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Abstract

This paper quantifies the relative importance of determinants of individual-level immigration preferences. We develop and estimate a new latent-factor model using survey data on eighteen countries from the European Social Survey from 2014 and 2015. On a metho-dological level, we address several potential problems causing biased estimates. Identifying individual-level economic concerns about immigration, worries about compositional amenities, racism, and altruism as drivers of immigration-related preferences, the estimation results show that racism is quantitatively the most important factor. It is about as important as the joint effect of worries about the economic and non-economic effects of immigration. Furthermore, we document that altruism raises significantly the support for immigration, although it is quantitatively less important than the other factors.

Keywords

Altruism, Compositional Amenities, Economic Concerns, Immigration Preferences, Racism.

JEL Classification

F22, H2, O15.

1 Introduction

Immigration is at the top of voters' concerns in almost all European countries, as documented by the 2016 Eurobarometer, a survey conducted on behalf of the European Commission. The topic has become increasingly important as migration to rich countries surged (OECD, 2017). Debates on immigration have split the European electorate into those who welcome migrants and those who oppose immigration. The latter materialized their preferences by, for example, the Brexit vote in June 2016 or the recent success of various right-wing politicians and parties.[1] This raises the question which factors determine at the individual level support for or opposition to immigration. Prior research has pointed out the role of specific drivers of preferences, such as labor market competition (Scheve and Slaughter, 2001), immigrant skill endowments (Mayda, 2006; O'Rourke and Sinnott, 2006), fiscal concerns (Facchini and Mayda, 2008, 2009), racial prejudice (Gang, Rivera-Batiz and Yun, 2013), sociotropic considerations (Hainmueller and Hiscox, 2010), and education (Hainmueller and Hiscox, 2007). However, there are few attempts to *quantify* the relative influence different factors have as drivers of preferences for immigration policies. One notable exception by Card, Dustmann and Preston (2012) finds that worries about compositional amenities —how immigration affects the cultural life, crime rates, and social cohesion— are up to five times more important than economic concerns over wages and taxes.[2] However, the paper by Card et al. does not model racism as a potential driver of preferences. Given that several papers in the literature highlight the importance of racism as a key determinant of opinions on immigration policies, it remains unclear whether the high relative importance of non-economic concerns about compositional amenities is a result of omitting racist traits as an explanatory variable.

In this paper, we intend to fill this gap in the literature by quantifying how different individual-level beliefs and preferences shape support for immigration. Specifically, we make two main contributions to the literature on immigration preferences. First, we update the work by Card, Dustmann and Preston (2012) in terms of data as well as modeling strategy. We use a recent survey data set covering 18 European countries in 2014/2015. Furthermore, we develop a Bayesian latent-factor model to quantify the *relative importance* of different

[1] The division between open- and closed-borders politics has become the core of political debates in Europe and has to some extent replaced the typical left- and right-wing division, according to an article entitled "Drawbridges up" published in *The Economist* on July 30, 2016.

[2] The authors emphasize the importance of this finding by pointing out the more negative attitude toward increased immigration held by older people which is a puzzle for models that ignore compositional amenities because many older respondents are retired.

factors shaping support for immigration.[3] Using a Bayesian modeling framework, we account for the uncertainty of individual beliefs and preferences as well as the correlation of latent factors. We tailor the model to fit the ordinal structure of the survey questions and use recently developed software tools to jointly estimate all parameters of the model. The overall identification strategy is to use several *specific* questions along each dimension (e.g. how immigration is expected to affect wages or taxes) to identify an individual's *general* beliefs along this dimension (i.e. how immigration will affect economic outcomes in general). This allows us to identify quantitatively how much immigration preferences are shaped by economic- and non-economic concerns, by racism, as well as by altruistic motives.

The second main contribution of this paper concerns the high relative importance of worries about compositional amenities found by Card, Dustmann and Preston (2012). We analyze whether such worries reflect negative externalities imposed on natives through immigration (e.g. reduced quality of public schools due to non-native students) or if it is mostly a proxy for xenophobia and racism. We do this by separately identifying racism at the individual level.[4] This allows us to disentangle racist views from non-racist individual expectations of the impact of immigration. As we show, this distinction turns out to be important. Individual beliefs about how immigration affects the economy (ECO) and compositional amenities (COM) are highly correlated. The consequence of this correlation is that when we analyze these two factors as the only determinants of immigration preferences, the uncertainty of the *relative* importance of COM/ECO will be very large. Although we can reproduce the results of Card, Dustmann and Preston (2012) in terms of coefficient estimates, we show that the *ratio* of the coefficients is highly uncertain. Once we add racism (RAC) as a separate latent factor, the uncertainty of COM/ECO is drastically reduced. Furthermore, racism shows a larger quantitative impact on immigration preferences than both economic- and non-economic concerns.

For our empirical analysis, we use the most recent wave of the European Social Survey (ESS) from 2014 and 2015. It includes several questions which ask participants about how they evaluate the impact of immigration on their country. This covers both economic as well

[3]The econometric methodology used in this paper allows us both to account for multiple identification issues and to quantify which factors are most important in shaping immigration preferences. This adds to Card, Dustmann and Preston (2012) as well as other studies on the determinants of immigration preferences (cf. Gang et al., 2013).

[4]Dustmann and Preston (2007) examine racism and cultural concerns in a latent-factor model, together with labor market concerns and welfare concerns, using data from Great Britain between 1983 and 1990.

as non-economic aspects such as the cultural life or crime. Furthermore, the survey includes a multitude of questions on xenophobic, racist, and altruistic character traits. Our modeling strategy is to pick questions from the ESS that are related to immigration preferences (IMM), beliefs of the economic impact of immigration (ECO), concerns over compositional amenities (COM), racism (RAC), and altruism (ALT). Using a parametric model we can then identify the individual, latent value for these five dimensions.

The results indicate which individual-level factors are quantitatively most important in shaping preferences over immigration. We find that worries about the economic impact such as employment or fiscal effects play a significant role. Furthermore, we find evidence in line with Card, Dustmann and Preston (2012) that concerns about compositional amenities —how immigration affects the cultural life or crime rate— are more important in shaping preferences than economic concerns. However, our results show further that racism is as important as the *combined* effect of both concerns over economic effects as well as compositional amenities. The quantitative impact of compositional amenities is reduced by more than 40 percent when accounting for racism, suggesting that almost half of it reflects racist views. When accounting for such views, we find that compositional concerns are around twice as important as worries about economic effects of immigration. Finally, we show that altruistic attitudes significantly raise support for immigration even when controlling for expectations about the costs and benefits of immigrants.[5] Overall, these findings indicate that individuals determine their preferred immigration policy not only from a purely self-interested perspective but also give weight to xenophobic prejudices as well as to the welfare of potential immigrants.

Adding to our main analysis, we explore the heterogeneity across Europe in the determinants of immigration preferences by running the latent-factor model for each of the 18 countries separately. The results show that estimated effects of the variables are largely similar across countries. In almost all countries, racism is quantitatively the most important driver of immigration preferences. However, we document that a precise identification is inherently more difficult for individual countries due to the high correlation of latent factors and the reduced amount of data at the country level.

The literature on the determinants of immigration preferences highlights the role of ed-

[5]Importantly, we show that altruism is not just the mirror image of racism but that the two attitudes are separate factors shaping preferences over immigration. A detailed discussion of how altruism increases the support for immigration is provided by Hansen and Legge (2016).

ucation (Hainmueller and Hiscox, 2007). Hence, we explore in detail how education affects directly and indirectly support for migration. Notably, our results show that about 75 percent of the effect of education on immigration preferences can be accounted for by the four latent factors we use in the analysis: economic and non-economic concerns, racism, and altruism. This raises the question how important education is quantitatively and also how it impacts beliefs about the effects of migrants. We find that *conditional* on individual levels of ECO, COM, RAC and ALT, higher education is still associated with a preference for more immigration. We further show that higher education is associated with more optimism in terms of the consequences of immigration as well as lower levels of racism and higher levels of altruistic character traits.

These findings complement a large body of research on the determinants of attitudes towards immigrants. The literature attempts to explain differences in preferences over immigration across individuals by their observable characteristics. Empirical evidence has been interpreted as reflecting both economic and non-economic expectations shaping policy preferences. In line with Bridges and Mateut (2014) as well as Murard (2015), our findings show that attitudes towards immigration are determined by expectations about how immigration affects the economy and life in the domestic country. With respect to economic effects of migration, voters choose their preferred level of immigration based on how they think migrants affect taxes, welfare benefits, wages, and employment (Mayda, 2006; Facchini and Mayda, 2009; Boeri, 2010). Despite a lack of clear evidence of substantial negative wage or employment effects, it remains unclear whether fears of labor market effects from immigrants actually shape policy preferences (Scheve and Slaughter, 2001; Hainmueller, Hiscox and Margalit, 2015). In addition, attitudes towards immigration are shaped by non-economic arguments. In a study by Hainmueller and Hiscox (2007), the authors use the European Social Survey and find that education has strong explanatory power, partly because it reduces racism and increases demand for cultural diversity. Similarly, Dustmann and Preston (2007) document that racial or cultural prejudice is an important determinant of attitudes towards immigration. Related to this research, exposure to migrants has been found to increase support for right-wing parties (Markaki and Longhi, 2013; Halla, Wagner and Zweimüller, 2016; Barone et al., 2016; Becker and Fetzer, 2016). With respect to the recent influx of refugees, however, Steinmayr (2016) finds evidence in line with the contact hypothesis, stating that the presence of refugees reduces support for the political right. Finally, there is an ongoing debate over to what extent preferences are shaped by self-interest and sociotropic concerns (Facchini, Mayda and Mendola, 2013; Hainmueller and Hopkins, 2014; Hatton, 2016). Several studies have focused on attributing deviations from a *homo oeconomicus* behavior as reflecting xenophobic views (Hainmueller and Hiscox, 2007).

We contribute to the literature by quantifying the relative importance of each determinant of policy preferences, including expected economic and non-economic effects as well as racism and altruism. Using a newly developed latent-factor model and recent survey data from 18 European countries, we are able to confirm prior research in finding significant effects of the respective factors on preferred levels of immigration. Furthermore, we document that racism is by far the most important factor shaping immigration preferences. The remainder of the paper is organized as follows. Section 2 provides information on the construction of our data set as well as several descriptive statistics. In Section 3, we present our latent-factor model to explain how individual preferences over immigration are determined and how we can use survey data to estimate the relative importance of each determinant. In Section 4, we show our main empirical results and discuss the findings. Finally, Section 5 concludes.

2 Data

In order to study determinants of individual immigration preferences, we employ the most recent data from the European Social Survey (ESS). Interviews took place in eighteen European countries in the years 2014 and 2015.[6] Importantly, the questionnaire includes a series of questions on individual attitudes towards immigration, expected effects of immigration, as well as several values and character traits. This allows us to examine how beliefs about immigrants as well as individual values map into immigration preferences. In addition, survey participants are asked a large set of questions on their characteristics, economic situation, or political views. Using this wealth of data, we can explore which determinants are quantitatively most important in shaping preferences over immigration.

Immigration Preferences — For preferences over immigration, we mainly rely on four

[6] The sample includes almost all countries that participated in the 7th wave of the ESS: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Israel, Lithuania, Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, United Kingdom. We omit Estonia due to lack of data on control variables. For Austria, we do not have data on question IMM4 of Table 1, for the Czech Republic RAC5 is missing.

questions: Each survey participant is asked how many immigrants he or she wants to allow to migrate to his or her country. This question is asked for four different types of migrants: (i) of the same race, (ii) of a different race, (iii) from poor countries in Europe, and (iv) from poor countries outside Europe. With respect to each question, participants can choose from a set of four possible answers: many, some, few, or none.[7] We summarize the questions and possible answers in Table 1. Note that the term immigrants can be misleading. While it should refer to people who were born outside their country of residence the translation of the word 'immigrants' can lead survey participants to include people who were born in the country but are not citizens. This is not a concern here as all the questions in the ESS questionnaire refer to people who come to live in a country rather than to immigrants.

Table 1: Immigration Questions and Possible Answers in the ESS

Code	Question	Possible Answers
IMM1	To what extent do you think [your country] should allow people of the same race or ethnic group as most [of your country]'s people to come and live here?	1 (allow none to come and live here) 2 (allow few) 3 (allow some) 4 (allow many)
IMM2	How about people of a different race or ethnic group from most [of your country]'s people?	1 (allow none to come and live here) 2 (allow few) 3 (allow some) 4 (allow many)
IMM3	And how about people from the poorer countries in Europe?	1 (allow none to come and live here) 2 (allow few) 3 (allow some) 4 (allow many)
IMM4	How about people from the poorer countries outside Europe?	1 (allow many to come and live here) 2 (allow some) 3 (allow few) 4 (allow none)

Note: The table shows the main four immigration questions from the 2014 European Social Survey that we use in our empirical analysis. In the third column, we show the range of possible answers that each survey participant is provided.

Economic Effects and Compositional Amenities — In order to measure how individuals perceive the economic effects as well as the impact on compositional amenities of immigration, we use a set of seven questions from the ESS. Both the questions and the possible answers are summarized in Table 2. We follow Card, Dustmann and Preston (2012) and separate them into economic (ECO) and compositional (COM) effects. The former include three questions

[7] Note that we, following Card, Dustmann and Preston (2012), remove all individuals who refuse to answer, do not answer, or say they do not know how to answer the question.

asking whether a survey participant thinks immigrants take away jobs, have a negative fiscal effect, and are generally bad for the economy. With respect to compositional amenities, we use four questions that ask whether immigrants undermine the cultural life, undermine religious beliefs and practices, worsen crime problems, and make the country generally a worse place to live. It is important to use individual views on the effects of immigration such as the impact on crime. Neither do individuals agree on what the 'true' effect is nor does the literature provide clear evidence: while Bianchi, Buonanno and Pinotti (2012) as well as Bell, Fasani and Machin (2013) find no significant effect of immigration on crime rates, a recent article by Piopiunik and Ruhose (2017) studies a mass influx of migrants into Germany in the 1990s and shows that this inflow increased crime substantially.[8]

Altruism and Racism — We are further interested in measuring both racism and altruism at the individual level. For altruism, we follow Cambridge Dictionary's definition as the 'willingness to do things that bring advantages to others, even if it results in disadvantage for yourself'.[9] Notably, when we allow altruistic motives to shape immigration preferences the model captures the idea that survey respondents determine their preferred immigration policy not only from a purely self-interested perspective but also give weight to the welfare of potential immigrants. To measure the level of altruism, we use three questions. The first one asks whether participants think it is important to help people and care for others' well-being. Specifically, the interviewer describes a person and asks on a scale from 1 (very much like me) to 6 (not at all like me) whether the survey participant thinks the person is similar to him/her. The statement reads "It is very important to her/him to help the people around her/him. She/he wants to care for their well-being." We define this question as ALT1 in Table 2. Second, for what we denote ALT2 we use a question on whether a survey participant thinks it is important that every person in the world is treated equally and has equal opportunities in life. Finally, each individual is asked whether it is important to listen to people who are different, even if he or she disagrees with them. We code this question

[8] Similarly, the effects of immigration on employment and wages in the domestic labor market are subject to debate in the economics literature (cf. Ottaviano and Peri, 2012; Bratsberg and Raaum, 2012; Dustmann, Frattini and Preston, 2013; Docquier, Ozden and Peri, 2013; Borjas, 2014; Card and Peri, 2016; Dustmann, Schönberg and Stuhler, 2016).

[9] Different types of altruism might play a role in shaping attitudes towards immigrants. We can think of pure altruism where individuals act in a way that benefits others without getting anything in return. Alternatively, attitudes towards immigration might be affected by impure altruism (Andreoni, 1989) or a warm-glow motive where individuals at the very least receive satisfaction from having a desire to help fulfilled.

Table 2: Questions and Possible Answers in the ESS

Code	Question	Possible Answers
ECO1	Would you say that people who come to live here generally take jobs away from workers in [your country], or generally help to create new jobs?	1 (take away) ... 11 (create jobs)
ECO2	Most people who come to live here work and pay taxes. They also use health and welfare services. On balance, do you think people who come here take out more than they put in or put in more than they take out?	1 (take out more) ... 11 (put in more)
ECO3	Would you say it is generally bad or good for [your country]'s economy that people come to live here from other countries?	1 (bad) ... 11 (good)
COM1	Would you say that [your country]'s cultural life is generally undermined or enriched by people coming to live here from other countries?	1 (undermined) ... 11 (enriched)
COM2	Do you think the religious beliefs and practices in [your country] are generally undermined or enriched by people coming to live here from other countries?	1 (undermined) ... 11 (enriched)
COM3	Are [your country]'s crime problems made worse or better by people coming to live here from other countries?	1 (worse) ... 11 (better)
COM4	Is [your country] made a worse or a better place to live by people coming to live here from other countries?	1 (worse) ... 11 (better)
RAC1	Do you think some races or ethnic groups are born less intelligent than others?	1 (no) 2 (yes)
RAC2	Do you think some races or ethnic groups are born harder working than others?	1 (no) 2 (yes)
RAC3	Thinking about the world today, would you say that some cultures are much better than others or that all cultures are equal?	1 (all equal) 2 (much better)
RAC4	In deciding whether someone born, brought up and living outside [your country] should be able to come and live here, how important should it be for them to be white?	1 (extremely unimportant) ... 11 (extremely important)
RAC5	Thinking of people who have come to live in [your country] from another country who are of a different race or ethnic group from most [your country] people. How much you would mind or not mind if someone like this was appointed as your boss?	1 (not mind at all) ... ... 11 (mind a lot)
ALT1	It is very important to her/him to help the people around her/him. She/he wants to care for their well-being.	1 (very much like me) ... 6 (not at all like me)
ALT2	She/he thinks it is important that every person in the world should be treated equally. She/he believes everyone should have equal opportunities in life.	1 (very much like me) ... 6 (not at all like me)
ALT3	It is important to her/him to listen to people who are different from her/him. Even when she/he disagrees with them, she/he still wants to understand them.	1 (very much like me) ... 6 (not at all like me)

Note: The table shows the questions from the 2014 European Social Survey that we use in our empirical analysis. In the third column, we show the range of possible answers that each survey participant is provided. For those questions where there is an integer number larger than two of answers, we show [...] between the most extreme answer options.

ALT3. For both ALT2 and ALT3, the participants can answer in the same way as to ALT1.

In order to identify racist attitudes, we again follow the Merriam-Webster textbook definition: "a belief that race is the primary determinant of human traits and capacities and that racial differences produce an inherent superiority of a particular race". The ESS questionnaire contains a question that reflects this concept (labeled RAC1 in Table 2). It asks whether the participant thinks some races or ethnic groups are born less intelligent. To account for a broader definition of racism (or xenophobia), we make use of several additional questions in the ESS. In particular, we take respondents' answers to the question on whether they think some races or ethnic groups are born harder working than others. Again, individuals can choose to answer either yes or no. Furthermore, the ESS asks participants to say whether they think all cultures are equal or whether some are much better than others. The fourth question we use to measure racist attitudes for each individual asks whether it is important for migrants to be white. Finally, each survey participant is asked whether he or she would mind if someone from another country and of a different race was appointed as his or her boss.[10] Note that we code all variables such that their lowest value is one and a higher value indicates a more racist or xenophobic attitude.

It is important to emphasize the relationship between altruism and racism in the ESS survey. In particular, we examine the correlation between individual answers to questions on both attitudes. Table A.1 in the Appendix provides both the raw as well as adjusted correlations. We observe that individuals respond similarly to different questions on the same attitude. However, the correlation between individual answers on altruism and racism is very small. For example, ALT1 ('it is important to help people around you and to care for their well-being') is barely correlated with any of the questions on racism. This rules out the idea that altruism is just the mirror image of racism.

Descriptive Statistics — We provide descriptive statistics on all variables in our data set by means of Table 3. In total, we have almost 22,000 interviews from eighteen European countries. These interviews took place between August 2014 and December 2015.

The data in Table 3 shows that the average participant in the survey was about forty-nine years old and there are about as many male as female participants. Thirty-six percent of

[10] There is a very similar question in the ESS that asks whether the participant would mind if a migrant of a different race married a close relative. Since the answers to both questions are highly correlated we decided to focus on one question.

Table 3: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
IMM1: Many/Few Immigrants: Same Race	2.97	0.81	1	4	21,905
IMM2: Many/Few Immigrants: Different Race	2.69	0.85	1	4	21,905
IMM3: Many/Few Immigrants: Poor Countries in Europe	2.64	0.88	1	4	21,905
IMM4: Many/Few Immigrants: Poor Countries outside Europe	2.50	0.91	1	4	21,905
ECO1: Jobs	6.05	2.23	1	11	21,905
ECO2: Fiscal Effect	5.63	2.14	1	11	21,905
ECO3: Bad for Economy	6.16	2.38	1	11	21,905
COM1: Cultural Life	6.91	2.45	1	11	21,905
COM2: Religious Beliefs	6.07	2.13	1	11	21,905
COM3: Crime Problems	4.77	2.01	1	11	21,905
COM4: Country Worse Place to Live	6.26	2.24	1	11	21,905
ALT 1: Important to Help Others	4.91	0.96	1	6	21,905
ALT 2: Important People are Treated Equally	5.04	1.01	1	6	21,905
ALT 3: Important to Understand Different People	4.73	1.03	1	6	21,905
RAC 1: Some Races Born Less Intelligent	1.15	0.36	1	2	21,905
RAC 2: Some Races born Harder Working	1.38	0.49	1	2	21,905
RAC 3: Some Cultures Better	1.44	0.50	1	2	21,905
RAC 4: Immigrants must be White	2.87	2.66	1	11	21,905
RAC 5: Would Mind if Boss was Different Race	3.56	2.86	1	11	21,905
High Education	0.36	0.48	0	1	21,905
Age	48.79	17.78	14	104	21,905
Male	0.50	0.50	0	1	21,905
Unemployed (currently)	0.04	0.20	0	1	21,905
Retired	0.24	0.43	0	1	21,905
Household Income Decile	5.60	2.79	1	10	21,905
Belong to Minority	0.05	0.22	0	1	21,905
Residence: City	0.19	0.40	0	1	21,905
Residence: Suburb	0.13	0.34	0	1	21,905
Residence: Town	0.32	0.47	0	1	21,905
Residence: Village	0.28	0.45	0	1	21,905
Residence: Farm	0.07	0.26	0	1	21,905

Note: The table presents descriptive statistics for all variables used in the empirical analysis. All variables are taken from the European Social Survey with interviews from eighteen countries conducted in 2014 and 2015. Higher values for IMM reflect more support for immigration, higher values for ECO or COM indicate more positive expectations about the effects of immigration, larger values on ALT and RAC show more altruistic or racist traits.

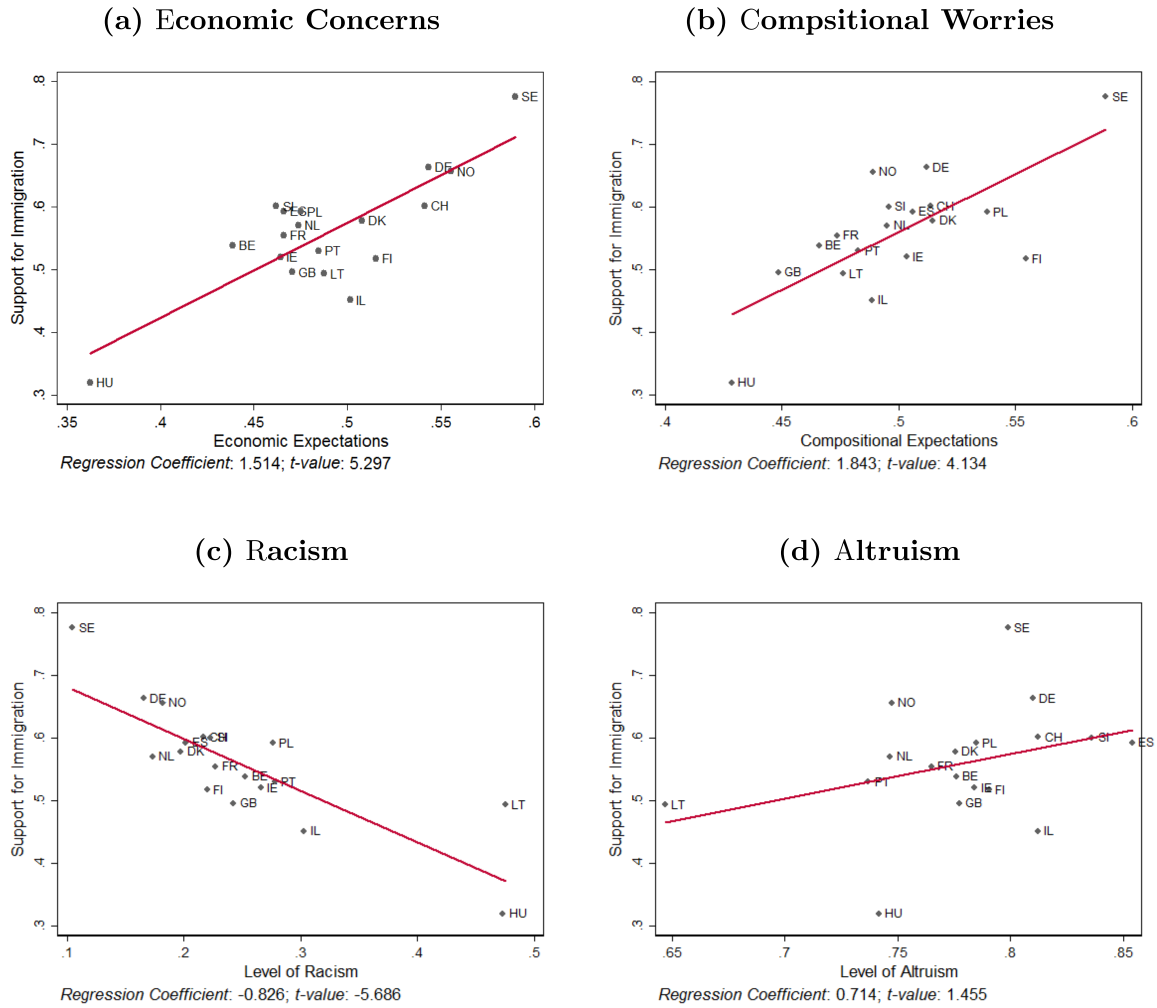
the respondents have a higher education and only four percent describe their current labor market status as unemployed. Using the questions and definitions outlined above, we obtain a large fraction of the survey participants showing altruistic traits. On the other hand, we can identify significant evidence of racist attitudes. For example, about 15 percent say that some ethnic groups are born less intelligent. In this regard, it is worth noting that there are substantial differences across countries. We show them in Table A.2 in the Appendix.

On a scale from zero to one with higher values indicating more positive views, the average expectations about immigration's impact on the economy (mean of 0.49), the labor market (0.48), or the fiscal budget (0.45) are fairly mixed. With respect to other effects of immigration, the views are much more negative. For example, the average survey participant expects more crime due to immigration. On the other hand, a majority support the notion that the cultural life in their country is enriched by migrants. At the country-level we see that, for example, Swedish survey participants show the lowest amount of racism, one of highest levels of altruism, and the most positive expectations about the effects of immigration. Given these numbers, it is not surprising to find that Sweden is listed as the country in our sample with the strongest support for immigration.

Descriptive Evidence — Before turning to the results of our latent-factor model, we briefly explore descriptively the relationship between support for immigration and the four determinants that we focus on: economic concerns, worries about compositional amenities, racism, and altruism. Aggregating individual survey responses, we first consider empirical correlations at the country level.

Figure 1: Country-Level Expectations and Immigration Preferences

(a) Economic Concerns (b) Compsitional Worries (c) Racism (d) Altruism



Note: The figures show on the vertical axis each country's average level of support for immigration as well as on horizontal axis the average value on economic concerns (ECO), worries about compositional amenities (COM), racism (RAC), and altruism (ALT). Note that we combine answers at the individual level such that zero reflects no support for any type of immigration, and one means maximum support for all four types of immigration. Similarly, the variables on the horizontal axis are defined: higher values imply more positive expectations, more racism, or more altruism. The questions are described in Tables 1 and 2. The solid lines show a linear fit.

Figure 1 plots each country's average level of support for immigration (i.e. the average of IMM1 to IMM4) against its average level of the four determinants. The correlations we obtain are all in line with our expectations. Countries in which the population holds more positive beliefs about how migrants affect economic and non-economic outcomes show greater support for immigration. Furthermore, more prevalent racist attitudes decrease the preferred level of immigration while altruistic character traits tend to raise the level. As an example, the country with the highest average support for immigration (Sweden) also has the most optimistic views on the economic and non-economic effects of immigration. Furthermore, it has the lowest level of racism. In contrast, the average survey participant from Hungary has very negative expectations about the effects of immigration, a high level of racism, and fairly low score on altruism. Not surprisingly then, we find that Hungary has the lowest average support for immigration.

3 Explaining Attitudes to Immigration

3.1 Theoretical Background

The focus of our analysis is on individual preferences for immigration. We use the subscript n to denote individuals. There are N individuals in our analysis, i.e. $n \in 1, .., N$. Define $\alpha_{n,IMM}$ as individual n's *general* level of preferred immigration. Later on, we will specify how this general preference relates to *specific* immigration issues. We can think of $\alpha_{n,IMM}$ as emerging from an optimization problem of the form

$$\alpha_{n,IMM} = \arg\max_{L} \quad \{u_n(c_n, \bullet_u), \ \ s.t. \ \ f_n(c_n, \bullet_f) \leq 0\} \tag{1}$$

where c_n is individual consumption, f_n are the constraints as perceived by the individual, and $\bullet_u, \bullet_f$ are variables relevant for the utility function and constraints, respectively. There is little we can say in general about the shape of the elements of the maximization problem on the right-hand side of equation (1), as there appears to hardly be a consensus of the economic impact of immigration, let alone what values and norms are relevant for the utility function. We therefore consider a first-order approximation to the right hand side of equation (1):

$$\alpha_{n,IMM} = \boldsymbol{Z}'_n \boldsymbol{\beta} + \varepsilon_n \tag{2}$$

where $\boldsymbol{Z}_n$ is a vector of variables and $\boldsymbol{\beta}$ are coefficients that we assume are the same for all individuals. Finally, there is an error term, ε, which captures higher order terms from the approximation, potential omitted variables, and misspecification caused by assuming coefficients to be similar across individuals. The goal of our empirical approach is to quantify the relative importance of beliefs on the consequences of immigration, racism and altruism for shaping preferences over immigration. In the hypothetical case where we observed all these items, we could estimate equation (2) with a linear regression. However, none of these preferences and beliefs can be pinned down directly by means of the survey questions. Therefore, we first need to specify how we can identify these individual-level parameters.

3.2 Identifying Preferences and Beliefs

3.2.1 Dimensions of Latent Factors and Survey Questions

Using data on ordinal survey responses, we are interested in five individual-level dimensions for beliefs and preferences:

$\alpha_{n,ECO}$	Latent worries about economic effects
$\alpha_{n,COM}$	Latent worries about compositional amentities
$\alpha_{n,RAC}$	Latent racism
$\alpha_{n,ALT}$	Latent altruism
$\alpha_{n,IMM}$	Latent preference for immigration

where we are interested in explaining $\alpha_{n,IMM}$. Note that $\alpha_{n,ECO}, \alpha_{n,COM}, \alpha_{n,RAC}$ and $\alpha_{n,ALT}$ can be components of $\boldsymbol{Z_n}$ in equation (2), depending on the specification. The general identification strategy is to use several questions along each dimension to estimate the latent factor for each individual.[11] Let D denote the set of latent explanatory factors used. In the main analysis, we have $D = \{\text{ECO, COM, RAC, ALT}\}$ although we will also estimate the model using only a subset of these latent factors. Hence, $\{\text{IMM}, D\}$ is a list over all the latent factors we will estimate.

For each of the five latent factors, we use a multitude of questions from the European Social Survey (ESS) as shown in Tables 1 and 2. We denote the questions belonging to each

[11] Gelman and Hill (2007), in particular in section 14.3 of their book, provide a very useful introduction to item-response and ideal-point models.

dimension as $Q_{\text{ECO}} = \{1, 2, 3\}$, $Q_{\text{COM}} = \{1, 2, 3, 4\}$, $Q_{\text{RAC}} = \{1, 2, 3, 4, 5\}$, $Q_{\text{ALT}} = \{1, 2, 3\}$, and $Q_{\text{IMM}} = \{1, 2, 3, 4\}$. Each survey participant is asked all questions and selects a response from a given set of possible answers. Let $R_{d,q}$ denote the number of possible responses to question q on dimension d. We code responses such that the 'lowest' response is always unity. Subsequently, each higher possible response is coded as the lower response plus one. Finally, we let $r_{d,q,n}$ denote the *observed* integer response of individual n to question q on dimension d.

3.2.2 Ordered Logit Model

At the core of the identification of individual level parameters are the ordered survey responses for which we use an ordered, logistic model. When a person is asked a specific question along a particular dimension, the individual's response will reflect both the latent *general* latent factor α for this dimension as well as an idiosyncratic component which captures how the response to the *specific* question might deviate from the individual general latent factor. As an example, an individual might *in general* believe that immigration is good for the economy. However, for *specific* questions the individual might be more or less positive than what the general level imply. This is the *specific, idiosyncratic* component. The observed response will then reflect the sum of the general and the specific, where we are interested in identifying the general part.

An important component of the ordinal logit model are cutpoints. A cutpoint is a threshold between possible responses, such that an individual will choose an answer to either side of this cutpoint depending on whether the sum of the general and specific latent factor is higher or lower than the cutpoint. Hence, for each question we need to estimate a separate cutpoint vector. We denote the cutpoints on question q on dimension d by $\boldsymbol{\chi}_{q,d}$, which is an increasing, ordered vector of length $R_{d,q} - 1$.

Furthermore, let $\lambda(z) \equiv (1 + exp(-z))^{-1}$ define the cumulative distribution function of the standard logistic distribution. Following the standard in the literature on ordinal logit models, we normalize the variance of the logistic distribution to $\pi^2/3$. We can then, with all the notation from above, write down the likelihood function of each individual response given the parameters:

$$\Lambda(r_{d,q,n}|\alpha_{n,q}, R_{d,q}, \boldsymbol{\chi}_{d,q}) = \begin{cases} 1 - \lambda\left(\alpha_{n,q} - \chi_{d,q}[1]\right) & if \;\; r_{d,q,n} = 1 \\ \lambda\left(\alpha_{n,q} - \chi_{d,q}[r_{d,q,n} - 1]\right) - \lambda\left(\alpha_{n,q} - \chi_{d,q}[r_{d,q,n}]\right) & if \;\; 1 < r < R_{d,q} \\ \lambda\left(\alpha_{n,q} - \chi_{d,q}[r_{d,q} - 1]\right) & if \;\; r = R_{d,q} \end{cases} \tag{3}$$

The ordered vector $\boldsymbol{\chi}_{q,d}$, captures the 'difficulty' of each question. As an example, it could be that the question on whether some races are born less intelligent is so extreme that even those individuals with some xenophobic inclinations are reluctant to answer yes. This will then be reflected in our estimate of $\boldsymbol{\chi}_{q,d}$, where it will be such that only individuals with very high xenophobic views are likely to answer 'yes'. Thus, observing a 'yes'-response to this question reveals that the individual is likely to be highly xenophobic, but a 'no'-response only tells us that the individual is not likely to have a high level of xenophobia. This intuition extends to responses with multiple, possible responses, where the cutpoints will give the distance between responses.[12] Next, we will define the priors for cutpoint and latent factors.

3.2.3 Priors

Starting with the explanatory latent factors, we want to specify a prior distribution that accomplishes two things. First, it should allow for a correlation between individual, latent factors. It could be the case that individual levels of e.g. Racism and Altruism are highly negatively correlated, and hence, a well specified model should be able to account for that. Second, the prior should impose some shrinkage. To see that this is desirable, consider an individual who answers each question with the highest level along one dimension. The likelihood will then be increasing as the individual parameter is going to infinity, and hence, we cannot pin down the individual level along this dimension. Hence, we need some regularization, which can be achieved by assuming that all individuals, even the extreme ones, are drawn from a common hyper distribution.

Let $\boldsymbol{\alpha}_{n,D}$ denote a vector containing all individual-level explanatory latent factors which we assume are drawn from a multivariate normal distribution:

$$\boldsymbol{\alpha}_{n,D} \sim MVN\left(0, \boldsymbol{\Sigma}\right) \tag{4}$$

[12]The book Greene and Hensher (2010) provides an excellent introduction to ordered choice models.

where $\boldsymbol{\Sigma}$ is a covariance matrix of appropriate dimension relative to the latent factors $\boldsymbol{\alpha}_{n,D}$. The covariance matrix will then reflect the degree of covariance between latent factors. We estimate the covariance matrix $\boldsymbol{\Sigma}$, and therefore need to specify a prior for it. This is an item where some care must be taken to ensure that the estimator is both efficient as well as numerically well behaved. To achieve this, we decompose the covariance matrix $\boldsymbol{\Sigma}$ into a scale vector $\boldsymbol{\sigma}$ and a correlation matrix $\boldsymbol{\Omega}$:

$$\boldsymbol{\Sigma} = \boldsymbol{\sigma}' \boldsymbol{\Omega} \boldsymbol{\sigma} \tag{5}$$

We use a normal distribution, truncated at zero, as a prior for each of the parameters in $\boldsymbol{\sigma}$ with $\boldsymbol{\sigma} \sim N^{+}(0,1)$. Finally, we place an LKJ-prior on the correlation matrix $\boldsymbol{\Omega}$.[13] The LKJ-distribution is a distribution over correlation matrices that takes only one parameter, $\nu > 0$. The higher ν, the more informative the prior in terms of forcing the posterior of $\boldsymbol{\Omega}$ to a diagonal matrix. Our choice of prior for this correlation matrix is not very important when we estimate the model on the full data set since there is so much data that the prior makes little influence. However, for the country-specific analysis where we operate with much smaller samples, a too uninformative prior will cause numerical problems as the posterior densities of the correlation parameters might approach unity. Therefore, we impose a soft constraint towards a diagonal correlation matrix using $\nu = 2$:

$$\boldsymbol{\Omega} \sim LKJ(2) \tag{6}$$

When we estimate the model for the full set of eighteen countries, we use an uninformative, flat prior on the cutpoint-vectors over the range of permissible values:

$$p\left(\chi_{d,q,c} | \chi_{d,q,c-1}\right) \propto \begin{cases} 1 & if\ \chi_{d,q,c} > \chi_{j,k,c-1} \\ 0 & if\ \chi_{d,q,c} \leq \chi_{j,k,c-1} \end{cases}, \chi_{d,q,0} = -\infty, \quad d \in [\text{IMM}, D],\ q \in Q_d,\ c \in R_{d,q} \tag{7}$$

Informally, this implies that, *a priori*, any value along the real line is equally likely for the lowest cutpoint of a given question. Then, for the second lowest cutpoint, the conditional prior density is such that any value higher than the first one is equally likely, whereas values

[13] See Lewandowski, Kurowicka and Joe (2009) or Gelman et al. (2014) page 582 for a brief introduction.

equal to or smaller than the first one are ruled out. The prior then extends similarly to all higher elements of the cutpoint vector. The next section will describe the prior distribution for $\alpha_{n,IMM}$, the individual level of support for immigration.

3.3 Attitudes towards Immigration

With the model in place, we can revert to the relationship of interest in equation (2): what determines individual attitudes towards immigration? First, we can split the vector of explanatory variables $\boldsymbol{Z}_n = [\boldsymbol{\alpha}_{n,D}, \boldsymbol{X}_n]$ into two parts, where $\boldsymbol{\alpha}_{n,D}$ reflects again the explanatory latent factors and $\boldsymbol{X}_n$ is a set of covariates. We can now link individual-level support for immigration to the two sets of explanatory variables:

$$\alpha_{n,IMM} = \boldsymbol{\alpha}_n'\boldsymbol{\beta}_\alpha + \boldsymbol{X}_n'\boldsymbol{\beta}_{\boldsymbol{X}} + \varepsilon_n \tag{8}$$

where the coefficient vector $\boldsymbol{\beta} = [\boldsymbol{\beta}_\alpha, \boldsymbol{\beta}_X]$ is split according to the number of covariates $\boldsymbol{X}$ and latent, explanatory factors $\boldsymbol{\alpha}_{n,D}$. The interpretation of coefficients is now that β_k shows the expected increase in $\alpha_{n,IMM}$ when variable k increases by one unit. We place a standard normal prior on all coefficients:

$$\begin{aligned} \boldsymbol{\beta} &\sim N(0,1) \\ \sigma_\varepsilon &\sim N^+(0,1). \end{aligned} \tag{9}$$

To facilitate a straightforward interpretation of the relative importance of the explanatory power of different factors, we will not present coefficients on the latent factors but report the posterior densities of $\hat{\boldsymbol{\beta}}_\alpha = \boldsymbol{\beta}_\alpha \circ \boldsymbol{\sigma}^{-1}$, where '$\circ$' denotes the element-wise product of two vectors, and $\boldsymbol{\sigma}^{-1}$ is a vector consisting of the standard errors of the latent factors. The elements of $\hat{\boldsymbol{\beta}}_\alpha$ will then show the expected increase in $\alpha_{n,IMM}$ if an element of $\boldsymbol{\alpha}_{n,D}$ increases by one standard deviation. For instance, we can examine how much support for immigration increases if an individual's expectations about the economic effects of immigration improve by one standard deviation. The final element we need to close the model is a prior for the error term ε. We place a normal prior on this, which implies that

$$\alpha_{n,IMM} \sim N\left(\boldsymbol{\alpha}_{n,D}'\boldsymbol{\beta}_\alpha + \boldsymbol{X}_n'\boldsymbol{\beta}_{\boldsymbol{X}}, \sigma_\varepsilon^2\right). \tag{10}$$

3.3.1 Country-Specific Model

As an additional analysis, we want to estimate the model separately for each of the eighteen countries in the ESS data set. To do this, we must make some small adjustment to the model. The general model uses very non-informative priors, in particular for the cutpoints $\boldsymbol{\chi}_{q,d}$. Given the large amount of data in the pooled sample as well as the variability of responses, we can recover proper posterior distributions for the parameters of interest. However, when we analyze each country separately there might not be enough data for this strategy. If we do not observe respondents in each category of possible responses, we will get a so-called "cutpoint-collapse", where the cutpoints around responses that are never chosen approach each other. Given the numerical constraint that the cutpoint-vectors are ordered, cutpoint collapse cause numerical instability.

For the country analysis, we therefore impose a slightly more informative prior for the cutpoints.[14] Specifically, let $\boldsymbol{\theta}_{q,d}$ denote a simplex vector (i.e. a vector with non-negative entries that sum to one) of length $R_{d,q} - 1$ with a Dirichlet prior distribution:

$$\boldsymbol{\theta}_{q,d} \sim Dir(2, ..., 2) \tag{11}$$

Next, we define two additional parameters $\kappa_{q,d}$ and $\nu_{q,d}$ with priors given by $\kappa_{q,d} \sim Exp(1)$ as well as $\nu_{q,d} \propto 1$. Note that we assign an exponential distribution to $\kappa_{q,d}$ and an improper, flat prior to $\nu_{q,d}$. The prior for $\kappa_{q,d}$ is somewhat restrictive but has the benefit of improving numerical stability. With these auxiliary parameters, we can now define the cutpoints themselves:

$$\chi_{d,q,c} = \kappa_{d,q} \sum_{j=1}^{c} \theta_{q,d,j} + \nu_{d,q}. \tag{12}$$

The cutpoints are modeled as the cumulative sums of the Dirichlet-vector $\boldsymbol{\theta}$, scaled by κ. This gives us an ordered vector. We add the intercept ν to each cutpoint such that it can cover negative and positive values.

[14]This prior was suggested by the developers of Stan. Note that it only applies to questions with more than two possible responses where we instead place an improper, uniform prior on the single cutpoint.

3.4 Estimation

The purpose of our empirical analysis is to use survey data from the European Social Survey to infer the relative importance of each determinant of individual support for immigration. If we denote the available data by y and the collection of all parameters by $\mathbf{\Theta}$, the conditional likelihood of the data is given by

$$p(y|\mathbf{\Theta}) = \sum_{n \in N} \sum_{d \in [\text{IMM}, D]} \sum_{q \in Q_d} \Lambda(r_{d,q,n} | \alpha_{n,q}, R_{d,q}, \boldsymbol{\chi}_{d,q}). \tag{13}$$

and the posterior densities of the parameters can then be found using Bayes rule:

$$p(\mathbf{\Theta}|y) \propto p(y|\mathbf{\Theta})p(\mathbf{\Theta}) \tag{14}$$

where $p(\mathbf{\Theta})$ is given by the set of priors. We estimate the model using Stan, following the convention of using several MCMC-chains, each initialized with random draws.[15]. We use standard tools to assess convergence.[16]

4 Results

We first present estimates of the full latent-factor model, estimated on the entire data set with all eighteen countries of the European Social Survey. Thereafter, we estimate the model separately for high- and low-educated individuals. Finally, we present estimates of the model for each country separately.

4.1 Determinants of Immigration Preferences

Table 4 shows the posteriors for the model presented in Section 3. In the first specification, we only include individual covariates. The results indicate that education is by far the most important factor. Higher educated survey participants show much greater support for immigration than individuals with lower educational status. As expected, older individuals and those living in more rural areas support immigration to a lesser extent.

[15]For more detailed information on the estimation procedure and technical implementation, we refer to 'Modeling Language User's Guide and Reference Manual' on the Stan website: `http://mc-stan.org/`.

[16]All parameters have converged in the sense of having $\hat{R} < 1.1$. We refer to (Gelman et al., 2014, p.285) for a discussion of this statistic.

Table 4: Estimates of Latent-Factor Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECO		0.615				0.079	0.198	0.199
		(0.012)				(0.043)	(0.044)	(0.043)
COM			0.792			0.704	0.411	0.408
			(0.014)			(0.054)	(0.060)	(0.058)
RAC				-1.452			-0.656	-0.614
				(0.041)			(0.040)	(0.043)
ALT					0.388			0.062
					(0.016)			(0.014)
Education	1.537	0.697	0.654	1.093	1.447	0.525	0.416	0.41
	(0.056)	(0.049)	(0.049)	(0.054)	(0.055)	(0.048)	(0.045)	(0.046)
Age	-0.942	-0.929	-0.629	-0.393	-0.914	-0.727	-0.495	-0.507
	(0.070)	(0.060)	(0.058)	(0.063)	(0.064)	(0.054)	(0.056)	(0.055)
Inc. Decile	0.555	0.191	0.242	0.464	0.552	0.16	0.156	0.162
	(0.057)	(0.049)	(0.047)	(0.052)	(0.057)	(0.048)	(0.046)	(0.045)
Unemployed	-0.102	0.111	0.032	-0.078	-0.161	0.106	0.097	0.071
	(0.128)	(0.109)	(0.106)	(0.118)	(0.125)	(0.101)	(0.102)	(0.098)
Retired	0.126	0.059	0.164	0.201	0.134	0.118	0.156	0.158
	(0.079)	(0.068)	(0.067)	(0.073)	(0.077)	(0.064)	(0.064)	(0.064)
Male	-0.113	-0.307	-0.072	0.019	0.071	-0.183	-0.12	-0.061
	(0.051)	(0.044)	(0.042)	(0.048)	(0.050)	(0.041)	(0.041)	(0.040)
Minority	-0.009	-0.323	-0.365	-0.078	-0.181	-0.398	-0.389	-0.441
	(0.116)	(0.102)	(0.096)	(0.110)	(0.113)	(0.095)	(0.094)	(0.095)
Suburb	-0.279	-0.167	-0.097	-0.233	-0.204	-0.099	-0.101	-0.079
	(0.093)	(0.079)	(0.075)	(0.088)	(0.090)	(0.075)	(0.074)	(0.073)
Town	-0.52	-0.213	-0.151	-0.404	-0.436	-0.117	-0.105	-0.088
	(0.074)	(0.064)	(0.062)	(0.072)	(0.072)	(0.059)	(0.058)	(0.058)
Village	-0.603	-0.212	-0.117	-0.443	-0.501	-0.08	-0.059	-0.035
	(0.077)	(0.067)	(0.065)	(0.073)	(0.074)	(0.062)	(0.060)	(0.062)
Farm	-0.618	-0.295	-0.17	-0.372	-0.478	-0.163	-0.094	-0.066
	(0.112)	(0.097)	(0.095)	(0.110)	(0.111)	(0.095)	(0.089)	(0.091)
σ_{Imm}	3.481	2.694	2.594	2.96	3.357	2.587	2.503	2.501
	(0.028)	(0.024)	(0.023)	(0.028)	(0.026)	(0.023)	(0.022)	(0.022)

Note: The table shows the estimates of the model explained in Section 3, where we use four survey questions (IMM1 to IMM4) to identify individual, latent preference for immigration. Plain numbers indicate posterior mean, and numbers in parentheses show the standard deviation of the posterior distribution. Note that the variables age and income decile have been standardized by two times their standard deviation.

In the second column of Table 4, we add concerns about the *economic* effect of immigration (ECO) to the model. Most notably, conditioning on individual beliefs on the economic effects of immigration reduces the impact of education by more than half. When adding worries about compositional amenities (COM) in column (3), we obtain a similar result. Note that coefficients of the latent factors are comparable across columns as we divide by the respective standard deviation. Columns (4) and (5) show that individual values –racism and altruism– also have a significant impact on support for migration. As expected, racist character traits (RAC) strongly reduce the preferred level of immigration while altruism (ALT) increases the level.

Note that the dependent variable in these regressions is the latent, *general* individual preference for immigration. Hence, although we can compare coefficients of the explanatory latent factors to assess how important they are, interpreting the dependent variable is harder.

One possibility is to take into account cutpoints to analyze to what extent a covariate might shift people from one level to the next. Here, it is more natural to compare coefficients with the distribution of general immigration preferences across all voters. We defer this discussion for section 4.4.

To compare the relative magnitude of the effects, we first add both expectations about the economic and non-economic effects of migration to the model. Column (6) documents a result that is in line with Card, Dustmann and Preston (2012): concerns about compositional amenities are much more important than economic concerns. However, we might wonder to what extent 'concerns about compositional amenities' (COM) pick up 'neutral' worries about the efficiency of public goods. It could also be that COM reflects racist views which we expect to have its own effect on immigration preferences. Hence, in column (7) we add a composite measure of racism to the model. We observe that this reduces the effect of compositional concerns by about forty percent. Moreover, the quantitative importance of economic concerns is now about half of non-economic worries. Most strikingly, the results show that racism is about as important as concerns about *both* economic as well as non-economic effects of immigration. Finally, in column (8) we add altruism as a further possible determinant of immigration preferences. As expected, we find that altruistic traits positively affect support for immigration. However, compared with the other determinants, altruism plays a minor role.

Table 5: Correlation Matrix of Latent-Factor Estimates

	ECO	COM	RAC	ALT
ECO	1			
COM	0.939	1		
RAC	-0.513	-0.615	1	
ALT	0.223	0.284	-0.433	1

Note: The table shows the estimates of the correlation matrix $\mathbf{\Omega}$, as explained in Section 3, where we use four survey questions (IMM1 to IMM4) to identify individual, latent preference for immigration. The table shows the posterior mean for each parameter. The results are from the full model, where we use $D = \{\text{ECO,COM,RAC,ALT}\}$ as explanatory latent factors, corresponding to the rightmost column in Table 4.

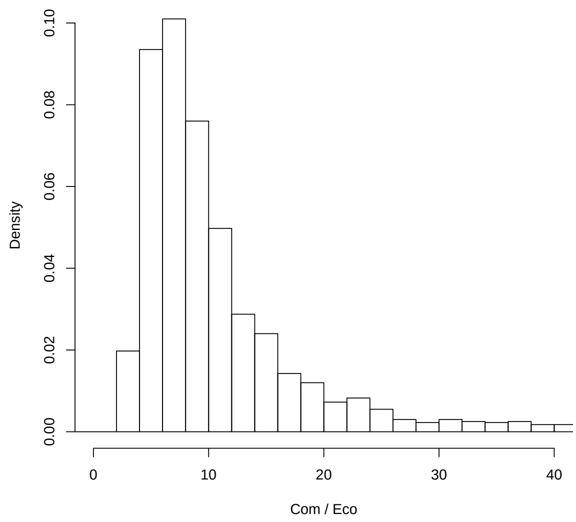
Table 5 shows the estimates of the correlation matrix $\mathbf{\Omega}$ from the full model with all latent, explanatory variables. These estimtes shows that the correlation of the latent factors ECO and COM is very high at 0.94. Apart from that, the signs of the correlations are as we would expect: higher levels of racism are negatively correlated with optimism about the economic and cultural effects of immigration. Correlation of explanatory variables makes it harder to identify coefficients individually and as we discuss in the next section, also ratios of coefficients. However, the estimate of the *sum* of coefficients for correlated variables need not be adversely affected. Appendix C illustrates these issues further with a simple simulation exercise.

4.1.1 Importance of Latent-Factors relative to Economic Concerns

One way of interpreting the results of Table 4 is to use one factor as a "numeraire" and evaluate the importance of other factors relative to the numeraire factor. Following Card, Dustmann and Preston (2012), we use ECO as numeraire. This allows us to study the main finding by Card, Dustmann and Preston (2012) that concerns compositional amenities were 2–5 times as important as worries about the economic impact of immigration. Given that this is a Bayesian analysis, we have to keep in mind that coefficients are random variables. This implies that, although we report the posterior means of coefficients in Table 4, the posterior mean of the *ratio* of coefficients will generally not be equal to the ratio of the posterior means. Therefore, we analyze the posterior distributions of ratios as separate parameters.[17] Using the results from the model in column (6), we find that the posterior mean of the ratio ECO/COM is 65.251. However, there is considerable uncertainty about this parameter. To illustrate this, we plot the posterior distribution of $\hat{\beta}_{COM}/\hat{\beta}_{ECO}$ in Figure 2.

[17]We can note that we can write this ratio as $(\beta_i/\sigma_i)\,/\,(\beta_j/\sigma_j) = \frac{\sigma_j}{\sigma_i}x$. Given that coefficients have a standard, normal prior, this implies that the prior on x is a Cauchy-distribution. Hence, this ratio does not *a priori* have a mean or variance. Whether the ratio is well behaved *a posteriori* depends on the data.

Figure 2: Posterior Densitites of Relative Coefficients: COM vs ECO



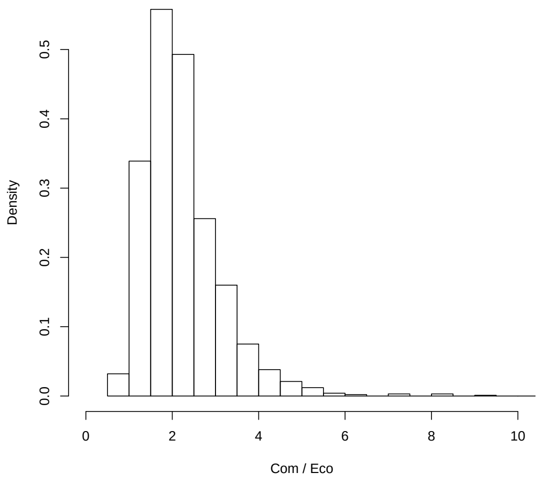
Note: The figure shows the posterior distributions of $\frac{\hat{\beta}_{COM}}{\hat{\beta}_{ECO}}$, from the model where we only control for ECO and COM. The posterior mean of $\frac{\hat{\beta}_{COM}}{\hat{\beta}_{ECO}}$ is 65.251, and median of 8.389, with a standard error of 1860.601. The figure shows only a small excerpt of the possible values of the ratio, as it extends to large positive and negative values.

The figure shows the posterior distributions of $\hat{\beta}_{COM}/\hat{\beta}_{ECO}$ from a model where we include ECO and COM as the only latent factors. The posterior of this ratio has a standard error of 1860.6, which highlights the difficulty of comparing the magnitudes of two factors if said factors are highly correlated, as well as using ratios when the denominator is close to zero. As is shown in Table A.1 in the Appendix, the simple correlation between worries about the economic and non-economic effects of immigration, $Corr_{ECO,COM}$, is 0.71 and even higher when controlling for country-fixed effects. In our latent-factor model, we explicitly allow for such dependencies among factors, and find the correlation of the ECO and COM is even higher than what simple correlations of responses show. It is therefore not surprising that it is hard to disentangle the separate effects of ECO and COM: the spread of the posterior of the ratio of the coefficients is very wide.

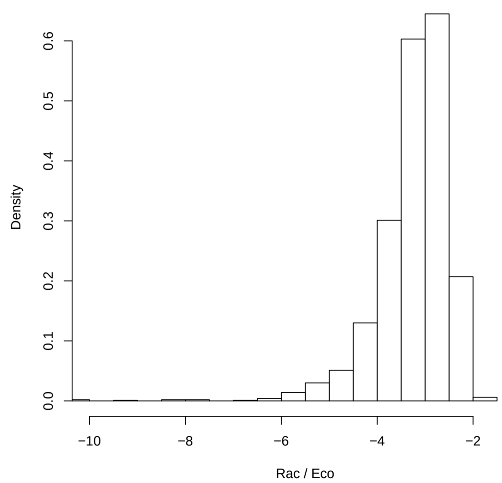
Another problem of considering the ratio $\hat{\beta}_{COM}/\hat{\beta}_{ECO}$ is that we might have an omitted variable bias if we do not control for other latent factors. Referring again to Table A.1 in the Appendix, we observe that in particular racism (RAC) has a large negative correlation with economic and non-economic expectations about immigration. Considering the model with all factors included (column (8) in Table 4), it turns out that including racism as a separate explanatory latent factor increases the precision of ratio estimates considerably. This is shown in Figure 3 which plots the posterior distributions of all the relative coefficients of latent factors.

Figure 3: Posterior Densitites of Relative Coefficients

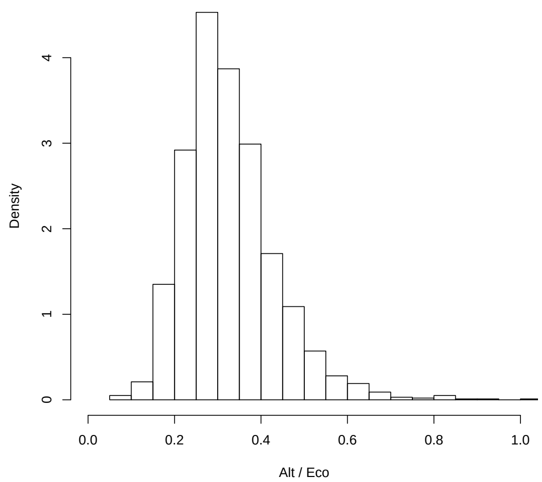
(a) COM and ECO



(b) RAC and ECO



(c) ALT and ECO



Note: The figure shows the posterior distributions of $\frac{\hat{\beta}_{COM}}{\hat{\beta}_{ECO}}$, $\frac{\hat{\beta}_{RAC}}{\hat{\beta}_{ECO}}$ and $\frac{\hat{\beta}_{ALT}}{\hat{\beta}_{ECO}}$. The respective posterior means are given by 2.244, −3.234 and 0.328, respectively. The standard deviations of the posterior distributions are given by 0.981, 0.784 and 0.112, respectively.

In this model, we observe that the effect of improving worries about compositional amenities is over twice as large as concerns about economic effects of immigration. The standard deviation of the ratio is 0.981. Racism is, on the other hand, clearly more important than expectations about economic effects: the posterior mean of the ratio is -3.2 with a standard error of 0.784. Finally, based on plot (c) we have a high confidence that altruism only has a small impact relative to economic concerns. As a final result, we can note that racism is as important as the *combined* effect of worries about economic and non-economic effects of immigration. To see this, we find that the posterior mean of $\frac{\hat{\beta}_{RAC}}{\hat{\beta}_{ECO}+\hat{\beta}_{COM}}$ is -1.014 with a small standard deviation of 0.096.

4.2 Education and Immigration Preferences

One important observation from the results discussed thus far is that the coefficient on education dropped by about 75 percent when controlling for economic and compositional effects (cf. Table 4, columns 1 and 6). Hence, we explore in more detail how education affects support for migration. Following prior research by Hainmueller and Hiscox (2007), we expect education to have a large impact for several reasons: First, it alters labor market performance and thus how people expect immigration to affect them economically. Second and beyond economic reasoning, education may provide individuals with a more tolerant mindset (i.e. reduce racist attitudes). In the results shown in Table 4, we always include a dummy for higher education. If we consider column (1), the estimate of 1.54 on education suggests that individuals with higher education have a far higher support for immigration compared to those without higher education.[18]

However, this estimate summarizes all channels through which education might affect immigration preferences. Once we add beliefs about the economic and non-economic effects of immigration to the model, the results in column (6) show that the coefficient on education is much smaller. When we add racism and altruism as additional factors, the coefficient on education is again significantly reduced, to about a quarter of its initial value.

As shown in Table 6, these channels —economic and non-economic expectations, racism, and altruism— play a similar role among individuals with and without higher education.

[18]The discussion section of the paper shows the total distribution of immigration preferences across the population, which gives an appropriate context for interpreting this coefficient.

Table 6: Estimates of Latent-Factor Model by Education

	(1) High Education	(2) No High Education
ECO	0.218	0.242
	(0.063)	(0.062)
COM	0.435	0.371
	(0.088)	(0.081)
RAC	-0.660	-0.639
	(0.071)	(0.054)
ALT	0.030	0.069
	(0.027)	(0.015)
Age	-0.149	-0.629
	(0.097)	(0.066)
Inc. Decile	0.065	0.182
	(0.079)	(0.053)
Unemployed	-0.290	0.200
	(0.207)	(0.111)
Retired	-0.004	0.197
	(0.124)	(0.075)
Male	-0.095	-0.065
	(0.074)	(0.049)
Minority	-0.828	-0.248
	(0.164)	(0.115)
Suburb	-0.107	-0.063
	(0.121)	(0.090)
Town	-0.125	-0.075
	(0.099)	(0.073)
Village	-0.012	-0.041
	(0.111)	(0.074)
Farm	0.064	-0.150
	(0.175)	(0.108)
σ_{Imm}	2.694	2.407
	(0.042)	(0.027)

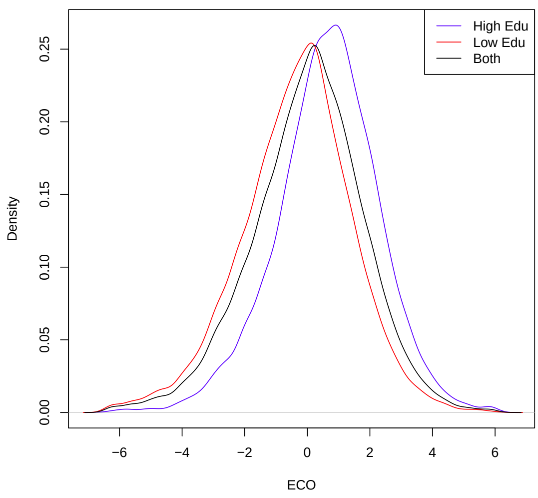
Note: The table shows the estimates of the model explained in Section 3, where we use four survey questions (IMM1 to IMM4) to identify individual, latent preference for immigration. Plain numbers indicate posterior mean, and numbers in parentheses show the standard deviation of the posterior distribution. Note that the variables age and income decile have been standardized by two times their standard deviation.

Hence, the mechanism through which latent factors influence immigration preferences are quite similar both for high- and low educated individuals. Thus, the mean difference in immigration preferences between the educational groups is the result of mean differences in the levels of latent factors. We emphasize that these conclusions are *conditional* on beliefs about the economic effects of immigration, compositional amenities, racism and altruism.

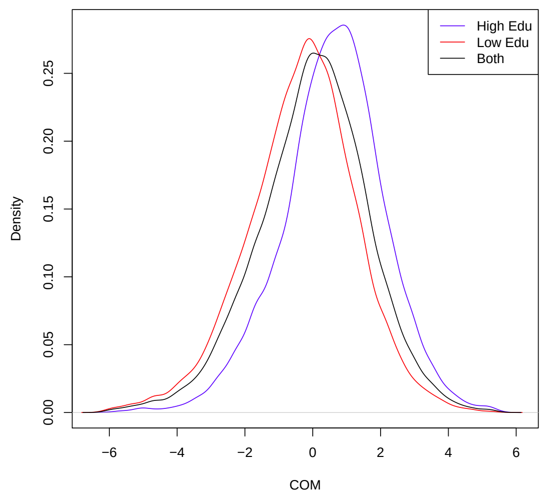
Hence, there might still be large differences in the observed responses to the immigration questions by the two groups. Figure 4 shows the estimated densities of the posterior means of latent factors for high- and low-educated individuals.

Figure 4: Distribution of Posterior Means of Latent Factors

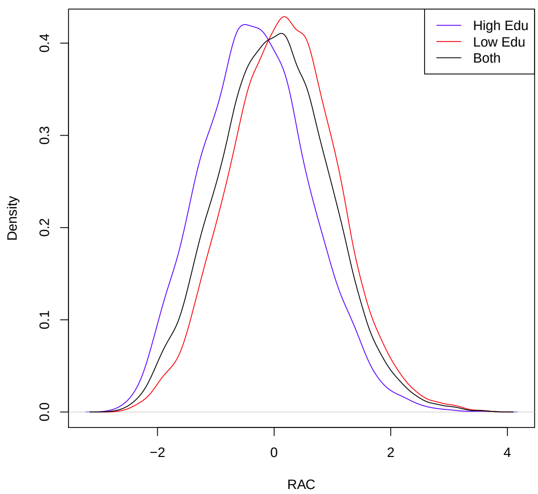
(a) ECO



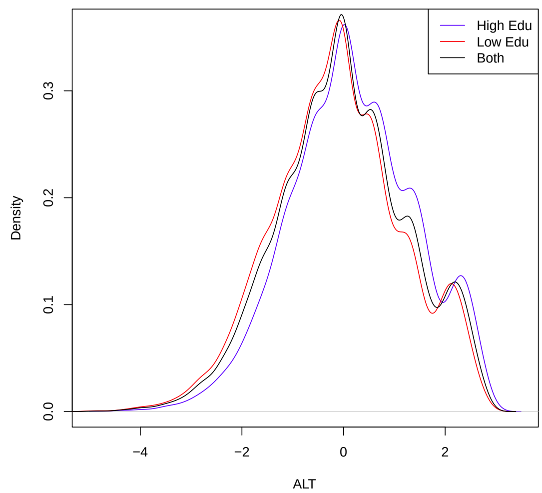
(b) COM



(c) RAC



(d) ALT



Note: The figure shows the densities of posterior means of latent, individual factors for high- and low-educated individuals, as well as the complete sample. The figures are based on results from the same model, with all latent factors and all countries, corresponding to column (8) in Table 4.

As is clear from the figure, lower educated are more pessimistic about the economic effects of immigration, more pessimistic about the effect of immigration on compositional amenities, and more racist. The difference between higher and lower educated in terms of altruism appears to be small.

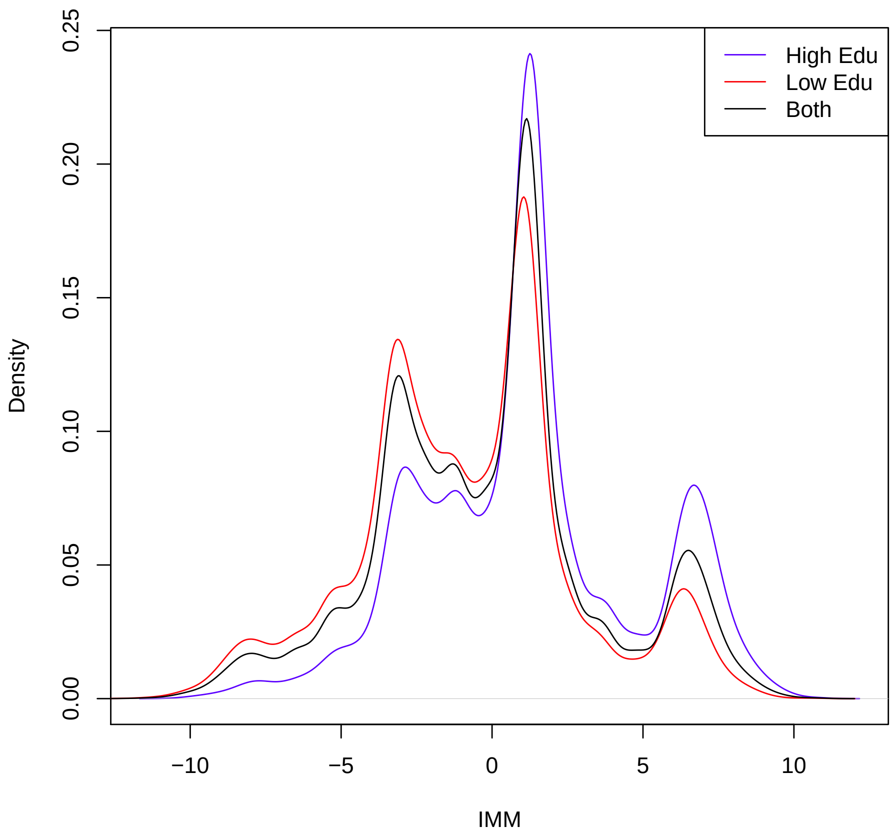
4.3 Country-Specific Latent-Factor Estimates

For our main analysis, we use survey data from the full sample of eighteen European countries. Given the diversity of past immigration experiences, public policies, and values across Europe, we intend to fit our model for each country separately. Table A.3 in the Appendix provides the results. Generally, the estimates are fairly similar across all countries. However, the problem of multicollinearity is more severe in this exercise due to the limited sample size for each country. While we have more than 20'000 observations when using a pooled data set of all countries, we only have about 1'000 to 2'000 observations per country. This is why the effect of, for example, economic concerns in Switzerland turns insignificant. Overall, the results show that racism is quantitatively the most important factor in almost all countries.

4.4 Discussion

Europeans are divided over immigration issues. Figure 5 illustrates the means of the posterior densities for immigration preferences, for high- and low-educated respectively. A striking feature of both distributions is that they are multimodal. There is a large mass of voters with very positive views on immigration, a large mass in the middle, and a large mass with considerable opposition to immigration. However, it is the highly educated that are most positive, and the low educated that are most negative. It is not surprising to find that aggregating these preferences into a common policy is a demanding task.

Figure 5: Posterior Means of Immigration Preferences



Note: The figure shows the densities of posterior means of latent, individual immigration preferences factors for high- and low-educated individuals. The figures are based on results from the same model, with all latent factors and all countries, corresponding to column (8) in Table 4.

Understanding what drives these differences could be the key to finding some common ground. In studies on trade, one might find proposals of transfers to eliminate unwanted distributional effects of efficient policies. Put differently, winners from trade liberalization can be taxed such that losers might be compensated. This ensures political support for efficient policies. In our context, such policies might also be part of a solution. As we have seen, both economic concerns and worries about the effect of immigration on compositional amenities are important determinants of immigration preferences. Countering the effect immigration might have on, for example, wages and the welfare state as well as improving integration outcomes might alleviate the effect of COM and ECO on support for immigration. However, racism is a separate and important determinant of immigration preferences as well. It appears to be a difficult task to alter the prevalence of racist character traits. While our analysis does not examine how latent factors such as racism can be altered, we inform policymakers on where to start if increasing the support for immigration is the policy goal. The results of our estimation provide an idea of the quantitative relationships between expectations about the effects of immigration, racism, altruism, and the level of support for migrants.

5 Conclusion

This paper examines which individual values and beliefs shape preferences over immigration policies. We empirically establish the *quantitative* importance of each determinant by means of a newly developed latent-factor model. Using data from the most recent European Social Survey, our results show that expectations about the economic and non-economic effects of immigration, racism, as well as altruism have a statistically and economically significant effect on preferences over immigration. While confirming some results of prior research, we contribute to the literature by documenting that racist character traits have quantitatively the largest explanatory power for individual immigration preferences. Our analysis reveals that —in line with previous research by Card, Dustmann and Preston (2012)— worries about compositional amenities are more important than concerns about economic effects of immigration. However, the impact of compositional worries is mitigated substantially once we add racism as an additional factor. This suggests that to a large extent concerns about the non-economic impact of immigration are driven by racist attitudes. Finally, our estimates indicate that altruism has a significant positive impact on the preferred level of immigration.

In addition, we complement previous research on a methodological level by developing a latent-factor model which allows us to quantify the relative importance of each determinant. This is essential to understand if policymakers want to make informed decisions about how to alter immigration preferences. While our analysis establishes that racism is the most influential determinant of support for immigration, exploring how racist traits can be altered appears to be a fruitful question for future research. This would also help to define policy implications if we think that racist views can be altered similar to how attitudes toward trade and globalization can be influenced (Hainmueller and Hiscox, 2006). Individual experiences and acknowledging concerns have been found to affect attitudes towards migrants and refugees (Steinmayr, 2016; Stöhr and Wichardt, 2016).

References

Andreoni, James. 1989. “Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence.” *Journal of Political Economy*, 97(6): 1447.

Barone, Guglielmo, Alessio D’Ignazio, Guido de Blasio, and Paolo Naticchioni. 2016. “Mr. Rossi, Mr. Hu and politics. The role of immigration in shaping natives’ voting behavior.” *Journal of Public Economics*, 136: 1–13.

Becker, Sascha O., and Thiemo Fetzer. 2016. “Does Migration Cause Extreme Voting?” *Warwick University Working Paper Series No. 306.*

Bell, Brian, Francesco Fasani, and Stephen Machin. 2013. “Crime and Immigration: Evidence from Large Immigrant Waves.” *Review of Economics and Statistics*, 95(4): 1278–1290.

Bianchi, Milo, Paolo Buonanno, and Paolo Pinotti. 2012. “Do Immigrants cause Crime?” *Journal of the European Economic Association*, 10(6): 1318–1347.

Boeri, Tito. 2010. “Immigration to the Land of Redistribution.” *Economica*, 77(308): 651–687.

Borjas, George J. 2014. *Immigration Economics.* Cambridge, Mass.:Harvard University Press.

Bratsberg, Bernt, and Oddbjørn Raaum. 2012. “Immigration and Wages: Evidence from Construction.” *Economic Journal*, 122(565): 1177–1205.

Bridges, Sarah, and Simona Mateut. 2014. “Should They Stay or Should They Go? Attitudes Towards Immigration in Europe.” *Scottish Journal of Political Economy*, 61(4): 397–429.

Card, David, and Giovanni Peri. 2016. “Immigration Economics: A Review.” *Journal of Economic Literature*, 54(4): 1333–1349.

Card, David, Christian Dustmann, and Ian Preston. 2012. “Immigration, Wages, and Compositional Amenities.” *Journal of the European Economic Association*, 10(1): 78–119.

Docquier, Frédéric, Caglar Ozden, and Giovanni Peri. 2013. “The Labour Market Effects of Immigration and Emigration in OECD Countries.” *The Economic Journal*, 124(579): 1106–1145.

Dustmann, Christian, and Ian P. Preston. 2007. “Racial and Economic Factors in Attitudes to Immigration.” *The B.E. Journal of Economic Analysis and Policy*, 7(1): Article 62.

Dustmann, Christian, Tommaso Frattini, and Ian P. Preston. 2013. “The Effect of Immigration along the Distribution of Wages.” *The Review of Economic Studies*, 80(1): 145–173.

Dustmann, Christian, Uta Schönberg, and Jan Stuhler. 2016. “Labor Supply Shocks and the Dynamics of Local Wages and Employment.” *Quarterly Journal of Economics*, forthcoming.

Facchini, Giovanni, and Anna Maria Mayda. 2008. “From Individual Attitudes towards Migrants to Migration Policy Outcomes: Theory and Evidence.” *Economic Policy*, 23: 651–713.

Facchini, Giovanni, and Anna Maria Mayda. 2009. “Does the Welfare State Affect Individual Attitudes toward Immigrants? Evidence across Countries.” *Review of Economics and Statistics*, 91(2): 295–314.

Facchini, Giovanni, Anna Maria Mayda, and Mariapia Mendola. 2013. “What Drives Individual Attitudes towards Immigration in South Africa?” *Review of International Economics*, 21(2): 326–341.

Gang, Ira N., Francisco L. Rivera-Batiz, and Myeng Su Yun. 2013. “Economic strain, education and attitudes towards foreigners in the European Union.” *Review of International Economics*, 21(2): 177–190.

Gelman, Andrew, and Jennifer Hill. 2007. *Data analysis using regression and multilevel/hierarchical models.* Cambridge University Press.

Gelman, Andrew, John B. Carlin, Hal S. Stern, David B. Dunson, Aki Vehtari, and Donald B. Rubin. 2014. *Bayesian Data Analysis.* . 3 ed., Boca Raton FL:Taylor and Francis.

Greene, William H., and David A. Hensher. 2010. *Modeling Ordered Choices: A Primer.* Cambridge:Cambridge University Press.

Hainmueller, Jens, and Daniel J. Hopkins. 2014. "Public Attitudes Toward Immigration." *Annual Review of Political Science*, 17(1): 225–249.

Hainmueller, Jens, and Michael J. Hiscox. 2006. "Learning to Love Globalization: Education and Individual Attitudes toward International Trade." *International Organization VO - 60*, , (2): 469.

Hainmueller, Jens, and Michael J. Hiscox. 2007. "Educated Preferences: Explaining Attitudes Toward Immigration in Europe." *International Organization*, 61(02): 399–442.

Hainmueller, Jens, and Michael J. Hiscox. 2010. "Attitudes toward Highly Skilled and Low-skilled Immigration: Evidence from a Survey Experiment." *American Political Science Review*, 104(01): 61–84.

Hainmueller, Jens, Michael J. Hiscox, and Yotam Margalit. 2015. "Do Concerns About Labor Market Competition Shape Attitudes Toward Immigration? New Evidence." *Journal of International Economics*, 97(1): 193–207.

Halla, Martin, Alexander F. Wagner, and Josef Zweimüller. 2016. "Immigration and Voting for the Far Right." *Journal of the European Economic Association*, forthcoming.

Hansen, Ole-Petter Moe, and Stefan Legge. 2016. "Drawbridges Down: Altruism and Immigration Preferences." *CESifo Working Paper No. 6204.*

Hatton, Timothy J. 2016. "Immigration, public opinion and the recession in Europe." *Economic Policy*, 31(86): 205–246.

Lewandowski, Daniel, Dorota Kurowicka, and Harry Joe. 2009. "Generating random correlation matrices based on vines and extended onion method." *Journal of Multivariate Analysis*, 100(9): 1989–2001.

Markaki, Yvonni, and Simonetta Longhi. 2013. "What Determines Attitudes to Immigration in European Countries? An Analysis at the Regional Level." *Migration Studies*, 1(3): 311–337.

Mayda, Anna Maria. 2006. "Who Is Against Immigration? A Cross-Country Investigation of Individual Attitudes toward Immigrants." *The Review of Economics and Statistics*, 88(3): 510–530.

Murard, Elie. 2015. "Less welfare or fewer foreigners? Immigrant inflows and public opinion towards redistribution and migration policy."

OECD. 2017. *International Migration Outlook.* Vol. 41st Ed.

O'Rourke, Kevin H., and Richard Sinnott. 2006. "The determinants of individual attitudes towards immigration." *European Journal of Political Economy*, 22(4): 838–861.

Ottaviano, Gianmarco I. P., and Giovanni Peri. 2012. "Rethinking the effect of immigration on wages." *Journal of the European Economic Association*, 10(February): 152–197.

Piopiunik, Marc, and Jens Ruhose. 2017. "Immigration, regional conditions, and crime: Evidence from an allocation policy in Germany." *European Economic Review*, 92: 258–282.

Scheve, Kenneth F., and Matthew J. Slaughter. 2001. "Labor Market Competition and Individual Preferences Over Immigration Policy." *Review of Economics and Statistics*, 83(1): 133–145.

Steinmayr, Andreas. 2016. "Exposure to Refugees and Voting for the Far-Right: (Unexpected) Results from Austria." *IZA Discussion Paper No. 9790.*

Stöhr, Tobias, and Philipp C. Wichardt. 2016. "Conflicting Identities: Cosmopolitan or Anxious? Appreciating Concerns of Host Country Population Improves Attitudes Towards Immigrants." *Kiel Working Papers No. 2045.*

Appendix

A Additional Figures and Tables

Table A.1: Correlation of Altruism and Racism

	Correlation with				
	(1) IMM	(2) ECO	(3) COM	(4) RAC	(5) ALT
(1) IMM	1.0000				
	–				
(2) ECO	0.558	1.0000			
	0.723	–			
(3) COM	0.573	0.705	1.0000		
	0.829	*0.758*	–		
(4) RAC	-0.463	-0.338	-0.392	1.0000	
	-0.486	*-0.271*	*-0.312*	–	
(5) ALT	0.219	0.161	0.205	-0.293	1.0000
	0.343	*0.191*	*0.222*	*-0.365*	–

Note: The table shows unweighted correlations of the latent factors. We combine answers at the individual level such that zero reflects no support for any type of immigration, and one means maximum support for all four types of immigration. Similarly, the variables on the horizontal axis are defined: higher values imply more positive expectations, more racism, or more altruism. The questions are described in Tables 1 and 2. Numbers shown in italics are adjusted correlations, based on regressions with country-fixed effects.

Table A.2: Country-Level Averages

	Mean Value of				
Country	Immigration Support	Economic Effects	Compositional Effects	Racism	Altruism
BE	0.538	0.439	0.466	0.253	0.776
CH	0.601	0.541	0.514	0.217	0.812
DE	0.663	0.543	0.512	0.166	0.810
DK	0.578	0.508	0.515	0.198	0.776
ES	0.592	0.466	0.506	0.202	0.854
FI	0.517	0.515	0.554	0.220	0.791
FR	0.555	0.466	0.474	0.227	0.765
GB	0.496	0.471	0.448	0.243	0.777
HU	0.320	0.363	0.429	0.473	0.742
IE	0.520	0.464	0.503	0.266	0.784
IL	0.451	0.501	0.488	0.303	0.812
LT	0.493	0.487	0.476	0.475	0.647
NL	0.571	0.474	0.495	0.173	0.747
NO	0.656	0.555	0.489	0.182	0.748
PL	0.592	0.475	0.538	0.276	0.785
PT	0.530	0.485	0.483	0.278	0.737
SE	0.776	0.590	0.589	0.105	0.799
SI	0.601	0.462	0.496	0.223	0.836

Note: The table shows country-level averages of the latent factor variables: preferred level of immigration, expected economic effects, expected compositional effects, racism, and altruism. Note that we combine answers at the individual level such that zero reflects no support for any type of immigration, and one means maximum support for all four types of immigration. Similarly, the variables on the horizontal axis are defined: higher values imply more positive expectations, more racism, or more altruism. The questions are described in Tables 1 and 2.

Table A.3: Country-Specific Estimates of the Latent Factor Model

Variable	BE	CH	DE	DK	ES	FI	FR	GB	HU	IE	IL	LT	NL	NO	PL	PT	SE	SI
Eco	0.243	-0.055	0.177	0.121	0.368	0.187	0.373	0.252	0.315	0.346	-0.261	0.26	0.362	0.28	0.368	0.361	0.23	0.805
	(0.134)	(0.24)	(0.063)	(0.077)	(0.231)	(0.166)	(0.196)	(0.104)	(0.146)	(0.159)	(0.198)	(0.112)	(0.12)	(0.156)	(0.198)	(0.219)	(0.185)	(0.255)
Com	0.388	0.649	0.427	0.319	0.709	0.454	0.35	0.305	0.019	0.059	0.743	0.211	0.475	0.378	0.333	0.415	0.755	0.006
	(0.198)	(0.229)	(0.081)	(0.095)	(0.375)	(0.176)	(0.227)	(0.132)	(0.169)	(0.252)	(0.25)	(0.108)	(0.166)	(0.143)	(0.29)	(0.317)	(0.346)	(0.228)
Rac	-0.632	-0.973	-0.455	-0.947	-0.44	-0.753	-0.72	-0.299	-0.326	-0.783	-0.59	-0.723	-1.012	-0.672	-0.938	-0.606	-0.863	-0.438
	(0.175)	(0.229)	(0.147)	(0.236)	(0.29)	(0.143)	(0.151)	(0.112)	(0.104)	(0.158)	(0.133)	(0.148)	(0.224)	(0.217)	(0.31)	(0.217)	(0.354)	(0.216)
Alt	0.061	-0.075	0.208	0.158	0.122	-0.005	0.058	0.191	0.076	0.204	-0.054	-0.07	-0.08	0.166	0.075	0.033	0.177	0.049
	(0.066)	(0.117)	(0.075)	(0.065)	(0.075)	(0.052)	(0.062)	(0.071)	(0.049)	(0.053)	(0.049)	(0.07)	(0.096)	(0.085)	(0.112)	(0.052)	(0.111)	(0.095)
Edu	0.398	0.672	0.397	-0.074	0.362	0.39	0.834	0.533	0.654	0.934	0.241	0.439	0.773	-0.02	0.27	0.305	0.025	0.402
	(0.189)	(0.217)	(0.129)	(0.187)	(0.338)	(0.162)	(0.182)	(0.185)	(0.219)	(0.233)	(0.139)	(0.238)	(0.22)	(0.208)	(0.355)	(0.282)	(0.295)	(0.274)
Age	-0.369	-0.329	-0.013	-0.611	-0.629	-0.731	-0.515	-0.527	-0.94	-0.627	-0.517	0.218	0.128	-0.413	-1.174	-0.408	-0.734	-1.262
	(0.22)	(0.232)	(0.157)	(0.223)	(0.315)	(0.199)	(0.234)	(0.238)	(0.245)	(0.249)	(0.157)	(0.292)	(0.249)	(0.248)	(0.339)	(0.286)	(0.341)	(0.309)
Inc.Decile	0.229	0.221	0.315	-0.072	0.714	-0.192	0.178	0.159	-0.133	0.287	0.17	0.097	-0.192	-0.076	-0.664	0.658	0.659	-0.108
	(0.179)	(0.199)	(0.127)	(0.195)	(0.315)	(0.162)	(0.175)	(0.191)	(0.198)	(0.216)	(0.141)	(0.24)	(0.202)	(0.205)	(0.298)	(0.234)	(0.278)	(0.271)
Unemployed	0.459	-0.813	-0.133	0.007	0.139	-0.433	0.098	0.379	-0.022	1.04	-0.331	0.542	0.403	-0.97	-0.07	0.177	-0.175	-0.034
	(0.377)	(0.51)	(0.306)	(0.38)	(0.438)	(0.374)	(0.325)	(0.439)	(0.408)	(0.381)	(0.328)	(0.591)	(0.433)	(0.585)	(0.622)	(0.372)	(0.564)	(0.486)
Retired	0.1	0.17	-0.104	0.042	0.277	-0.027	0.01	-0.06	0.148	0.263	-0.013	-0.267	0.141	0.063	-0.123	0.202	0.348	-0.046
	(0.722)	(0.718)	(0.728)	(0.728)	(0.732)	(0.725)	(0.713)	(0.714)	(0.695)	(0.716)	(0.695)	(0.718)	(0.723)	(0.747)	(0.756)	(0.737)	(0.718)	(0.728)
Male	0.115	0.19	-0.191	0.037	0.235	-0.007	0.064	-0.035	0.186	0.302	0.018	-0.269	0.138	0.044	-0.093	0.199	0.348	0.014
	(0.718)	(0.715)	(0.722)	(0.748)	(0.749)	(0.727)	(0.719)	(0.717)	(0.695)	(0.719)	(0.694)	(0.713)	(0.724)	(0.731)	(0.745)	(0.743)	(0.712)	(0.722)
Minority	-0.057	-0.478	-0.827	-0.731	-0.137	-0.107	-0.122	-0.694	0.122	0.424	-0.699	0.035	-1.141	-0.409	-0.089	0.222	-1.101	-0.227
	(0.364)	(0.363)	(0.274)	(0.447)	(0.72)	(0.544)	(0.36)	(0.305)	(0.378)	(0.465)	(0.174)	(0.393)	(0.41)	(0.452)	(0.83)	(0.544)	(0.59)	(0.634)
Suburb	0.127	-0.008	-0.004	-0.221	-0.1	-0.328	0.232	-0.231	-0.782	0.015	0.071	-0.359	0.273	-0.007	-0.434	0.461	-0.055	-0.552
	(0.323)	(0.375)	(0.201)	(0.234)	(0.525)	(0.248)	(0.267)	(0.306)	(0.591)	(0.36)	(0.21)	(0.77)	(0.362)	(0.331)	(0.578)	(0.368)	(0.4)	(0.458)
Town	0.045	-0.399	0.077	-0.186	0.541	-0.114	-0.143	-0.227	-0.719	0.086	-0.048	-0.398	0.038	-0.032	0.141	0.432	-0.087	-0.16
	(0.25)	(0.337)	(0.169)	(0.228)	(0.367)	(0.204)	(0.214)	(0.289)	(0.216)	(0.353)	(0.156)	(0.258)	(0.269)	(0.301)	(0.364)	(0.283)	(0.362)	(0.349)
Village	0.394	-0.339	0.372	-0.03	-0.532	-0.008	-0.176	-0.471	-0.121	0.139	0.177	-0.905	0.329	-0.297	0.481	0.509	0.32	-0.668
	(0.237)	(0.315)	(0.178)	(0.27)	(0.352)	(0.237)	(0.216)	(0.317)	(0.242)	(0.386)	(0.174)	(0.261)	(0.244)	(0.331)	(0.353)	(0.301)	(0.399)	(0.319)
Farm	0.289	-0.493	0.444	-0.303	0.276	-0.06	-0.466	-0.763	0.814	0.282	0.843	0.101	0.027	-0.12	-0.206	-0.927	-0.441	-1.06
	(0.385)	(0.474)	(0.393)	(0.309)	(0.692)	(0.23)	(0.334)	(0.513)	(0.761)	(0.352)	(0.503)	(0.898)	(0.488)	(0.319)	(0.771)	(0.689)	(0.502)	(0.551)
σ_{Imm}	2.607	2.465	2.246	2.196	3.832	2.463	2.556	2.938	1.904	2.99	1.547	2.835	3.1	3.018	3.379	2.611	3.781	2.538
	(0.089)	(0.11)	(0.068)	(0.102)	(0.155)	(0.084)	(0.089)	(0.095)	(0.104)	(0.104)	(0.091)	(0.116)	(0.115)	(0.112)	(0.167)	(0.114)	(0.156)	(0.145)
σ_{Eco}	2.008	1.471	1.983	1.954	2.039	1.645	1.8	2.391	2.108	2.236	1.528	2.055	1.828	1.645	1.826	1.728	2.133	1.582
	(0.06)	(0.06)	(0.05)	(0.069)	(0.074)	(0.048)	(0.056)	(0.067)	(0.091)	(0.068)	(0.06)	(0.075)	(0.059)	(0.056)	(0.085)	(0.071)	(0.066)	(0.077)
σ_{Com}	1.707	1.574	1.903	1.963	1.68	1.747	1.742	2.178	1.908	1.82	1.399	2.108	1.656	1.771	1.625	1.567	1.702	1.71
	(0.048)	(0.054)	(0.041)	(0.06)	(0.059)	(0.045)	(0.048)	(0.056)	(0.073)	(0.054)	(0.055)	(0.071)	(0.048)	(0.054)	(0.07)	(0.059)	(0.051)	(0.075)
σ_{Rac}	1.087	1.123	1.043	1.084	1.087	1.319	1.206	1.331	1.156	1.156	1.02	1.17	1.115	1.071	1.123	1.24	1.148	1.21
	(0.046)	(0.057)	(0.04)	(0.055)	(0.056)	(0.044)	(0.047)	(0.045)	(0.061)	(0.049)	(0.051)	(0.052)	(0.052)	(0.05)	(0.067)	(0.06)	(0.063)	(0.072)
σ_{Alt}	1.413	1.266	1.202	1.489	1.629	1.61	1.473	1.473	1.593	1.767	1.572	1.437	1.383	1.408	1.434	1.791	1.427	1.459
	(0.057)	(0.068)	(0.045)	(0.064)	(0.079)	(0.057)	(0.06)	(0.056)	(0.084)	(0.066)	(0.071)	(0.07)	(0.062)	(0.059)	(0.088)	(0.083)	(0.063)	(0.095)
$\rho_{Eco,Com}$	0.934	0.892	0.877	0.843	0.939	0.91	0.944	0.946	0.935	0.952	0.913	0.895	0.871	0.876	0.876	0.899	0.937	0.882
	(0.011)	(0.021)	(0.012)	(0.018)	(0.013)	(0.014)	(0.011)	(0.009)	(0.014)	(0.009)	(0.019)	(0.016)	(0.017)	(0.017)	(0.024)	(0.02)	(0.011)	(0.023)
$\rho_{Eco,Rac}$	-0.527	-0.488	-0.498	-0.481	-0.388	-0.569	-0.523	-0.502	-0.376	-0.43	-0.124	-0.468	-0.453	-0.513	-0.428	-0.38	-0.59	-0.43
	(0.033)	(0.044)	(0.029)	(0.042)	(0.047)	(0.028)	(0.031)	(0.028)	(0.045)	(0.035)	(0.049)	(0.04)	(0.037)	(0.04)	(0.052)	(0.047)	(0.038)	(0.055)
$\rho_{Eco,Alt}$	0.285	0.155	0.284	0.322	0.133	0.397	0.241	0.268	0.009	0.11	-0.041	0.054	0.256	0.176	0.119	0.137	0.373	0.196
	(0.035)	(0.048)	(0.031)	(0.039)	(0.044)	(0.031)	(0.036)	(0.033)	(0.048)	(0.035)	(0.045)	(0.046)	(0.038)	(0.043)	(0.055)	(0.045)	(0.036)	(0.06)
$\rho_{Com,Rac}$	-0.462	-0.548	-0.553	-0.489	-0.355	-0.579	-0.503	-0.531	-0.258	-0.326	-0.141	-0.419	-0.481	-0.446	-0.479	-0.41	-0.578	-0.488
	(0.035)	(0.048)	(0.035)	(0.038)	(0.037)	(0.032)	(0.035)	(0.034)	(0.039)	(0.029)	(0.031)	(0.04)	(0.039)	(0.038)	(0.053)	(0.039)	(0.043)	(0.056)
$\rho_{Com,Alt}$	0.285	0.288	0.332	0.423	0.148	0.441	0.284	0.321	0.057	0.191	0.055	0.001	0.373	0.256	0.182	0.147	0.384	0.242
	(0.036)	(0.044)	(0.03)	(0.036)	(0.043)	(0.03)	(0.035)	(0.031)	(0.047)	(0.036)	(0.045)	(0.045)	(0.036)	(0.039)	(0.055)	(0.044)	(0.036)	(0.056)
$\rho_{Rac,Alt}$	-0.428	-0.485	-0.475	-0.488	-0.231	-0.545	-0.411	-0.514	0.03	-0.409	-0.41	-0.053	-0.494	-0.421	-0.308	-0.34	-0.45	-0.4
	(0.041)	(0.05)	(0.038)	(0.045)	(0.052)	(0.032)	(0.037)	(0.033)	(0.057)	(0.039)	(0.049)	(0.052)	(0.043)	(0.048)	(0.061)	(0.048)	(0.046)	(0.058)

Note: The table shows the estimates of the model explained in section 3, where we use four survey questions (IMM1, IMM2, IMM3 and IMM4) to identify individual, latent preference for immigration. Plain numbers indicate posterior mean, and numbers in parentheses show the standard deviation of the posterior distribution. The model is estimated on each country separately. Note that the variables age and income decile have been standardized by two times their standard deviation.

B Additional Questions from the ESS

In the empirical analysis, we employ data provided by the European Social Survey (ESS) from 2014 and 2015. Below we explain in more detail which questions are used for several of the control variables. In addition, we indicate the possible answers to each question.

Education — We rely on the International Standard Classification of Education (ISCED) and code everyone with ISCED 5A, 5B, and 6 (short, medium, or long) as highly educated. This includes the first and second stage of tertiary education. Notably, the same coding is use for the education of partners and parents.

Household Income — The ESS provides data on households' total net income from all sources. This is grouped into ten country-specific deciles.

Employment Status — We distinguish three different types of employment status, each one with a separate dummy variable. Based on an individual's main source of household income, we define those as wage earners who answer with 'wages or salaries' as main source. We codify as retired all those who choose 'pensions' as answer. Finally, we mark all individuals as unemployed who say that they have been unemployed in the last 7 days and actively looking for a job.

Residence — Each survey participant is asked to choose one option that best describes the area where he or she lives. The options presented are (i) a big city, (ii) the suburbs or outskirts of a big city, (iii) a town or a small city, (iv) a country village, or (v) a farm or home in the countryside.

C Correlation Among Latent Factors

In the main part of our empirical analysis, we assume that latent factors that shape immigration preferences are independent from each other. Section 3 discusses how we can allow for non-independence and how the estimates of the latent factor model change. Here, we briefly illustrate a simple example to highlight the instability of estimates in the presence of high correlation among explanatory variables.

Consider two variables, x_1 and x_2, drawn from a bivariate normal distribution with unit variances and $Cov(x_1, x_2) = \rho$. The sum of the two variables as well as some normally distributed error term (ε) yield the dependent variable:

$$y = \beta_1 x_1 + \beta_2 x_2 + \varepsilon. \tag{15}$$

We use parameters $\beta_1 = \beta_2 = 1$ and $\varepsilon \sim N(0,1)$, and simulate this simple model 10,000 times for differing values of ρ. Each simulation is a data set with 1000 observations.

Table C.1: Instability of Estimates with Non-Independent Factors

	Correlation ρ between x_1 and x_2				
	0	0.5	0.8	0.9	0.99
	(1)	(2)	(3)	(4)	(5)
$sd\left(\hat{\beta}_1 - \beta_1\right)$	0.03	0.04	0.05	0.07	0.23
$sd\left(\hat{\beta}_2 - \beta_2\right)$	0.03	0.04	0.05	0.07	0.23
$sd\left(\hat{\beta}_1/\hat{\beta}_2 - \beta_1/\beta_2\right)$	0.05	0.06	0.10	0.14	0.60
$sd\left(\hat{\beta}_1 + \hat{\beta}_2 - \beta_1 - \beta_2\right)$	0.04	0.04	0.03	0.03	0.03

Note: The table shows the results of 10,000 repetitions of OLS-estimates of equation (15) with varying correlation between x_1 and x_2.

Table C.1 shows that the standard deviation of the estimates increases with the correlation between x_1 and x_2. Furthermore, estimates of the *ratio* of the coefficients become even more unstable as the correlation between x_1 and x_2 increases. If the true value of β_2 were to be closer to 0, $sd\left(\hat{\beta}_1/\hat{\beta}_2 - \beta_1/\beta_2\right)$ could easily be diverging. However, the variance of the sum of the two estimated coefficients remains stable across different correlations. In the empirical analysis of this paper, we document that *ECO* and *COM* are highly correlated (cf. Tables A.1). Section 3 discusses how this affects the findings concerning the relative importance of economic and non-economic expectations in shaping preferences over immigration.