels of manual skills report more negative attitudes toward immigration. We note that the IV estimate for this variable is larger in absolute value than the corresponding OLS estimate, suggesting downward bias in OLS.[28] We also note that manual intensity has a comparable effect at high and low levels of education. Note finally that women and individuals living in rural areas have less pro-immigration views than comparable men and individuals living in cities. Also, having a foreign born mother increases pro-immigration attitudes. The effect of the foreign born share of respondents' region is positive and significant in some, but not all, specifications.

In column 6 the full specification model is re-estimated using communicational intensity instead of manual-dexterity intensity. Communicational intensity has a large positive effect on pro-immigration attitudes, yet this effect is somewhat smaller in absolute terms than the effect found when using manual dexterity. Also note that communicational intensity absorbs virtually all the effect of formal education and a substantial part of the effect of SHK, none of which is significant in this specification. Communicational intensity also has the same effect for high and low-levels of education (not shown).[29]

Thus, the two new skill-based measures of exposure to immigrant competition that we have analyzed seem to have significant and distinct effects on individual attitudes toward immigration. We find that the effect of job-specific human capital seems to be restricted to individuals with high education. This is not the case for our task-specific measures, which are clearly significant across the educational spectrum (the magnitude of the estimates for all the skill measures is discussed in Section 6.1 below).

We conclude this section with a brief note on the direction of the endogeneity bias. As it is clear in Table 6, the IV estimates for our measures of skill-based protection from immigration other than schooling (SHK and manual and communication intensity) are larger in absolute terms than the corresponding OLS estimates.[30] Our interpretation for the downward bias in the OLS estimates of SHK and communication intensity is that individuals who dislike immigrants search more intensively for jobs that are highly protected from immigration. As a result individuals sort into jobs that, given their qualifications, require higher job-specific human capital or are more intensive in communication tasks. Analogously, the OLS estimate for our measure of exposure to competition from immigrants (manual intensity) is upwardly biased for the same reason.[31] It is interesting to note that the endogeneity bias that we uncover is similar to the one documented by Dustmann and Preston (2001). Their results suggest that individuals sort spatially according to their attitudes toward minorities.

6. Robustness

We now conduct sensitivity analysis on our main results. First, we examine whether our treatment of pro-immigration attitudes as a continuous variable is driving our results. Second, we experiment with alternative definitions of our pro-immigration index.

6.1. Dichotomous dependent variable

The original ESS questions on immigration attitudes are categorical. However, in our analysis we have treated them as a numerical, continuous variable. One may be concerned that such treatment may impose a non-existing linearity on the outcome variable. In the spirit of Dustmann and Preston (2001), we deal with this concern by transforming the outcome variable into a dichotomous variable that has a value of one when the individual supports admitting some or many more immigrants, and zero otherwise. We then estimate linear probability models on this transformed variable.

The results are summarized in Table 7, which is directly comparable to Table 6. Broadly speaking, the results emerging from this table are highly consistent with those in Table 6. Namely, the most highly significant determinant of attitudes toward immigration is the manual/communicational intensity in the respondents' current occupations. Secondly, job-specific human capital also appears to play a positive and significant role but only for individuals with more than 12 years of schooling (column 4). Finally, education appears to have a small, positive effect, once the other measures of exposure are included in the regression. Unlike in Table 6, the IV estimate of the effect of education is not significantly different from zero when models include controls for individual values (columns 3 to 8).

Using the estimates in column 3 (Table 7), let us now provide an idea of the magnitude of the effects of education, specific human capital and manual intensity on the determinants of pro-immigration attitudes. Specifically, we compute the effect on the probability of being pro-immigration associated to a one standard deviation increase in years of education, job learning time (SHK), and manual intensity. Respectively, the standard deviations of these variables are 3.5 years, 13.9 months and 0.21 points.[32] The resulting increases in the probability of being pro-immigration are 2.1, 6.2, and negative 13.6 percentage points. On the basis of these figures we conclude that the relative manual intensity of the respondent's occupation is the main determinant of pro-immigration attitudes in a quantitative sense.

[27] Recall that SHK is measured in months whereas education is measured in years.

[28] Besides the endogeneity bias discussed earlier, the OLS estimate is likely to suffer from substantial attenuation bias. Our measure of manual intensity in the respondent's current occupation is a bit rough. For instance, due to data unavailability, we are forced to use the task descriptions of US occupations as proxies for the tasks of the same occupations in the European countries in our sample. While we have argued in the paper that this is reasonable, we are also aware that this undoubtedly introduces non-negligible amounts of measurement error.

[29] Columns 7 and 8 confirm that the results are robust to the exclusion of the regional foreign-born share, which is a potentially endogenous regressor.

[30] In line with the literature we view years of education as exogenous. The idea is that in response to a surge in immigration most individuals may change jobs but will most likely not go back to school.

[31] Note that our findings suggest that the OLS estimates of SHK suffer a much larger relative bias than the OLS estimates of communication or manual intensity. This pattern is not surprising since within-occupation job-mobility seems a less costly response to immigration than between-occupation mobility. In other words, we think it is more likely for an individual with a marginally lower unobserved pro-immigration attitude to search for a more protected job within his/her occupation, than to search for a job in a different occupation. This could explain why we observe a larger endogeneity bias for our job-skill measure (SHK) than for our occupational scores (manual and communicational intensity).

[32] The respective unconditional means are 12.8 years of education, 8.9 months of job learning time, and 0.53 points in manual intensity.

Table 7
Robustness (1) — dichotomous dependent variable.
Source: ESS 2004–2005.

Estimation sample	1	2	3	4	5	6	7	8
	OLS	IV	IV	IV	IV	IV	IV	IV
	All	All	All	High edu (>12 years)	Low edu (<13 years)	All	All	All
Years edu	0.0185***	0.00981*	0.00615	0.00712	0.000969	−0.000646	−0.00176	0.00627
	[0.00145]	[0.00510]	[0.00479]	[0.00536]	[0.00699]	[0.00758]	[0.00706]	[0.00426]
SHK	0.000200	0.00439	0.00447	0.00811***	0.00168	0.00316	0.00286	0.00399
	[0.000316]	[0.00296]	[0.00297]	[0.00306]	[0.00439]	[0.00294]	[0.00284]	[0.00286]
Manual	−0.110***	−0.596***	−0.650***	−0.523**	−0.756**			−0.638***
	[0.0244]	[0.230]	[0.218]	[0.259]	[0.294]			[0.190]
Comm.						0.540***	0.566***	
						[0.198]	[0.184]	
FB share	0.122	−0.0360	−0.0162	0.111	−0.217	0.0309		
	[0.103]	[0.118]	[0.109]	[0.116]	[0.177]	[0.107]		
Female	−0.0261***	−0.0475*	−0.0633**	−0.0221	−0.102**	−0.0370*	−0.0402**	−0.0642***
	[0.00987]	[0.0282]	[0.0265]	[0.0271]	[0.0418]	[0.0199]	[0.0189]	[0.0237]
Rural	−0.0393***	−0.0218*	−0.0226*	−0.0349**	−0.0155	−0.0231*	−0.0216*	−0.0222**
	[0.0104]	[0.0119]	[0.0118]	[0.0140]	[0.0166]	[0.0125]	[0.0118]	[0.0110]
FB mother	0.0570***	0.0704***	0.0685***	0.0552**	0.0846***	0.0717***	0.0745***	0.0694***
	[0.0162]	[0.0185]	[0.0187]	[0.0219]	[0.0276]	[0.0191]	[0.0181]	[0.0174]
Obs.	12,893	12,983	12,893	6583	6310	12,893	14,143	14,143
R-squared	0.128	0.051	0.065		0.056	0.092	0.103	0.086
Fixed effects	Country	Country	Country	Country	Country	Country	Country	Country
Ind. values	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is a dummy variable taking the value one if the pro-immigration index implies supporting many or some immigrants to come into the country. All regressions are weighted using the ESS design weights and include a constant and controls for the age, age squared, and dummy variables for having children. Specifications with controls for ideology include ideology, religiosity, happiness, trust and social capital.
Standard errors, in brackets, clustered by region and robust to heteroskedasticity.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

The degree of specific human capital in the respondent's job matters half as much while the respondent's years of education matter roughly six times less. It is also interesting to examine the magnitude of the effects associated to the control variables. Based on column 3 in Table 7, observe that women are 6 percentage points less likely to be pro-immigration. Similarly, living in a rural area reduces the probability of being pro-immigration by 2 percentage points while having a foreign-born mother increases the probability by over 7 percentage points.[33]

6.2. Alternative definitions of the pro-immigration index

We now consider three alternative definitions of our pro-immigration attitudinal measure. Recall that our measure is an average of three questions regarding the desired immigration levels. In this section we estimate our preferred specification (column 3 in Table 6) using as dependent variable alternative pro-immigration indices built using each question on immigration attitudes separately.

Table 8 reports our instrumental-variables estimates. In columns 1–3 the dependent variable is a pro-immigration index based, respectively, on the desired level of immigration from the same ethnic group as the majority in the country (dependent variable 1), from a different ethnic group (dependent variable 2), and from poor countries outside Europe (dependent variable 3).[34] Each variable has been re-scaled to range between 25 and 100. Comparing column 3 in Table 6 to columns 1–3, we observe a large similarity between the estimates, both in terms of magnitudes and significance. Namely, education has a positive and significant effect on pro-immigration attitudes (columns 1–3) while specific human capital has a positive but not significant effect for the whole population.[35] As was the case earlier, manual intensity is the most significant determinant of attitudes toward immigration in all specifications.

Columns 4–6 report estimates of analogous models as the previous three columns but now the dependent variables are dichotomous versions of dependent variables 1, 2 and 3, respectively. Compared to column 3 in Table 7, we verify that manual intensity is the clearest determinant of immigration attitudes. Note also that the point estimates are very similar to the corresponding ones in Table 7. The coefficient on education is now larger and appears to be more precisely estimated.

In sum our main results appear robust to alternative definitions of our pro-immigration index.

7. Conclusions

This paper has analyzed the role of labor-market competition in the determination of individual preferences over immigration using several measures of exposure to competition from immigrants: schooling, specific human capital, and manual/communication skills. Our estimates have accounted for the potential endogeneity of job choices by employing instrumental variables based on the assumption that the types of jobs available in one's regional labor market affect workers' job and occupational choices. We have found evidence for significant roles of our three dimensions of exposure, with manual/communication intensity being quantitatively the most important.

The link between manual/communication intensity and pro-immigration attitudes provides indirect support for the endogenous

[33] In order to emphasize the point that the key identifying variation is at the individual and regional level, we have re-estimated the model in column 3 of Table 7 on the subsample of German respondents (7% of the sample). Reassuringly, we obtain very similar point estimates of the main measures of exposure. But, naturally, the associated standard errors are much larger (available on request).

[34] The exact wording for these questions can be found in the Appendix.

[35] The effects of SHK seem again circumscribed only to those with more than 12 years of schooling (results available on request).

Table 8
Robustness (2) — alternative definitions of the pro-immigration index.
Source: ESS 2004–2005.

IV	1	2	3	4	5	6
	Dep.var1	Dep.var2	Dep.var3	LPM1	LPM2	LPM3
Years edu	0.445*	0.523***	0.431**	0.0126***	0.0118***	0.00795*
	[0.235]	[0.186]	[0.194]	[0.00446]	[0.00452]	[0.00458]
SHK	0.128	0.156	0.0250	0.00172	0.00356	0.000126
	[0.140]	[0.131]	[0.122]	[0.00297]	[0.00288]	[0.00272]
Manual	−29.25***	−34.29***	−31.00***	−0.385*	−0.681***	−0.678***
	[10.32]	[8.649]	[9.033]	[0.205]	[0.214]	[0.215]
Obs	13,040	13,041	13,016	13,040	13,041	13,016
R-squared	0.096	0.124	0.150	0.105	0.106	0.119
Fixed effects	Country	Country	Country	Country	Country	Country
Ind. values	Yes	Yes	Yes	Yes	Yes	Yes

All columns report instrumental-variables estimates. The dependent variable used in each column is described below:

(1) The dependent variable is a pro-immigration index based on attitudes toward immigrants of the same ethnicity as the majority of the population in the country. For the exact wording see question B35 in the Appendix.

(2) The dependent variable is a pro-immigration index based on attitudes toward immigrants of different ethnicity as the majority of the population in the country (question B36).

(3) The dependent variable is a pro-immigration index based on attitudes toward immigrants from poor countries outside of Europe (question B37).

(4) Linear probability model 1. The dependent variable is a dummy variable taking the value of one if the response to question B35 was to allow some more or many more immigrants into the country.

(5) Linear probability model 2. The dependent variable is a dummy variable taking the value of one if the response to question B36 was to allow some more or many more immigrants into the country.

(6) Linear probability model 3. The dependent variable is a dummy variable taking the value of one if the response to question B37 was to allow some more or many more immigrants into the country.

Notes: All regressions weighted using design weights and include a constant and controls for age, age squared, the regional foreign-born share, and dummy variables for having children, living in a rural area, and having a foreign-born mother, in addition to controls for individual values (ideology, religiosity, happiness, trust and social capital).
Standard errors, in brackets, clustered by region and robust to heteroskedasticity.

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

job specialization theory postulated by Peri and Sparber (2009). According to these authors, native workers respond to immigration by moving from manual-intensive occupations, where they face greater exposure to competition, to more communication intensive ones, where natives have a comparative advantage by virtue of being relatively better at communication-intensive tasks.

In terms of future research, we think it is important to explore the role of labor market institutions in accounting for the large observed cross-country differences in average attitudes toward immigration. We believe the new definitions of labor market exposure and the overall empirical strategy developed in this paper can provide a helpful stepping stone.

Appendix 1. Definition of the dependent variable

Here we provide detailed definitions of our main dependent variable, as well as two alternative dependent variables that are used in the robustness section.

Pro-immigration index	Freq.	Percent	Cum.
25	607	4.67	4.67
33.34	332	2.55	7.23
41.67	572	4.4	11.63
50	2354	18.11	29.74
58.33	1527	11.75	41.49
66.67	1246	9.59	51.08
75	4045	31.12	82.2
83.34	630	4.85	87.05
91.67	330	2.54	89.59
100	1353	10.41	100
Total	12,996	100	

Our main dependent variable is a simple average of the three questions regarding the respondents' views on the desired level of immigration, namely questions B35, B36 and B37 that we reproduce below. Each of the questions refers to a different group of immigrants.

B35~ CARD 14. Now, using this card, to what extent do you think [country] should[36] allow people of the *same race or ethnic group* as most [country's] people to come and live here[37]?
(1) Allow many to come and live here, (2) Allow some, (3) Allow a few, (4) Allow none or, (8) Don't know.

B36~ STILL CARD 14. How about people of a *different* race or ethnic group from most [country] people? Still use this card. Values re-scaled as above.

B37~ STILL CARD 14. How about people of a *poorer countries outside Europe*? Use the same card. Values re-scaled as above.

We re-scale each of these variables to take values ranging from 25 (allow none) to 100 (allow many). As said earlier, our main dependent variable is a simple average of the (re-scaled) responses to these three questions.

Additionally, we consider three alternative dependent variables. Respectively, alternative dependent variables 1, 2 and 3, are based on questions B35, B36, and B37.

As a robustness check we also build a dichotomous version of our dependent variable. More specifically, we build a dummy variable taking the value one if the pro-immigration index implies supporting some or many immigrants to come into the country.

[36] "Should" in the sense of 'ought to'; not in the sense of 'must'.
[37] "Here" = country throughout these questions.

Appendix 2. Construction indices for communication and manual intensity

	Months	Freq.	Percent	Cum.
1 day or less	0.017	460	3.54	3.54
2–6 days	0.133	1168	8.99	12.53
1–4 weeks	0.58	2214	17.04	29.56
1–3 months	2.00	2929	22.54	52.1
More than 3 months, up to 1 year	7.50	3566	27.44	79.54
More than 1 year, up to 2 years	18.25	1593	12.26	91.8
More than 2 years, up to 5 years	42.58	831	6.39	98.19
More than 5 years	73.00	235	1.81	100
Total		12,996	100	

O*NET reports descriptors for up to 449 different US Census (year 2000) occupations at the maximum level of disaggregation. Each individual observation in the European Social Survey is assigned a communicational-intensity and a manual-intensity score on the basis of his/her occupation, which is coded using the International System of Occupational Coding, ISCO-88 at 4 digits (N=488). Score assignment is therefore based on the matching of the 2000 US Census occupations into their ISCO-88 4-digit equivalents. Some ISCO-88 4-digit occupations lack a perfect match in the 2000 US Census coding. In such cases we use the next most disaggregated crosswalk that is feasible, as explained below.

For the construction of our indices we proceed as follows: First, informed by factor analysis, we compute communicational intensity and manual intensity scores using the O*NET dataset. This procedure assigns both a communicational intensity and a manual intensity score to each of the 449 occupations of the O*NET dataset, which are coded using the 2000 US Census scheme. Then, we convert 2000 US Census occupations into their ISCO-88 4-digit equivalents using a crosswalk provided by the Centre for Longitudinal Studies, Institute of Education, University of London (see: http://www.cls.ioe.ac.uk/text.asp?section=000100010005001600002).[38] This matching procedure assigns communication-intensity and manual-intensity values to over 70% of the 2004 ESS sample with identifiable occupations. For the remaining 30% we lack an exact occupational matching at 4 digits. Manual and communicational-intensity scores for this latter group are computed as follows: First, we go back to the O*NET dataset and convert all the US 2000 Census occupations into 3-digit ISCO-88 equivalents using the corresponding crosswalk. This way we move up from the level of unit groups (4-digits) to the level of minor groups (3-digits). All the O*NET occupational descriptors, as well as our two measures of communication and manual skill intensity are recalculated for each of these ISCO-88 minor groups by averaging the original scores at the 3-digit level. This information is then matched to the ESS data for those respondents for whom we lack an exact 4-digit matching. This still leaves a residual 4% of respondents with identifiable occupation in the ESS without exact matching. Information for this group is matched by repeating the procedure above at 2 digits (major occupational groups). The construction of the skill indices in O*NET was informed by exploratory factor analysis. Principal-component factor analysis with orthogonal varimax rotation identified 10 different factors out of the 277 skill descriptors in the O*NET dataset (US 2000 Census occupations). The first factor accounted for 25.6 of the variance. Skill-descriptors with rotated factor loadings higher than 0.6 in this first factor included both skills directly involved in *communication* (i.e. oral comprehension, oral expression, written comprehension, written expression, speech recognition, and speech clarity) as well as skills relating to *abstract thinking* (i.e. fluency of ideas, originality, problem sensitivity, deductive and inductive reasoning, information ordering, category flexibility, memorization, etc.). Our communication intensity measure only uses the 6 communication skills, since there is no reason to suppose any comparative advantage of natives in abstract thinking. The index is the result of averaging the task-importance and the observed ability scores of these 6 communicational skills for each of the 449 occupations,[39] which were later matched into their ISCO-88 equivalents as explained above. Although we only focus on direct communicational skills, it must be noted that occupations were communicational skills are on demand tend to be those that also require abstract thinking.

The fourth factor of the principal component analysis identified 7 different skills/abilities relating to *physical dexterity* (i.e. visualization, arm-hand steadiness, manual dexterity, finger dexterity, control precision, wrist-finger speed and visual color discrimination). These 7 skills correspond to the descriptors with rotated factor scores higher than 0.55. The *manual dexterity* factor accounted for 10.1% of the skill variance. The manual intensity index is constructed by averaging the task-importance and observed ability scores of these 7 skills.

The correlation between our communication-intensity and manual-intensity indices in the European Social Survey is −0.64, which seems sufficiently high so as to discourage the estimation of both effects simultaneously.

Appendix 3. Tabulation of the main variables

Main dependent variable: the pro-immigration index constructed by average of questions B35-B37 (see previous appendix), rescaled to range between 25 and 100.

Occupations ISCO (2 digits)	Score	Freq.	Percent	Cum.
Mining, manufacturing and construction laborers	.09	464	2.31	2.31
Other craft and related trades workers	.108	454	2.26	4.56
Precision, handicraft, printing and related wrkrs.	.12	128	0.64	5.20
Agricultural, fishery and related laborers	.123	81	0.40	5.60
Machine operators and assemblers	.148	538	2.67	8.27
Stationary plant and related operators	.188	175	0.87	9.14
Extraction and building trade workers	.207	1013	5.03	14.18
Metal, machinery and related trades workers	.212	1037	5.15	19.33
Skilled agricultural and fishery workers	.242	704	3.50	22.83
Drivers and mobile plant operators	.247	819	4.07	26.90
Sales and services elementary occupations	.26	916	4.55	31.45
Models, salespersons and demonstrators	.363	1049	5.21	36.66
Personal and protective services workers	.469	1692	8.41	45.07
Office clerks	.482	1630	8.10	53.17
Physic., math. and eng. associate professionals	.52	880	4.37	57.55
Customer service clerks	.538	474	2.36	59.90
Teaching associate professionals	.56	283	1.41	61.31
Life sci and health associate professionals	.638	685	3.40	64.71
Other associate professionals	.657	1768	8.79	73.50
Physic., mathematics and engineering profs.	.687	691	3.43	76.93
General managers	.711	878	4.36	81.30
Teaching professionals	.715	1115	5.54	86.84
Other professionals	.759	1086	5.40	92.23
Life science and health professionals	.76	443	2.20	94.43
Corporate managers	.807	1067	5.30	99.74
Total		20,123	100.00	

Specific human capital: the table below summarizes the distribution of the job-learning time variable for our main sample. The exact phrasing of the question was:

"If somebody with the right education and qualifications replaced you in your job, how long would it take for them to learn to do the job reasonable well?"

[38] We thank Jane Elliott and Vania Gerova (Centre for Longitudinal Studies, Institute of Education, University of London) for making their crosswalk publicly available.

[39] For each skill involved in any given occupation, O*NET experts evaluate 2 different dimensions: 1) how important is this given skill/ability for the occupation and 2) the average observed levels of such skill in the occupation. Both dimensions correlate very highly. Factor analysis and hence our indices use both types of descriptors so for each of the skills involved in our indices we actually average 2 different descriptors, one referring to task-importance and the other referring to observed levels.

Communication intensity index: this table reports the ranking of 2-digit ISCO occupations by communication intensity.

Manual intensity index: this table reports the ranking of 2-digit ISCO occupations by manual intensity.

Appendix 4. Analysis of consistency of reported job-learning time across countries

The subjective nature of the question on specific human capital raises concerns about its comparability across countries. It is for instance possible that differences in social norms lead two individuals performing the exact same job in two different countries to report different SHK values. In order to address this concern about the cross-country comparability of the SHK measure, we report the results of two validity tests.

First, we compare the within-occupation, cross-country dispersion in SHK using the (unit-free) coefficient of variation. Given our limited sample size, and in order to avoid an excessive number of empty occupation-country cells, we restrict the analysis to 2-digit ISCO occupations. Table A4.1 (left panel) reports the results. Note that the

Occupations ISCO (2 digits)	Score	Freq.	Percent	Cum.
General managers	.244	878	4.36	4.36
Legislators and senior officials	.276	53	0.26	4.63
Other professionals	.328	1086	5.40	10.02
Teaching professionals	.334	1115	5.54	15.56
Other associate professionals	.344	1768	8.79	24.35
Teaching associate professionals	.359	283	1.41	25.76
Customer service clerks	.379	474	2.36	28.11
Corporate managers	.39	1067	5.30	33.41
Office clerks	.426	1630	8.10	41.51
Sales and services elementary occupations	.465	916	4.55	46.07
Physic., mathematics and engineering profs.	.487	691	3.43	49.50
Personal and protective services workers	.509	1692	8.41	57.91
Models, salespersons and demonstrators	.517	1049	5.21	63.12
Life science and health professionals	.536	443	2.20	65.32
Mining, manufacturing and construction laborers	.623	464	2.31	67.63
Life science and health associate professionals	.631	685	3.40	71.03
Skilled agricultural and fishery workers	.679	704	3.50	74.53
Drivers and mobile plant operators/Physic., math. and eng. associate professionals	.693	1699	8.44	82.97
Agricultural, fishery and related laborers	.708	81	0.40	83.38
Extraction and building trade workers	.741	1013	5.03	88.41
Stationary plant and related operators	.756	175	0.87	89.28
Machine operators and assemblers	.793	538	2.67	91.95
Metal, machinery and related trades workers	.83	1037	5.15	97.11
Other craft and related trades workers	.841	454	2.26	99.36
Precision, handicraft, printing and related wrkrs.	.86	128	0.64	100.00
Total		20,123	100.00	

Table A4.1
Between-country variation in the average job-learning time by 2-ISCO digit occupations.

	Job-learning time (months)		
	Mean	Std. dev.	Variation coeff.
Corporate managers	13.85	3.16	0.23
Managers of small enterprises	11.71	7.48	0.64
Physical, mathematical and engineering prof.	13.15	4.55	0.35
Life science and health prof.	14.04	8.71	0.62
Teaching prof.	13.37	5.43	0.41
Other prof.	11.86	3.39	0.29
Physical and engineering science assoc. prof.	11.94	4.37	0.37
Life science and health ass, prof.	10.31	5.87	0.57
Teaching ass. Prof.	7.04	3.18	0.45
Other associate prof.	9.03	2.97	0.33
Office clerks	6.31	1.82	0.29
Customer services clerks	4.92	2.68	0.55
Personal and protective service wkrs.	5.65	2.84	0.50
Models, sales persons and demonstrators	4.20	2.15	0.51
Skilled agricultural and fishery wkrs	3.71	3.02	0.81
Extraction and building wkrs.	11.30	5.77	0.51
Metal and machinery trade wkrs.	13.49	5.13	0.38
Other craft and related trade wkrs	7.46	6.84	0.92
Stationary plant operators	13.50	9.49	0.70
Machine operators and assemblers	5.55	3.94	0.71
Drivers and mobile plant operator	5.67	2.03	0.36
Sales and services elementary occ.	2.15	1.43	0.66
Laborers in mining, const. manufact. and trans.	4.38	2.92	0.67

Table A4.2
Correlation matrix of country rankings according to mean job-learning time (SHK) in the occupation.

	AT	CH	CZ	DE	EE	FI	FR	GB	IE	NL	NO	PL	PT	SE	TR
Austria	1														
Switzerland	0.92	1													
Czech Rep.	0.85	0.79	1												
Germany	0.86	0.76	0.88	1											
Estonia	0.93	0.87	0.89	0.86	1										
Finland	0.8	0.78	0.67	0.63	0.76	1									
France	0.84	0.74	0.85	0.9	0.75	0.79	1								
Great Britain	0.78	0.7	0.9	0.88	0.73	0.7	0.96	1							
Ireland	0.84	0.79	0.72	0.75	0.67	0.81	0.91	0.8	1						
Netherlands	0.69	0.61	0.45	0.73	0.55	0.59	0.74	0.59	0.74	1					
Norway	0.9	0.86	0.69	0.69	0.76	0.83	0.81	0.74	0.87	0.76	1				
Poland	0.92	0.89	0.95	0.85	0.96	0.83	0.84	0.84	0.75	0.51	0.8	1			
Portugal	0.75	0.85	0.76	0.78	0.74	0.75	0.8	0.83	0.69	0.59	0.73	0.82	1		
Sweden	0.91	0.81	0.73	0.71	0.77	0.9	0.86	0.8	0.89	0.67	0.95	0.84	0.73	1	
Turkey*	0.91	0.85	0.82	0.81	0.84	0.94	0.93	0.84	0.92	0.67	0.88	0.9	0.8	0.95	1

Note: To avoid excessive missing values we have used 2-digit ISCO occupations and limited to countries for which the ESS 2004 has at least 1700 observations. The Table also includes Turkey, even though this country is not part of our analytical sample.
The mean entry in the Table is 0.80 (excluding the main diagonal). The maximum is 0.96 (France and Great Britain) and the minimum is 0.45 (Netherlands and Czech Republic).

cross-country mean SHK ranges from 2.15 (sales and elementary service occupations) to 14.04 months (life science and health professionals), as can be seen in the first column of the table. The second and third columns report two measures of dispersion: standard deviations and coefficients of variation, respectively. The degree of cross-country within-occupation variation is moderate (the mean coefficient of variation taking all occupations into account is 0.51).

Secondly, for each country we rank occupations by their mean SHK and then we compute the cross-country correlation coefficient among these vectors of rankings. Table A4.2 reports the resulting correlation matrix. Glancing over the entries of the matrix we observe fairly high correlations, ranging from a low of 0.45 (Netherlands and Czech Republic) to a high of 0.96 (Great Britain and France). The mean entry in the matrix is 0.80. This means that overall the same 2-digit occupations score high or low in terms of job-learning time across different institutional and cultural contexts, even if average scores for all occupations vary across countries. To further illustrate this point, we have included Turkey in the correlation matrix. Turkey is not part of the empirical analysis carried out in our paper. Yet Turkey is probably the “most” culturally-different country of the ESS sample. Hence it is illustrative to show that the ranking of occupations according to job-learning time in Turkey hardly differs from those found for the “core” European nations.

In sum, the overall picture is one of very similar SHK rankings by occupation across European countries. We view this finding as confirming the validity of pooling individual data from several countries in our analysis.

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