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Growing up in a Recession Increases Compassion? The Case of Attitudes towards Immigration

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PRELIMINARY DRAFT. DO NOT CITE OR CIRCULATE. COMMENTS WELCOMED!

Macroeconomic conditions during young adulthood have a persistent impact on people's attitudes and preferences. The seminal paper by Giuliano and Spilimbergo (2014) shows that people who grew up in a recession are more likely to favor government redistribution and assistance to the poor. Moreover, they are more likely to believe that bad luck rather than a lack of hard work causes poverty, i.e. they seem to be more compassionate towards the poor. In this paper, we investigate how inclusive this increase in compassion is by studying how macroeconomic conditions when young affect attitudes towards immigration. Using data from the General Social Survey and the World Value Survey, we find strong evidence that bad macroeconomic circumstances when young strengthen attitudes against immigration for the rest of people's lives. In line with this, we also find that people who grew up in a recession are more likely to agree that, when jobs are scarce, employers should give priority to native-born citizens rather than to immigrants. Our results thus suggest that the underlying motive for more government redistribution in response to a recession does not originate from a universal increase in compassion, but rather seems to be more self-interested and restricted to one's own in-group.

Keywords: Immigration, Attitudes, Social preferences, Redistribution, Macroeconomic conditions, Impressionable years.
JEL codes: D9, E7, J1

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1 Introduction

Growing up in difficult macroeconomic circumstances has a substantial impact on people. Not only does a recession during young adulthood affect incomes and careers for a long period of time (e.g. Kahn, 2010; Schwandt and Von Wachter, 2019), it also shapes criticial political and economic preferences for the rest of people's lives (e.g. Giuliano and Spilimbergo, 2014; Cotofan et al., 2023). These findings are consistent with an extensive literature in political science and psychology showing that experiences during impressionable years (between 18 and 25 years old) play an important role in the formation of people's attitudes and worldviews (e.g. Krosnick and Alwin, 1989; Bianchi, 2013, 2014; Inglehart, 1971).[1]

In a highly influential paper, Giuliano and Spilimbergo (2014) examine how recessions shape preferences for redistribution. They show that people who grow up in a recession are more strongly in favor of government redistribution and assistance to the poor during the rest of their lives. A recession during young adulthood also makes people believe that success in life is determined more by luck than effort, a critical mediator for preferences for redistribution (Alesina and Giuliano, 2011). Research in psychology additionally shows that growing up in a recession reduces narcissism and that recessions lower individualism (Bianchi, 2014, 2016). These results suggest that people who grow up in difficult macroeconomic conditions become more caring and gracious to other people, in particular towards the poor. But how universal is this increase in compassion?

In this paper we investigate how growing up in difficult macroeconomic conditions affects attitudes towards immigration. Immigration is one of the most controversial issues in the last decades, both in the US and in the rest of the world. Our study contributes to an explanation for why people hold such different opinions on this issue by pointing to different macroeconomic experiences they went through during young adulthood. In addition, our results contribute to a better understanding of the main driving force of Giuliano and Spilimbergo (2014)'s result that people who grew up in a recession support more government redistribution. If recessions increase support for redistribution because of a universal increase in compassion for the poor, then we would expect support for immigration to go up as well, as immigration tends to reduce global poverty (Clemens, 2011). If, instead, recessions increase support for redistribution out of self-interest or that of one's in-group, then we predict support for immigration to decrease, as less immigration may weaken competition for jobs and benefits, something which may be particularly valuable during a recession when jobs and benefits are scarce (Hatton, 2016).[2]

Using rich survey data from the US and the rest of the world, and following the methodology in Giuliano and Spilimbergo (2014), we find strong evidence that growing up in a recession significantly lowers acceptance of immigration. In line with this, we also find that people who grow up in a recession are more likely to agree that, when jobs are scarce, employers should give priority to native-born citizens rather than to immigrants. Our results thus suggest that recessions do not lead to a universal increase compassion towards the poor. The positive effect

[1] Other research shows that people's experiences more generally have a long-lasting effect on economic preferences (e.g. risk and time preferences) and political views (Alesina and Fuchs-Schündeln, 2007; Malmendier and Nagel, 2011, 2015; Fuchs-Schündeln and Schündeln, 2015; Slotwinski and Stutzer, 2018; Laudenbach et al., 2019; Falk and Hermle, 2018; Corneo and Neher, 2014; Fisman et al., 2015; Billings et al., 2020).

[2] While this view about the impact of immigration on natives is not necessarily consistent with empirical studies (e.g Card, 1990; Borjas, 2003; Peri, 2014; Ottaviano and Peri, 2012; Foged and Peri, 2016; Dustmann et al., 2016), it is widely held across demographic groups. Survey data show that a large majority of people believe that immigration has harmful consequences for wages and unemployment (see Haaland and Roth, 2020).

of growing up in a recession on preferences for redistribution found by Giuliano and Spilimbergo (2014) can better be understood as a self-interested response to a weakening of people's (perceived) economic position or that of their in-group, turning them more strongly in favor of redistribution and at the same time more strongly opposed to immigration in an attempt to restore their economic position.[3] Consistent with this interpretation, we find that our results are most pronounced for low-skilled workers in rich countries, a group that is arguably most directly competing with immigrants for jobs and government transfers. Our results are consistent with earlier studies in political science and economics showing that attitudes towards immigrants and preferences for redistribution are closely related and in an important way driven by self-interested concerns (e.g. Facchini and Mayda, 2009; Emmenegger and Klemmensen, 2013; Alesina et al., 2023).

While our paper is, to our knowledge, the first paper to analyze the effect of experiencing different macroeconomic conditions when young on life-time attitudes towards immigration, our prediction is based on research about how *concurrent* macroeconomic conditions affect attitudes towards immigrants.

First, previous research theorizes that increased competition for jobs or government transfers are important factors that increase negative attitudes towards immigrants, e.g. Esses et al. (1998); Scheve and Slaughter (2001); Mayda (2006) (for a critical review of different theories, see Hainmueller and Hopkins, 2014). Labor market competition theories make two main predictions: first, recessions intensify competition between immigrants and native workers for the same jobs or government transfers. Such increased competition will negatively affect natives' pro-immigrant attitudes. Second, especially unskilled workers in richer countries will be opposed to immigration as they are most impacted by inflow of unskilled immigrants (e.g. O'Rourke, 2006; Mayda, 2006). Existing empirical results on the effect of labor market competition on mass attitudes toward immigration are, however, mixed (see Hainmueller and Hopkins, 2014). While some paper such as Mayda (2006) find evidence consistent with the labor market competition theory, others do not show strong support (e.g. Hainmueller et al., 2015). Indeed, there is large unexplained individual heterogeneity in pro-immigration attitudes.

Second, another large literature focuses not particularly on immigration but investigates a related question: how competition and economic downturns affect out-group hostility – going back to Sherif's famous Robber's Cave experiment (Sherif, 1966). A number of studies in multiple disciplines show that competition increases group conflict and out-group hostility (e.g. Bornstein et al., 2002; Posner, 2004; Choi and Bowles, 2007; Bowles, 2009; Goette et al., 2012).[4] In addition, Bianchi et al. (2018) shows that economic downturns negatively affect *concurrent* attitudes towards other race – adding to a literature on macroeconomic conditions and outgroup hostility that has more mixed results (Green et al., 1998; McLaren, 2001; Quillian, 1995).[5]

In contrast to the existing literature, we do not focus on the effect of current macroeconomic conditions but analyze people's experience of macroeconomic conditions when young. Hence, our study stresses that attitudes towards immigration and in-group bias are shaped much earlier and

[3] In the same spirit, Cotofan et al. (2023) find that people who grew up in a recession put more priority on earnings and less on meaning when choosing jobs.

[4] A related literature looks at income and prosocial behavior in general (see, e.g. Piff and Robinson, 2017; Meer and Priday, 2021) and in-group bias in particular (Aksoy and Palma, 2019; Boonmanunt and Meier, 2023).

[5] Inspired by this literature, we consider in section 3.3 how macroeconomic conditions when young affect out-group bias using several measures from the World Value Survey data. We find some evidence that growing up in a recession increases out-group bias against people of a different race, people of a different religion, and immigrants or foreign workers.

are more persistent than implied by previous research. Current macroeconomic downturns will as such have negative consequences for attitudes towards immigration for decades to come. On the flip side, good macroeconomic conditions create cohorts who are more open to immigration – experiencing prosperous times when young has “moral consequences” a la Friedman (2006). Differences in experiences during impressionable years can thus explain part of the significant heterogeneity in in-group bias or moral universalism (documented for example by Enke et al., 2022).

The paper proceeds as follows. In the next section, we analyze representative US data from the General Social Survey. Next, in Section 3, we turn to data from the World Value Study. Section 4 concludes.

2 Evidence using the General Social Survey

This section studies formation of attitudes against immigration in the US. We use data from the General Social Survey, which is a repeated cross-section survey of the US population which has been running since 1972 and currently has 30 waves. The GSS has detailed information on the socio-political and economic beliefs of a representative sample of US respondents, as well as background information about a rich set of demographics. In the Materials and Methods section in the Appendix we describe the data in more detail. Table A.1 in Appendix A1 provides some descriptive statistics.

2.1 Data and Methodology

Attitude towards immigration is the key outcome variable in our analysis and is measured by a question asked in 10 of the 30 GSS waves, between 1994 and 2016. Specifically, respondents in those waves were asked the following question: “Do you think that the number of immigrants to America nowadays should be”, where possible answers are measured on a 5-point scale, ranging from “Increased a lot” to “Reduced a lot”. We re-code attitudes towards immigration such that a higher number represents a more negative attitude. We refer to this measure in the Tables as “Anti Immigration”. The average response in the full sample is 3.7 – that is, in between the categories ”remain the same” and ”reduce a little”. The standard deviation is slightly more than 1, indicating that there is quite some variation in attitudes. Figure 1 depicts the data in some more detail. Interestingly, attitudes towards immigration have become more favorable over time in the US. While in 1994 two-third of the respondents was in favor of reductions in immigration, in 2016 this percentage has shrunk to slightly more than 40%. A similar percentage thinks that the number of immigrants should remain the same, while the remaining 20% is in favor of increased immigration. In total, over 13,000 respondents have answered the question across the multiple waves.

[6]

Our key explanatory variable is experienced macroeconomic conditions during the “impressionable years,” where impressionable years are defined as the years during which the respondent

[6] The question has been at times adjusted across waves, leading to three slightly different versions, see our discussion in the section Material and Methods in the GSS of the Appendix. In the main analysis we pool data across all three versions of the question. In Table A.2 in Appendix A2 we show that this does not affect our main results.

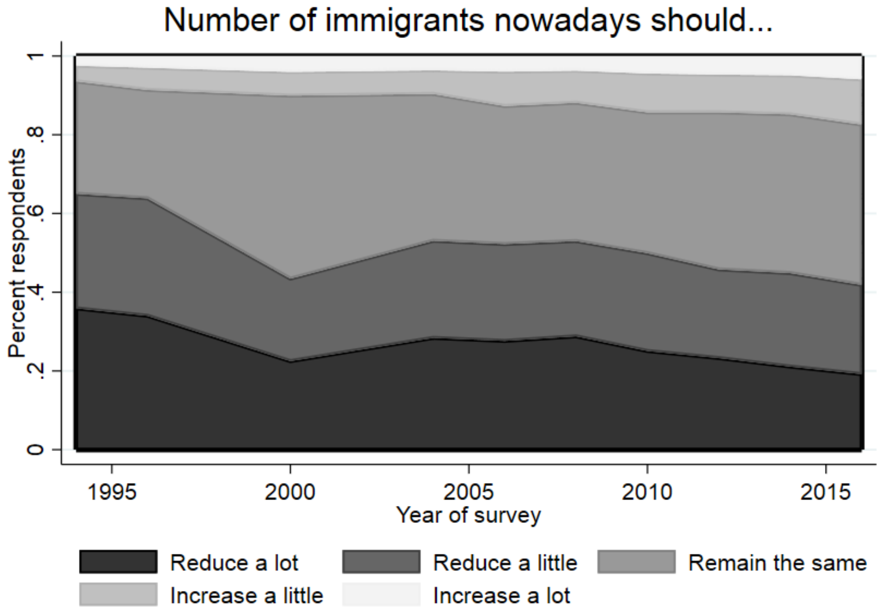

Figure 1 : Attitudes towards immigraton in the GSS

was between 18 and 25 years old. In most of our paper we focus on experiences during this period, but we will also investigate the effects of experiences during other periods (see Appendix A3) and of current macroeconomic conditions (Appendix A13). In addition to variation over time, we make use of regional variation in experienced macroeconomic conditions. This enables us to control for common shocks at the national level.[7] The data distinguish nine different regions across the US. In the Materials and Methods section in the Appendix we provide additional details on how states are grouped into regions. The GSS provides information on the region in which respondents resided both at the time of the survey and when they were aged 16. Unfortunately, data on where the respondent resided between age 18 and 25 is missing. The region at the age of 16 is our closest proxy to the geographical location of each respondent during their impressionable years. In Appendix A5 we show that restricting the sample to those respondents who live in the same region at the time of the survey as when they were 16 does not change our results, suggesting that selection effects due to respondents moving across regions are not a major concern in our setting. Our main explanatory variable is the average regional income during a respondent's impressionable years in the region in which the responded resided at the age of 16.

We construct our main explanatory variable using annual state-level income data from the Bureau of Economic Analysis (BEA), which are available for each year since 1929.[8] Our main

[7]In Appendix A4 we also construct a measure of experienced national income during impressionable years and show that, although the estimates are more noisy in the absence of regional variations, our main conclusions remain unchanged.

[8]In Appendix A6 we follow a closer approach to Giuliano and Spilimbergo (2014) and we replace experienced income levels during impressionable years with a binary indicator which takes value 1 if a respondent experienced at least one year in which income growth was lower than -2.5%, corresponding to the 10th lowest percentile of the income growth distribution for the 9 U.S regions since 1929 to 2016. While the results estimated using a recession indicator are somewhat weaker, they are consistent with our main estimates using income levels and do not change our conclusions overall.

explanatory variable $IncomeLevel^{18-25}$ is the logarithm of a weighted average of the regional income level that a respondent experienced between the age of 18 and 25 in the region in which he/she resided at age 16.[9] The regional income level is adjusted for inflation using CPI indexes and is expressed in 2017 $US. In the Materials and Methods section of the Appendix we provide a detailed account of how the measure is constructed.

We estimate the following equation:

$$Att_{i,r,t} = \beta_0 + \beta_1 IncomeLevel^{18-25}_{i,r,t} + \beta_2 X_{i,r,t} + \tau_t + \rho_r + \rho_r^{age16} + \epsilon_{i,r,t} \tag{1}$$

where $Att_{i,r,t}$ is the attitude towards migrants of respondent i at time t, who at the age of 16 resided in region r. $IncomeLevel^{18-25}_{i,r,t}$ is the the logarithm of experienced income level during impressionable years of respondent i at time t, who at the age of 16 resided in region r. We carefully control for time fixed effects τ_t, region of residence at the time of the survey fixed effects ρ_r, and region of residence at 16 fixed effects ρ_r^{age16}. To avoid the well-known collinearity issue between birth year, age, and year of the survey fixed effects we choose a flexible specification for age (including linear, quadratic, and cubic terms), and control for birth decade instead of birth year. This imposes the additional assumption that the effect of the birth year on attitudes towards immigration is the same for all individuals born within the same decade. In Appendix A8 we experiment with various flexible specifications in controlling for age, birth and year effects and show that our findings are robust across all the models.

$X_{i,r,t}$ is a vector controlling for a rich set of background characteristics, including a flexible specification for respondent's age, gender, years of education, father's and mother's education, race, marital status, number of children, squared household size, the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. The standard errors $\epsilon_{i,r,t}$ are clustered at the level of the region in which a respondent resided aged 16. Since the GSS only provides information on 9 different regions, the number of clusters is smaller than the required number to estimate reliable standard errors. We address this issue by closely following the approach of Giuliano and Spilimbergo (2014) and implementing the wild bootstrap procedure developed by Cameron et al. (2008) which provides reliable standard errors even when the number of clusters is very small. In all our results we additionally provide the corresponding p-values from the wild bootstrap and rely on them to interpret the statistical significance of our estimates.

2.2 Results

Table 1 reports the results from estimating equation (1), using OLS. Table A.9 in the Appendix shows the results from estimating equation (1) using an ordered probit model instead. The coefficient in column 1 indicates that respondents who experienced a higher level of regional income during their impressionable years are less likely to have a negative attitude towards immigrants, and more likely to be open to increasing immigration. The coefficient is both economically and statistically significant, as a doubling of income during impressionable years results into being 0.4 points less anti-immigration on a five-point scale. To put the coefficient

[9] Instead of regional income levels we could also use unemployment levels to construct a measure of experienced macroeconomic conditions. The limitation of this approach is that data on regional unemployment is only available since 1976 onward. Instead, we construct a measure of experienced national unemployment and in Appendix A7 we show that our results are consistent. However, these results rely only on variation in age at the time of the survey.

into perspective, a doubling of experienced regional income during impressionable years has a much larger effect on attitudes that a doubling in household income (0.013 points on a 5-point scale) or than the effect of unemployment (-0.063 on a 5-point scale), and is equivalent to 75% of the effect of having both parents as immigrants to the US (-0.554 on a 5-point scale). Figure A.2 in the Appendix plots the regional level of income over time and across regions, and shows substantial variation across different areas, with differences across regions of up to 105% in income levels.

In Table A10 in the Appendix we additionally control for the standard deviation of experienced regional income levels during the impressionable years. We undertake this additional check to to control for the fact that our measure of income levels does not discriminate against respondents who have lived through much more volatile times. The standard deviation of income levels does not appear to predict immigration attitudes, nor does it change our key conclusions in any important way. Similarly, we accommodate the fact that experienced income during impressionable years might correlate with experienced immigration inflows, which could lead to a bias in our estimates. For example, recessions might be associated with both low levels of income and reduced inflows of immigration, while in good times the reverse could hold. To investigate the extent to which our results are driven by this, we also construct a measure of experienced immigration inflows during impressionable years. In Appendix A11 we show that while experiencing higher immigration inflows when entering the labor market leads to more negative attitudes towards migrants, our main results hold even after controlling for these experiences.

Table 1: Experienced regional income during the impressionable years and attitudes towards immigration

	Anti Immigration	**Anti Immigration**
Income level 18-25	-0.404**	-0.410**
	(0.215)	(0.216)
	[0.039]	[0.040]
Household income	✓	X
Years of education	✓	X
Labor market status	✓	X
Demographic variables	✓	✓
Year FE	✓	✓
Region at 16 FE	✓	✓
Region FE	✓	✓
Age polynomials	✓	✓
Decade of birth FE	✓	✓
N	11,860	11,860

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

The second column in Table 1 estimates equation (1) without controls for education, household income at the time of the survey, and labor market status. The very similar coefficients in columns one and two indicate that experienced regional income levels during impressionable years do not appear to partly work through these channels. As a result, we control for education, household income at the time of the survey, and labor market status in all subsequent tables. In a similar vein, in Appendix A12 we also also add a full set of industry fixed effects and show that our conclusions remain unchanged, suggesting that attitudes towards immigration are not affected by industry sorting as a results of different macroeconomic experiences upon entering the labor market. Finally, we also check how our conclusions change if we additionally control for the regional income level at the time of the survey. The results in Appendix A13 show that while current income matters too, and in the same way as income during impressionable years, our conclusions in Table 1 remain unchanged.

In an additional step, we ask whether the impact of experienced macroeconomic conditions during impressionable years decays over time, or is persistent throughout the life cycle. In Table 2 we estimate interaction terms between $IncomeLevel_{i,r,t}^{18-25}$ and different age groups, where the baseline category captures the impact of experienced macroeconomic conditions for those still in their impressionable years. Strikingly, there appears to be virtually no decay as respondents become older, suggesting that the experienced income level when entering the labor market results into a permanent shift in attitudes towards immigration.

Table 2: Experienced regional income during the impressionable years and attitudes towards immigration: life-time decay

	Anti Immigration
Income level 18-25	-0.413**
	(0.215)
	[0.043]
Income level 18-25 * 26-50 age group	-0.006
	(0.006)
	[0.530]
Income level 18-25 * 51-75 age group	0.004
	(0.007)
	[0.537]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	11,860

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

In Appendix A3 we examine whether not only experiences during the impressionable years, but also experiences during other years affect attitudes towards immigration. In Table A.3.2, we estimate equation (1) including experienced macroeconomic conditions at various ages from 0 to 49 years old, partitioned into age categories of 8 years each. A drawback of this approach is that we lose all respondents under the age of 49, which constitute more than half of our sample. The estimates in Table A.3.2 are, as a result, quite imprecise. The only statistically significant coefficient is the one for the impressionable years (18-25 years old). In Table A.3.1, we follow an alternative approach and study 'horse races' between impressionable years and one other age category. The impressionable years consistently show up with a negative and sizeable coefficient, most often more sizeable than the coefficient for the competing age category, though not always statistically significant.

A growing literature (references) has documented that there is a large and unexplained heterogeneity in preferences towards immigration. Mayda (2006) and O'Rourke (2006) argue that labor market competition plays an important role in the formation of attitudes towards immigrants, and that the direction of the effect depends both on the composition of natives' and immigrants' skill. They provide empirical evidence that in rich countries it is particularly the low skilled workers who have negative attitudes towards immigrants, as they are more likely to compete with a higher influx of low-skilled migrants. Our paper further explores this question by asking whether positive macroeconomic conditions when entering the labor market mediates the attitudes of low-skilled workers towards immigrants.

In our sample, the median respondent has completed 13 years of education while the father of the median respondent has completed 12 years of education on average. Consistent with a theory of labor market competition, respondents with an education level below median hold an more negative attitude towards immigration (0.27 points on a 5-points scale, or about 25% of a standard deviation) than those who are more educated. Similarly, the average attitude against immigration of respondents whose father's education was below the median is 0.20 points on a 5-points scale higher (about 20% of a standard deviation) than those whose fathers were more educated.

Table 3 explores this heterogeneity by estimating equation (1) separately for those who have 12 years of education or less (column 1) and for those who have more than 12 years of education (column 2). Likewise, column 3 and 4 of Table 3 show the regression results for those whose father has 12 years of education or less and for those whose father has more than 12 years, respectively. Strikingly, it appears that the findings in Table 1 are mostly driven by those respondents who are less educated and whose fathers are less educated.

Table 3: Experienced regional income during the impressionable years and attitudes towards immigration: HTE by respondent education and the respondent's father education

	Anti Immig. **Low educ.**	**Anti Immig.** **High educ.**	**Anti Immig.** **Low father educ.**	**Anti Immig.** **High father educ.**
Income level 18-25	-0.770*	-0.119	-0.567**	-0.263
	(0.306)	(0.309)	(0.294)	(0.326)
	[0.065]	[0.758]	[0.031]	[0.262]
Household income	✓	✓	✓	✓

Years of education	✓	✓	✓	✓
Labor market status	✓	✓	✓	✓
Demographic variables	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Region at 16 FE	✓	✓	✓	✓
Region FE	✓	✓	✓	
Age polynomials	✓	✓	✓	✓
Decade of birth FE	✓	✓	✓	✓
N	4,937	6,923	5,754	6,106

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

Experiencing a doubling of regional income levels during impressionable years prompts lower educated respondents to be 0.770 points more positive towards immigrants (on a 5-point scale). On the other hand, highly educated respondents are 0.119 points more positive towards immigrants (on a 5-point scale). The p-value from testing whether the difference between the two coefficients is statistically significant is 0.131. Similarly, respondents with lower educated fathers report to be 0.567 points more positive towards migrants, as compared to 0.263 points for respondents whose fathers were higher educated. The p-value from testing whether the difference between the two coefficients is statistically significant is 0.486. These findings have important consequences for socio-political outcomes in the United States, and suggest that lower-educated respondents who grow up in comparatively difficult times are more likely to harbor anti-immigration attitudes for the rest of their lives.

3 Evidence using the World Value Survey

In this section we present cross-country evidence on the impact of shared macroeconomic experiences on attitudes towards immigration. We use data from the World Value Survey which is a repeated cross-section survey which was conducted in approximately 100 developed and developing economies in six waves since 1981. The WVS documents the social, economic, and political preferences of a representative sample of respondents across the participating countries, and provides a rich set of background variables in each wave. Due to a small number of countries in the first wave and missing data on some of our outcome variables, we focus on the five most recent waves, namely: 1989-1993 (18 countries), 1994-1998 (56 countries), 1999-2004 (40 countries), 2005-2009 (58 countries), and 2010-2014 (60 countries). In part of the analysis we distinguish between economically highly developed and economically less developed countries. We classify as highly developed countries the countries which were a member of the OECD already before the 1980s, with the exception of Turkey.[10] From this group of advanced economies,

[10]We exclude Turkey, which became a member in 1961, but which scores significantly lower on a number of development indices and is not recognized as a developed economy by either the UN, the World Bank, or the IMF.

15 of them have also been surveyed in the WVS, namely Australia, Canada, Finland, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Spain, Switzerland, the United Kingdom, and the United States. In the Materials and Methods section in the Appendix we provide a detailed overview of the data and Table A.14 provides some descriptive statistics.

3.1 Data and Methodology

For our main results, we make use of a question asked in the WVS to measure attitudes towards immigrants. The question asks respondents to state their views regarding immigration policy within their country with possible answers being recorded on a 4-point scale : (i) Let anyone in, (ii) Let people in as long as jobs are available, (iii) Impose strict limits on immigration, (iv) Prohibit people from coming in. We re-code the variable such that it takes value 1 for the most lenient attitudes towards immigration and value 4 for the most anti-immigration views. The question is asked in three out of the five WVS waves, namely in 1994, 1999, 2005. The average score is in between the second and third category, both in the 15 most developed countries and in the rest of the sample. There is substantial variation in the responses; the standard deviation is about 0.8.

Our measure of experienced income during impressionable years is based on Angus Maddison's estimates of GDP per capita globally. Bolt et al (2018) revise and improve the original Maddison database and provide more accurate estimates, providing country-level yearly data on real GDP per capita for 97 countries which are also surveyed in the WVS. There is some variation in the time series length across countries, with most developed countries being captured since the 1800s, while for some developing countries data on GDP per capita is only available since late 1900s. As a result, in these countries, we will only be able to capture the relatively younger respondents. Following a similar approach to the one outlined in section 2.1, we use the logarithm of the experienced income level during impressionable years within each country. The Materials and Methods section in the Appendix describes the data on historical income and gives a detailed account on how the measure is constructed.

We estimate the following equation:

$$Att_{i,c,t} = \beta_0 + \beta_1 IncomeLevel^{18-25}_{i,c,t} + \beta_2 X_{i,c,t} + \tau_t + \rho_c + \epsilon_{i,c,t} \tag{2}$$

where $Att_{i,c,t}$ captures the attitude of respondent i, in country c, at time t, as defined above. $IncomeLevel^{18-25}_{i,c,t}$ represents the experienced income level per capita during impressionable years by respondent i, living in country c, and answering the survey at time t. $X_{i,c,t}$ is a vector of controls including age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies.[11] τ_t is a year of survey fixed effects, ρ_c is a country fixed effect, and the standard error $\epsilon_{i,c,t}$ is clustered at the country level. WVS country specific weights are used in the regression analysis, in order to ensure that the sample is representative of each country's population. When available, we use information on citizenship and country of birth to restrict the sample to those respondents who were born in the country in which they are currently residing.[12]

[11] In Appendix A16 we investigate how our estimates are impacted if we use different approaches to control for age and cohort and show that our results are robust across all specifications.

[12] The question on citizenship in only asked in 3 out of the 5 WVS waves. In a robustness check, when data on citizenship was not available we instead excluded those respondents whose parents were immigrants as they

3.2 Results

Table 4 below presents the results from estimating equation (1) where the outcome variable captures attitudes towards immigrants, namely imposing some restriction on the number of immigrants allowed to come into the country ("Restrict numbers").

The global evidence appears to be consistent with the findings for the US in Section 2.[13] A doubling of experienced income levels during impressionable years translates into more negative attitudes towards immigrants. Again, the coefficient is both statistically and economically significant. The effect of experiencing a doubling of income during impressionable years is equivalent to moving between 6 and 8 deciles in the country-level household income distribution. Globally, the logarithm of experienced income during impressionable years exhibits substantial variation across countries, with a standard deviation of one but ranging between 6.1 and 12.3 in the sample.

In Appendix A18 we additionally control for the standard deviation of income during impressionable years to capture the fact that some individuals have experienced more volatile times when entering the labor market. Our results remain unchanged when performing this additional robustness check. We also investigate how current national income relates to attitudes towards immigration. The results in Appendix A19 show that current income plays a much smaller part globally, and it does not impact our estimates in Table 4.

Table 4: Experienced regional income during the impressionable years and attitudes towards immigration in the WVS

	Restrict numbers
Income level 18-25	-0.064***
	(0.016)
Household income decile	✓
Education category	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Country FE	✓
Age FE	✓
Decade of birth FE	✓
N	139,560
R-squared	0.12

Notes: Regressions are estimated using OLS. Demographic variables include controls for ge dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. Sample re-weighted using the population weights in the WVS. Significance levels: *** p<.01, ** p<.05, * p<.1.

In Table 5 we investigate whether shocks to immigration attitudes caused by macroeconomic experiences during impressionable years are persistent throughout the life cycle, or if they tend to decay over time. We estimate interactions between $IncomeLevel_{i,c,t}^{18-25}$ and age groups, where the

are more likely to be immigrants themselves. Our results were also robust to this alternative check.

[13] In Appendix A17 we show the results in Table 4 when the sample is restricted to just the United States. The estimates are largely consistent with the conclusions from the GSS.

baseline categories is made up of the experienced income level of those still in their impressionable years. Consistent with the evidence from the US, there appears to be little to no decay as respondents age, suggesting that these shocks are permanent.

In Appendix A15 we explore how experiences during years other than the impressionable years impact attitudes towards immigration. Like in the previous section, we run several regressions, adding experiences during another age category to the main regression equation (2). The results show quite consistently that the effect of experiences during impressionable years is robust to controlling for experiences in other years. Moreover, in a vast majority of cases, the experiences during impressionable years matter more than experiences in other years.

Table 5: Experienced regional income during the impressionable years and attitudes towards immigration in the WVS: life-time decay

	Restrict numbers
Income level 18-25 -0.071***	
	(0.016)
Income level 18-25 * age 26-50	0.013
	(0.009)
Income level 18-25 * age 51-75	0.012
	(0.012)
Household income decile	✓
Education category	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Country FE	✓
Age FE	✓
Decade of birth FE	✓
N	139,560
R-squared	0.12

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. Sample re-weighted using the population weights in the WVS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

In a next step we explore the heterogeneity of our effects across the 15 economically most developed and the other countries, classifying developed economies in the way described at the start of section 3.

Table 6 below estimates equation (2) for both developed economies and for the remaining countries in our sample. Since the number of rich countries in column 1 is relatively small, the clustered standard errors are corrected by applying the wild bootstrap procedure developed by Cameron et al. (2008). In brackets we present the corresponding p-values from the wild bootstrap exercise and interpret the significance of our estimates accordingly. We find that in developed countries, the attitudes towards immigrants are much more responsive to variation in macroeconomic conditions during impressionable years than in less developed countries.

Following a similar procedure as in section 2.2, we investigate whether we observe differences in how attitudes towards immigration respond to economic conditions between high and low educated workers in rich and poorer countries. The median respondent in our sample has completed some form of secondary education such as technical or vocational schooling. As such, we define those with secondary education or less as low educated and those with additional education as high educated. Table A.14.2 in the Appendix shows that in rich countries, less educated workers clearly hold more negative attitudes towards immigration and immigrants. In contrast, in poorer countries, the difference in attitudes between high and low educated workers are very small.

Table 6: Experienced regional income during the impressionable years and attitudes towards immigration in the WVS: effects in rich countries compared to the rest of the world

	Restrict numbers (Rich)	**Restrict numbers** (Rest)
Income level 18-25	-0.170	-0.056**
	(0.061)	(0.017)
	[0.148]	
Household income decile	✓	✓
Education category	✓	✓
Labor market status	✓	✓
Demographic variables	✓	✓
Year FE	✓	✓
Country FE	✓	✓
Age FE	✓	✓
Decade of birth FE	✓	✓
N	24,291	115,269
R-squared	0.08	0.13

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. In column 1 p-values are reported in brackets, estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the boottest estimator developed by Roodman et al. (2019), with 5000 replications. In column 2 standard errors are not bootstrapped since the number of clusters is sufficiently large. Sample re-weighted using the population weights in the WVS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

Table 7 shows how high and low educated workers' attitudes relate to economic conditions when young in the 15 richest and the other countries, respectively. Consistent with our findings from the US, we find a stronger response for less educated workers in both rich and poorer countries, although the difference in the rich countries between education groups is relatively small. The p-value from testing whether the difference between the two coefficients is statistically significant is 0.771 in rich countries and 0.013 in the rest of the world.

Table 7: Experienced regional income during the impressionable years and attitudes towards immigration in the WVS: effects in rich countries and the rest of the world, by education

	Restrict numbers		Restrict numbers	
	LE (Rich)	HE (Rich)	LE (Rest)	HE (Rest)
Income level 18-25	-0.185**	-0.167	-0.076***	-0.024
	(0.052)	(0.062)	(0.021)	(0.018)
	[0.026]	[0.226]		
Household income decile	✓	✓	✓	✓
Education category	✓	✓	✓	✓
Labor market status	✓	✓	✓	✓
Demographic variables	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Decade of birth FE	✓	✓	✓	✓
N	11,367	12,924	62,431	52,838
R-squared	0.06	0.08	0.13	0.13

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. In columns 1 and 2 p-values are reported in brackets, estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the boottest estimator developed by Roodman et al. (2019), with 5000 replications. In columns 3 and 4 standard errors are not bootstrapped since the number of clusters is sufficiently large. Sample re-weighted using the population weights in the WVS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

3.3 In-group mentality

We check whether experiences during Impressionable years also have spill-overs on attitudes towards other groups such as racial minorities, people of different religions, and people of different ethnicity. This is driven by the idea that entering the labor market during relatively bad economic times can make people feel closer to their peers, and more competitive towards people who have different attributes (regardless of whether they are immigrants or not). Reversely, people who enter the labor market during comparatively good times might have a less pronounced in-group mentality and be more open towards people with different traits.

The World Value Survey provides a number of questions which are appropriate for measuring such in-group bias. Specifically, we use responses a question asked in every wave which ask individuals to name "groups of people they would not like as neighbours" and focus on two possible answers, namely "People of a different race" and "People of a different religion". We create two binary indicators which take value 1 if a respondent mentioned one of the former groups, and zero otherwise.

Additionally, we complement our analysis in section 3.2 with two additional questions which capture different aspects of attitudes towards immigration. The first question asks respondents to "name groups of people they would not like as neighbours", where one of the possible answers is "Immigrants or foreign workers". We code answers to this question as a binary variable which takes value 1 if respondents mention "Immigrants or foreign workers" and 0 otherwise. 23% of the full sample mentions immigrants or foreign workers as a group they would not like as neighbours. In the 15 economically most developed countries in our sample the corresponding percentage is 11%.

The second question asks respondents to state their opinion of the following statement: "When jobs are scarce employers should give priority to (adjective for nation) people rather than to immigrants", where possible answers are "Agree", "Disagree", and "Neither". We re-code the variable to take value 1 if respondents agree and value 0 if the disagree or if they neither agree or disagree. 72% of the full sample agrees with the statement, while in the 15 most developed countries about 50% agrees.

In Table 8 we estimate equation (2) where the dependent variable is replaced by attitudes towards people of a different race ("No other race" in column 1), attitudes towards people of a different religion ("No other religion" in column 2), attitudes towards having immigrants as neighbours ("No neighbours" in column 3), and attitudes towards immigrants and jobs ("No jobs" in column 4). The estimated coefficients are remarkably similar to those in Table 4. In Panel A we show the results for the full sample. A doubling of experienced income level during impressionable years results in respondents being 3.2% less likely to not want people of a different race as neighbours, and 1.3% less likely to not want people of a different religion as neighbours. Similarly, a doubling of experienced income results in respondents being 2.4% less likely to not want immigrants of neighbours and to think that employers should prioritize immigrants when jobs are scarce.

In Panel B and Panel C we split the sample by developed economies and the rest of the world. In line with previous results, the estimated coefficients are much larger in developed economies, suggesting that positive macroeconomic conditions during impressionable years have substantial effects not just on attitudes towards immigration but also towards other groups which differ from the respondents in terms or race and religion.

In line with a theory of labor market competition, the coefficients are particularly large in column 4 which captures attitudes towards immigration in the labor market, and less so in column 3 which captures a broader attitude towards migrants. A doubling of income during impressionable years translates into respondents being 4.4 percentage points less likely to mention that they would not want immigrants as neighbours, and 13.2 percentage points less likely to think that employers should prioritize jobs for natives. In poorer countries these effects are much smaller, but statistically significant, see Table 12.

Again, these findings have severe implications for global socio-political outcomes, suggesting that entering the labor market during comparatively bad times can fuel long-lasting negative attitudes towards historically disadvantaged groups, and that the effects extend beyond attitudes towards immigration.

Table 8: Experienced regional income during the impressionable years and attitudes towards immigration in the WVS

Panel A: Full sample	No other race	No other relig.	No neighbours	No Jobs
Income level 18-25	-0.032**	-0.013*	-0.024**	-0.024**
	(0.013)	(0.007)	(0.008)	(0.007)
N	226,193	159,574	224,959	219,781
R-squared	0.10	0.12	0.11	0.13
Panel B: Rich	**No other race**	**No other relig.**	**No Neighbours**	**No Jobs**
Income level 18-25	-0.079***	-0.045**	-0.044***	-0.132**
	(0.015)	(0.015)	(0.014)	(0.027)
	[0.002]	[0.034]	[0.001]	[0.011]
N	36,482	23,764	37,068	37,211
R-squared	0.05	0.11	0.08	0.10
Panel C: Rest	**No other race**	**No other relig.**	**No neighbours**	**No Jobs**
Income level 18-25	-0.030**	-0.012*	-0.023***	-0.019**
	(0.014)	(0.007)	(0.008)	(0.008)
N	189,711	135,810	187,891	182,570
R-squared	0.09	0.10	0.10	0.08
Household income decile	✓	✓	✓	✓
Education category	✓	✓	✓	✓
Labor market status	✓	✓	✓	✓
Demographic variables	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Decade of birth FE	✓	✓	✓	✓

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. In parentheses, heteroskedasticity robust standard errors are reported. In Panel B p-values are reported in brackets, estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the boottest estimator developed by Roodman et al. (2019), with 5000 replications. In In Panels A and C standard errors are not bootstrapped since the number of clusters is sufficiently large. Sample re-weighted using the population weights in the WVS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

4 Discussion and Concluding remarks

Appendix for "Growing up in a Recession Increases Compassion? The Case of Attitudes towards Immigration"

Contents

Material and Methods in the GSS

Descriptives

The General Social Survey has gathered data on attitudes and behaviors in the US in 30 waves, since 1973 and up to and including 2016. The study is a repeated cross-section on a representative sample of the adult US population, conducted through predominantly in-person interviews.

In this paper we focus on 10 waves, between 1994 and 2016, in which 13,000 respondents were asked to state their opinion about immigration to the Unites States. Over time, the question measuring attitudes towards immigration has been slightly altered in three different versions, as described below:

(i) In 1994 and 2000 the question was: "Do you think the number of immigrants from foreign countries who are permitted to come to the United States to live should be"

1 Increased a lot
2 Increased a little
3 Same as now
4 Decreased a little
5 Decreased a lot
8 Don't know
9 No answer
0 Not applicable

(ii) In 1996, 2004, and 2014 the question was: "Do you think the number of immigrants to America nowadays should be"

1 Increased a lot
2 Increased a little
3 Remain the same as it is
4 Reduced a little
5 Reduced a lot
8 Cant choose
9 No answer
0 Not applicable

(iii) In 2004, 2006, 2008, 2010, 2012, 2014, and 2016 the question was: "Do you think the number of immigrants to America nowadays should be"

1 Increased a lot
2 Increased a little
3 Remain the same as it is
4 Reduced a little
5 Reduced a lot, or
8 Don't know
9 No answer
0 Not applicable

We create one variable which pools the answers across all ten waves, and in Appendix A2 we perform additional robustness checks to show that our results are the same (and stronger) if we instead only use the most commonly asked version of the question, described in (iii). The dependent variable we construct is on a 5-point scale (1 is "immigration should be increased a lot", and 5 is "immigration should be decreased a lot") scale where a higher number translates into a more negative attitude towards the number of immigrants in the US.

Figure 1 shows the distribution of attitudes towards immigration in the sample, between 1994 and 2016.

Gender is a dummy variable taking value 0 for males, and 1 for females. *Race* is a categorical variable, divided into white, black, and other. *Marital status* is classified as married, widowed, divorced, separated, and never married. The *number of children* and the *household size* are numerical variables on a scale from 1 to 8 or more, and 1 to 16 respectively. *Labor market status* is a categorical variable divided into working full-time, working part-time, temporarily not working, unemployed, retired, in school, keeping house, or other. *Age* and *education* are continuous variables, where age runs from 18 to 75 in our selected sample, and years of education run from 0 to 20.

Parent immigrant status is a categorical variable with nine possible options: both born in the US, mother only, father only, mother born in the US and father unknown, father born in the US and mother unknown, mother not born in the US and father unknown, father not born in the US and mother unknown, both parents born outside of the US, both parents unknown.

Household income represents the real family income in constant US$. When a respondent did not fill in an amount (7% of the relevant sample), we imputed their household income using responses on socio-demografic questions (respondent's education, labor market status, age, household size, gender, marital status), and dummies for survey year and region of residence at the time of the survey. In all our specifications we control for respondents whose income was imputed, using a binary indicator. Imputation is performed using the *impute* function in Stata.

Birth decades are defined using the birth year of each respondent, in intervals of 10 years between 1898 and 2000. According to this definition, 10 different generations exist in our sample, with the oldest generation including those born between 1904 and 1910, and the youngest generation being made up of respondents born between 1990 and 1998.

Parent education is captured by two numerical variables counting the years of education of the mother and the father of each respondent, ranging from 0 to 20. When a respondent did not fill in a number (20% of the relevant sample for mother education and 30% for father education), we imputed their parents' education using the average mother's and father's education level in the sample. In all our specifications we control for respondents whose parents' education was imputed, using a binary indicator. Imputation is performed using the *impute* function in Stata.

Household income at the age of 16 is defined as a categorical variable on a 5-point scale, ranging from "far below average" to "far above average". When a respondent did not fill in a category (7% of the relevant sample), we imputed their household income at the age of 16 using the average level in the sample. In all our specifications we control for respondents whose income at the age of 16 was imputed, using a binary indicator. Imputation is performed using the *impute* function in Stata.

In the GSS, states are grouped into nine macro regions: 1. New England (Maine, Vermont, New Hampshire, Massachusetts, Connecticut, Rhode Island), 2. Middle Atlantic (New York, New Jersey and Pennsylvania), 3. East North Central (Wisconsin, Illinois, Indiana, Michigan and Ohio), 4. West North Central (Minnesota, Iowa, Missouri, North Dakota, Nebraska, Kansas), 5. South Atlantic (Delaware, Maryland, West Virginia, Virginia, North Carolina, South Carolina, Georgia, Florida, District of Columbia), 6. East South Central (Kentucky, Tennessee, Alabama, Mississippi), 7. West South Central (Arkansas, Oklahoma, Louisiana, Texas), 8. Mountain (Montana, Idaho, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico), 9. Pacific (Washington, Oregon, California, Alaska, Hawaii).

Those who only moved to the US after the age of 16 are coded as foreigners (5.4%). Since we do not know whether these respondents were in the US during their impressionable years, their experiences in that period are unknown and they are not included in the sample.

Table A.1 shows descriptive statistics for the sample.

Income, unemployment, and immigration inflows

The U.S. Bureau of Economic Analysis (BEA) provides yearly data on state-level personal income (SAINC1 Personal Income Summary: Personal Income, Population, Per Capita Personal Income) since 1929.

The Bureau of Labor Statistics provides yearly data on the unemployment rate at the state level since 1976. Since using this measure would restrict our sample size significantly, in regressions with unemployment experience during the impressionable years we use national-level data on unemployment. National unemployment rates are available from the BLS since 1929.

The Migration Policy Institute (MPI) provides annual figures on the number of new legal permanent residents to the US. The data is provided at the national level since 1820, and we adjust the percentage of legal immigrants each years by the US population.

Constructing experienced regional income during the impressionable years

Income data spans from 1929 to 2016. As the BEA data is at the state level, we use state-level income per capita and state level-population to calculate the regional income per capita:

$$IncCapR_{r,t} = \frac{\sum_i IncCapS_{i,t} * PopS_{i,t}}{\sum_i PopS_{i,t}} \tag{A-1}$$

where income per capita in each state i in region r at time t ($IncCapS_{i,t}$) is weighted by the population of each state i at time t ($PopS_{i,t}$) in region r to obtain the regional income per capita $IncCapR_{r,t}$.

In the next step, the regional income per capita is adjusted to control for inflation. To do this, we re-weight regional income per capita using data on US national-level CPI factors since 1929. We choose 2017US$ as the base, and adjust regional income per capita with the corresponding factor of 245.1, such that:

$$IncCapR^{adj}_{r,t} = \frac{IncCapR_{r,t} * 245.1}{cpi_t} \tag{A-2}$$

where cpi_t is the consumer price index each year, between 1929 and 2014.

Next, using the age of each respondent in the survey and the year of the survey, we identify the years in which individuals were between 18 and 25 years of age. Using $IncCapR_{r,t}^{adj}$ each year between 1929 and 2016, we create the average experienced regional income during the impressionable years, such that:

$$IncomeLevel_{i,r,t}^{18-25} = \log\left(\frac{\sum_{t=1}^{T} IncCapR_{r,t}^{adj}}{T}\right) \tag{A-3}$$

where $IncomeLevel_{i,r,t}^{18-25}$ is the log of the average of the adjusted regional income per capita in each of the eight years when respondent i was in the impressionable years (between 18 and 25 years old). When a respondent is below 25 at the time of the survey, the experience is a weighted average of income in the subset of years between 18 and up to the current age.

Additional Tables

A1 Descriptive statistics

Table A.1 Descriptive Statistics

	Mean	Standard deviation	N
Attitudes and preferences			
Immigration should be reduced (5-point scale)	3.67	1.04	11,860
Socio-Demographics			
% Female	54	50	11,860
Years education	13.70	2.70	11,860
Age	44.44	15.13	11,860
Birth year	1962.06	16.24	11,860
Annual income	34,409.17	33,226.99	11,860
Household size	2.50	1.39	11,860
No. children	1.73	1.60	11,860
% Married	46	50	11,860
% White	79	41	11,860
% Full-time employed	54	50	11,860
% Part-time employed	12	32	11,860
% Temporarily not working	2	15	11,860
% Unemployed	4	20	11,860
% Retired	12	32	11,860
% In school	4	19	11,860
% Keeping house	10	30	11,860
Mother years education	11.98	3.23	10,605
Father years education	11.89	3.86	8,830
Household income at 16 (1-5)	2.79	0.91	8,862
Experiences 18-25			
National unemployment	5.93	1.60	11,860
Regional income (2017US$)	44,917.66	6,138.90	11,860
National income (2017US$)	45,283.82	4078.20	11,860
Immigrant inflow (% of the population)	0.264	0.089	11,860

A2 Robustness checks dependent variable

Table A.2 Experienced regional income during the impressionable years and attitudes towards immigration: non-pooled dependent variable

	Anti Immigration
Income level 18-25	-0.473***
	(0.295)
	[0.003]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	8,507

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** p<.01, ** p<.05, * p<.1.

A3 Impressionable years vs. other age groups in the GSS

Following research in psychology, we focus on the impact of macroeconomic conditions experienced during impressionable years, namely when respondents were between between 18 and 25 years old. In this section we investigate the possibility that the impressionable years are not the only important period in the formation of attitudes towards immigration. We separately investigate the effects of experienced regional income level at different ages. Specifically, we look at two additional intervals prior to the impressionable years (ages 0-9 and ages 10-17), and three equal-length intervals after them (ages 26-33, ages 34-41, and ages 42-49).

As the alternative "impressionable years" are further away from the age of 16, the likelihood that the individual moved to another region between the age of 16 and the time of the survey is much higher. In line with Giuliano and Spilimbergo (2014), we address this issue by restricting the sample to those individuals who did not move between the age of 16 and the time of the survey. As results in Table A.3.1 indicate, these non-movers appear to be representative of the whole sample.

In the first column in Table A.3.1 we estimate equation (1) separately for each of the five different age intervals. In the second column of Table A.3.1 we add experienced income during the impressionable years. Generally, experiences during other years do not appear to explain much of the variation in attitudes towards immigration. In a "horse race" between impressionable years and other years, the impressionable years are almost without exception the most important when it comes to attitudes towards immigration.

To assess the effect of experiences at each of these ages on attitudes towards immigration requires additional restrictions on the sample size. Controlling for experienced macro-economic conditions after the "impressionable years" (26-33, 34-41, and 42-49) mechanically restricts the sample to those individuals who are at least as old as that. For this reason, in Table A.3.1 we do not incorporate all different experience variables in one model but instead look at their effect on preferences for meaning and income separately. As an additional robustness check and keeping the sample restrictions in mind we also estimate equation (1) with the full set of possible experiences, for the sub-sample of individuals who are 42 and older. Table A.3.2 confirms that indeed experiences during impressionable years remain the most important, even after controlling for all other macro-economic conditions experienced at different ages.

Table A.3.1: Experienced regional income during other years and attitudes towards immigration

	Anti Immigration	**Anti Immigration**
Panel A: Ages 0-9		
Income level 0-9	-0.445**	-0.402
	(0.153)	(0.184)
	[0.021]	[0.106]
Income level 18-25		-0.124
		(0.292)
		[0.541]
N	9,245	9,245
Panel B: Ages 10-17		
Income level 10-17	-0.277**	-0.092
	(0.199)	(0.245)
	[0.039]	[0.685]
Income level 18-25		-0.398*
		(0.299)
		[0.087]
N	9,251	9,251
Panel C: Ages 26-33		
Income level 26-33	0.343	0.722**
	(0.305)	(0.390)
	[0.411]	[0.015]
Income level 18-25		-0.561**
		(0.330)
		[0.015]
N	7,982	7,982
Panel D: Ages 34-41		
Income level 34-41	-0.320	-0.143
	(0.417)	(0.471)
	[0.386]	[0.790]
Income level 18-25		-0.291
		(0.329)
		[0.270]
N	6,373	6,373
Panel E: Ages 42-49		
Income level 42-49	-0.014	0.200
	(0.596)	(0.614)
	[0.985]	[0.728]
Income level 18-25		-0.648
		(0.347)
		[0.120]
N	4,820	4,820

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by

Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

Table A.3.2: Joint estimation of experienced regional income in different years and attitudes towards immigration

	Anti Immigration
Income level 0-9	-0.189
	(0.302)
	[0.495]
Income level 10-17	0.021
	(0.338)
	[0.949]
Income level 18-25	-0.780*
	(0.427)
	[0.084]
Income level 26-33	1.026
	(0.714)
	[0.102]
Income level 34-41	-0.506
	(0.682)
	[0.375]
Income level 42-49	0.033
	(0.719)
	[0.964]
N	4,814

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

A4 Experienced national income

Table A.4: Experienced national income during the impressionable years and attitudes towards immigration

	Anti Immigration
National income level 18-25	-0.401
	(0.478)
	[0.403]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	11,860

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** p<.01, ** p<.05, * p<.1.

A5 Restricting sample to non-movers

Table A.5: Experienced regional income during the impressionable years and attitudes towards immigration: non-movers

	Anti Immigration
Income level 18-25	-0.462**
	(0.242)
	[0.011]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	9,251

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

A6 Results with a recession indicator

Table A.6: Experienced recession income during the impressionable years and attitudes towards immigration

	Anti Immigration
Recession indicator	0.027
	(0.029)
	[0.100]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	11,860

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

A7 Experienced national unemployment

Table A.7: Experienced national unemployment during the impressionable years and attitudes towards immigration

	Anti Immigration
Unemployment level 18-25	0.036**
	(0.015)
	[0.013]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	11,860

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

A8 Alternative specifications for birth and age

Table A.8: Experienced regional income during the impressionable years and attitudes towards immigration: alternative specifications for birth and age

	Anti Immig.	**Anti Immig.**
Income level 18-25	-0.305***	-0.411***
	(0.236)	(0.244)
	[0.009]	[0.003]
Household income	✓	✓
Years of education	✓	✓
Labor market status	✓	✓
Demographic variables	✓	✓
Year FE	✓	✓
Region at 16 FE	✓	✓
Region FE	✓	✓
Age FE	✓	X
Decade of birth FE	X	✓
Age groups (intervals of 5)	X	✓
Decade of birth groups (intervals of 5)	✓	X
N	11,860	11,860

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** p<.01, ** p<.05, * p<.1.

A9 Main results estimated with an ordered probit

Table A.9: Experienced regional income during the impressionable years and attitudes towards immigration: ordered probit

	Anti Immigration	**Anti Immigration**
Income level 18-25	-0.486**	-0.493**
	(0.237)	(0.235)
Household income	✓	X
Years of education	✓	X
Labor market status	✓	X
Demographic variables	✓	✓
Year FE	✓	✓
Region at 16 FE	✓	✓
Region FE	✓	✓
Age polynomials	✓	✓
Decade of birth FE	✓	✓
N	11,860	11,860

Notes: Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. Since the wild bootstrap procedure suggested by Cameron et al. (2008) is not compatible with an ordered probit estimation method, we abstain from clustering standard errors. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** p<.01, ** p<.05, * p<.1.

A10 Average income vs standard deviation of income

Table A.10: Experienced regional income during the impressionable years and attitudes towards immigration: average income vs standard deviation of income

	Anti Immigration
Income level 18-25	-0.399**
	(0.217)
	[0.046]
Standard deviation of income 18-25	-0.004
	(0.027)
	[0.803]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	11,806

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

A11 Immigration inflows

Table A.11: Experienced regional income and experienced national immigration inflows during the impressionable years

	Anti Immigration
Income level 18-25	-0.400**
	(0.221)
	[0.017]
Immigration 18-25 Q2	0.071
	(0.062)
	[0.283]
Immigration 18-25 Q3	0.252**
	(0.091)
	[0.035]
Immigration 18-25 Q4	0.283**
	(0.115)
	[0.023]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	11,860

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** p<.01, ** p<.05, * p<.1.

A12 Industry fixed effects

Table A.12: Experienced regional income during the impressionable years and attitudes towards immigration: controlling for industry

	Anti Immigration
Income level 18-25	-0.357
	(0.222)
	[0.125]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
Industry fixed effects	✓
N	11,392

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** p<.01, ** p<.05, * p<.1.

A13 Income level 18-25 vs. current level of income

Table A.13: Experienced regional income during the impressionable years and attitudes towards immigration: Income level 18-25 vs. current level of income

	Anti Immigration
Income level 18-25	-0.396**
	(0.215)
	[0.046]
Income level at survey	-0.321
	(0.436)
	[0.376]
Household income	✓
Years of education	✓
Labor market status	✓
Demographic variables	✓
Year FE	✓
Region at 16 FE	✓
Region FE	✓
Age polynomials	✓
Decade of birth FE	✓
N	11,860

Notes: Regressions are estimated using OLS. Demographic variables include controls for age, gender, education, father and mother education, marital status, number of children, household size (squared), the logarithm of household income, the logarithm of household income at the age of 16, work status, decade-of-birth dummies, and the immigrant status of the parents. In parentheses, heteroskedasticity robust standard errors are reported. In brackets, p-values are reported estimated using the wild bootstrap procedure suggested by Cameron et al. (2008), by clustering standard errors at the level of the region at age 16. Since the number of clusters is small, the more conservative Webb weights are used (Webb, 2013), implemented using the *boottest* estimator developed by Roodman et al. (2019), with 5000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

Materials and Methods in the WVS

Descriptives WVS

The World Value Survey has gathered data through a nationally representative survey on people's values and beliefs across 100 countries since 1981. The study is a repeated cross-section and it currently has six waves, with the first one between 1981 and 1984, and the most recent one between 2010 and 2014. The survey is carried out mostly through face-to-face and phone interviews and covers respondents aged 18 and older.

In this paper we focus on three questions regarding attitudes towards immigration:

(1) "On this list are various groups of people. Could you please mention any that you would not like to have as neighbors?"

The question has been asked in all waves. A number of possible answers are available to respondents, and we single out those who picked the category "Immigrants/Foreign workers". We construct a binary indicator which takes value 1 if the category was chosen and 0 otherwise.

(2) "Do you agree, disagree or neither agree nor disagree with the following statements? When jobs are scarce: Employers should give priority to (nation) people than immigrants"

The questions has been asked in the five most recent waves. We re-code the variable into a binary indicator which takes value 1 if the respondent agrees with the statement and value 0 otherwise.

(3) "How about people from other countries coming here to work. Which one of the following do you think the government should do? "

The question has been asked in three waves. Respondents can choose an answer on a 4-point scale, ranging from "Let anyone come" to "Prohibit people from coming". We re-code the variable such that a higher number corresponds to a mre negative attitude towards immigration.

To explore the extent to which experiences during impressionable years lead to more in-group mentality, we look at negative attitudes towards people on two different dimensions: religion and race. We following question:

"On this list are various groups of people. Could you please mention any that you would not like to have as neighbors?"

Potential answers include "People of a different race" and "People of a different religion". We re-code answers to the question into two binary indicators which take value 1 if one of the categories is mention and 0 otherwise.

Gender is a dummy variable which takes value 0 for males and value 1 for females. *Age* is a numerical variable recording the age of each respondent in years. We restrict our sample to respondents aged 18 to 75. *Education* is a categorical variable with 9 different possible choices, ranging between no formal education and university degree/higher education. Marital status is classified as married, living together, divorced, separated, widowed, and single. *Number of children* is a numerical variable counting the number of children a respondent has. *Employment status* is a categorical variable classified as working full-time, working part-time, self-employed, retired, housewife, students, unemployed, other. *Household income* is self-reported and measured on a 10-point scale. *Birth decades* are defined using the birth year of each respondent and grouped in intervals of 10 years. The oldest generation is made-up of respondents born between

1900 and 1909 and a very small number of respondents born prior to 1900.

Constructing experienced income during the impressionable years

To construct a measure of experienced income levels globally we make use of the Maddison database compiled by Angus Maddison and refer to recent updated and improved estimates by Bolt et al (2018). While Bolt et al (2018) provide two measures of GDP, we focus on the measure most appropriate for studying relative income levels across countries (*cgdppc*).[14] This measure constructs real GDP per capita based on multiple benchmark comparisons of prices and incomes across countries. The variable is expressed in 2011 $US by correcting for inflation rates in the United States such that the measure closely reflects direct historical income comparisons and provides magnitudes that are comparable over time.

The Maddison data set provides historical data on income levels for 97 countries which are also surveyed in the World Value Survey. Due to variation in administrative records, the length of the time series differs across countries. This implies that while for most developed countries we can calculate experiences during impressionable years for all respondents, for a small number of developing economies only younger respondents will be captured in our analysis.

Using the age of each respondent at the time of the survey and the year in which the survey was conducted, we identify the calendar years in which each respondent was between 18 and 25 years old. Using the GDP per capita in each country expressed in 2011 $US, we construct our measure of experienced macroeconomic conditions during impressionable years:

$$IncomeLevel_{i,c,t}^{18-25} = \log\left(\frac{\sum_{t=1}^{T} IncCap_{c,t}^{2011\$US}}{T}\right) \tag{A-4}$$

where $IncomeLevel_{i,c,t}^{18-25}$ is the average income level that respondent i surveyed at time t in country c experienced between 18 and 25 years old, expressed in 2011 $US.

[14]In additional robustness checks we have also used an alternative measure of GDP which is constructed by tracking the real growth rate of GDP per capita reported in national accounts (*rgdpnapc*). Our conclusions are similar across both measures, and the results using *rgdpnapc* are available on request.

Additional Tables

A14 Descriptive statistics

Table A.14.1: Descriptive statistics

	Mean			SD			N	
	All	Rich	Rest	All	Rich	Rest	Rich	Rest
Attitudes								
No neighbours (binary)	0.23	0.11	0.26	0.42	0.31	0.44	37,068	187,891
No other race (binary)	0.18	0.07	0.20	0.38	0.25	0.40	36,482	189,711
No other religion (binary)	0.20	0.08	0.23	0.40	0.31	0.42	23,764	135,810
No jobs (binary)	0.72	0.50	0.77	0.45	0.50	0.42	37,211	182,570
Restrict numbers (4-point scale)	2.47	2.41	2.48	0.84	0.68	0.87	24,291	115,269
Socio-Demographics								
% Female	52	53	51	50	50	50	59,535	276,893
Education category (9-point scale)	4.43	4.91	4.33	2.43	2.25	2.45	49,591	260,885
Age	41.65	45.34	40.91	15.67	16.15	15.47	78,495	392,396
Birth year	1962	1954	1964	17.52	18.36	16.80	59,331	265,051
Household income (decile)	4.62	5.14	4.51	2.33	2.61	2.26	51,572	256,491
No. children	1.92	1.66	1.97	1.84	1.49	1.90	58,997	267,579
% Married	58	57	58	49	50	49	60,225	276,113
% Full-time employed	0.35	40	33	0.48	49	47	59,352	270,125
% Part-time employed	8	11	7	27	31	26	59,352	270,125
% Self-employed	11	6	13	32	23	33	59,352	270,125
% Retired	12	20	10	32	40	33	59,352	270,125
% Housewife	16	11	17	36	31	37	59,352	270,125
% Students	8	5	8	26	22	27	59,352	270,125
% Unemployed	10	6	10	30	23	30	59,352	270,125
Experiences 18-25								
National income (2011US$)	10,283	20,957	8,027	11, 812	10,481	10,800	78,495	371,405

Table A.14.2:

	Rich HE	**Rich LE**	**Rest HE**	**Rest LE**
No neighbours				
Mean	0.09	0.13	0.25	0.26
Standard deviation	0.29	0.34	0.43	0.44
N	20,051	17,017	88,540	99,351
No jobs				
Mean	0.42	0.60	0.76	0.78
Standard deviation	0.49	0.49	0.43	0.41
N	20,633	16,578	85,364	97,206
Restrict numbers				
Mean	2.32	2.52	2.47	2.49
Standard deviation	0.66	0.69	0.82	0.91
N	12,924	11,367	52,838	62,431
No race				
Mean	0.05	0.09	0.18	0.22
Standard deviation	0.22	0.29	0.39	0.41
N	19,853	16,629	89,782	99,929
No religion				
Mean	0.07	0.09	0.20	0.25
Standard deviation	0.25	0.28	0.40	0.43
N	13,314	10,450	62,640	73,170

A15 Impressionable years vs. other time periods in the WVS

Table A.15: Experienced regional income during other years and attitudes towards immigration in the WVS

	No neighbours		No jobs		Restrict numbers	
Panel A: Ages 0-9						
Income level 0-9	-0.026***	-0.020***	-0.020**	-0.013	-0.063***	-0.038**
	(0.006)	(0.007)	(0.010)	(0.009)	(0.019)	(0.016)
Income level 18-25		-0.019**		-0.019**		-0.059***
		(0.009)		(0.007)		(0.018)
N	210,620	210,592	205,894	205,870	130,041	130,015
Panel B: Ages 10-17						
Income level 10-17	-0.024***	-0.014*	-0.025***	-0.014	-0.073***	-0.045*
	(0.007)	(0.008)	(0.009)	(0.009)	(0.018)	(0.024)
Income level 18-25		-0.014		-0.015**		-0.036*
		(0.010)		(0.007)		(0.022)
N	219,013	218,988	214,076	214,055	135,557	135,534
Panel C: Ages 26-33						
Income level 26-33	-0.020**	0.001	-0.012	0.005	-0.038**	-0.008
	(0.009)	(0.009)	(0.007)	(0.008)	(0.018)	(0.020)
Income level 18-25		-0.032***		-0.024***		-0.056***
		(0.009)		(0.008)		(0.021)
N	182,454	179,444	178,748	175,882	113,038	110,992
Panel D: Ages 34-41						
Income level 34-41	-0.015	-0.003	-0.004	0.005	-0.023	-0.013
	(0.011)	(0.011)	(0.010)	(0.009)	(0.020)	(0.018)
Income level 18-25		-0.042***		-0.019**		-0.065***
		(0.009)		(0.008)		(0.021)
N	139,009	133,804	136,232	131,286	85,817	82,008
Panel E: Ages 42-49						
Income level 42-49	-0.009	-0.003	-0.006	0.007	-0.018	-0.045*
	(0.014)	(0.019)	(0.010)	(0.012)	(0.022)	(0.027)
Income level 18-25		-0.041***		-0.021		-0.056**
		(0.014)		(0.014)		(0.025)
N	98,421	92,272	96,474	90,672	60,105	55,438

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. Sample re-weighted using the population weights in the WVS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

A16 Various specifications for age and birth fixed effects in the WVS

Table A.16: Experienced regional income during the impressionable years and attitudes in the WVS: alternative specification for birth and age

	No neighbours		No jobs		Restrict numbers	
	(1)	(2)	(1)	(2)	(1)	(2)
Income level 18-25	-0.025***	-0.024***	-0.025***	-0.024***	-0.064***	-0.064***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.016)	(0.016)
Household income decile	✓	✓	✓	✓	✓	✓
Education category	✓	✓	✓	✓	✓	✓
Labor market status	✓	✓	✓	✓	✓	✓
Demographic variables	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Age FE	✓	X	✓	X	✓	X
Decade of birth FE	X	✓	X	✓	X	✓
Age (intervals of 5)	X	✓	X	✓	X	✓
Decade of birth (intervals of 5)	✓	X	✓	X	✓	X
N	224,959	224,959	219,781	219,781	139,560	139,560
R-squared	0.11	0.11	0.13	0.13	0.12	0.12

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. Sample re-weighted using the population weights in the WVS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

A17 WVS results for the US

Table A.17: Experienced regional income during the impressionable years and attitudes towards immigration in the WVS: US only

	No neighbours	**No jobs**	**Restrict numbers**
Income level 18-25	-0.436	-0.484	-0.034
	(0.363)	(0.633)	(1.475)
Household income decile	✓	✓	✓
Education category	✓	✓	✓
Labor market status	✓	✓	✓
Demographic variables	✓	✓	✓
Year FE	✓	✓	✓
Country FE	✓	✓	✓
Age FE	✓	✓	✓
Decade of birth FE	✓	✓	✓
N	4,032	3,985	2,167
R-squared	0.04	0.06	0.14

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. Sample re-weighted using the population weights in the WVS. Significance levels: *** p<.01, ** p<.05, * p<.1.

A18 Experienced income-level vs. standard deviation of income in the WVS

Table A.18: Experienced regional income during the impressionable years and attitudes towards immigration in the WVS: average income vs standard deviation of income

	No neighbours	**No jobs**	**Restrict numbers**
Income level 18-25	-0.027***	-0.026***	-0.069***
	(0.008)	(0.007)	(0.018)
Standard deviation of income 18-25	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Household income decile	✓	✓	✓
Education category	✓	✓	✓
Labor market status	✓	✓	✓
Demographic variables	✓	✓	✓
Year FE	✓	✓	✓
Country FE	✓	✓	✓
Age FE	✓	✓	✓
Decade of birth FE	✓	✓	✓
N	216,858	212,068	134,479
R-squared	0.11	0.13	0.12

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. Sample re-weighted using the population weights in the WVS. Significance levels: *** p<.01, ** p<.05, * p<.1.

A19 Experienced income-level at the time of the survey in the WVS

Table A.19: Experienced regional income during the impressionable years and attitudes towards immigration in the WVS: income level 18-25 vs current level of income

	No neighbours	**No jobs**	**Restrict numbers**
Income level 18-25	-0.027***	-0.026***	-0.064***
	(0.007)	(0.007)	(0.015)
Income level at survey	0.054	0.037	0.001
	(0.047)	(0.026)	(0.157)
Household income decile	✓	✓	✓
Education category	✓	✓	✓
Labor market status	✓	✓	✓
Demographic variables	✓	✓	✓
Year FE	✓	✓	✓
Country FE	✓	✓	✓
Age FE	✓	✓	✓
Decade of birth FE	✓	✓	✓
N	224,959	219,781	139,560
R-squared	0.11	0.13	0.12

Notes: Regressions are estimated using OLS. Demographic variables include controls for age dummies, education categories, gender, marital status, number of children at home, employment status, income decile, and cohort dummies. In parentheses, heteroskedasticity robust standard errors are reported. Sample re-weighted using the population weights in the WVS. Significance levels: *** p<.01, ** p<.05, * p<.1.

References

Aksoy, Billur and Marco A Palma, "The effects of scarcity on cheating and in-group favoritism," *Journal of Economic Behavior & Organization*, 2019, *165*, 100–117.

Alesina, Alberto and Nicola Fuchs-Schündeln, "Goodbye Lenin (or Not?): The Effect of Communism on People's Preferences," *American Economic Review*, September 2007, *97* (4), 1507–1528.

_____ **and Paola Giuliano**, "Preferences for Redistribution," in Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, eds., *Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, eds.*, Vol. 1 of *Handbook of Social Economics*, North-Holland, 2011, pp. 93 – 131.

_____ **, Armando Miano, and Stefanie Stantcheva**, "Immigration and redistribution," *Review of Economic Studies*, 2023, *90* (1), 1–39.

Bianchi, Emily C, "The bright side of bad times: The affective advantages of entering the workforce in a recession," *Administrative Science Quarterly*, 2013, *58* (4), 587–623.

_____ , "Entering adulthood in a recession tempers later narcissism," *Psychological Science*, 2014, *25* (7), 1429–1437.

_____ , "American individualism rises and falls with the economy: Cross-temporal evidence that individualism declines when the economy falters.," *Journal of Personality and Social Psychology*, 2016, *111* (4), 567.

_____ **, Erika V Hall, and Sarah Lee**, "Reexamining the link between economic downturns and racial antipathy: Evidence that prejudice against blacks rises during recessions," *Psychological Science*, 2018, *29* (10), 1584–1597.

Billings, Stephen B, Eric Chyn, and Kareem Haggag, "The long-run effects of school racial diversity on political identity," *American Economic Review: Insights*, 2020, p. Forthcoming.

Boonmanunt, Suparee and Stephan Meier, "The Effect of Financial Constraints on In-Group Bias: Evidence from Rice Farmers in Thailand," *Journal of Economic Behavior and Organization*, 2023, *207*, 96–109.

Borjas, George J, "The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market," *The Quarterly Journal of Economics*, 2003, *118* (4), 1335–1374.

Bornstein, Gary, Uri Gneezy, and Rosmarie Nagel, "The effect of intergroup competition on group coordination: An experimental study," *Games and Economic Behavior*, 2002, *41* (1), 1–25.

Bowles, Samuel, "Did warfare among ancestral hunter-gatherers affect the evolution of human social behaviors?," *Science*, 2009, *324* (5932), 1293–1298.

Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller, "Bootstrap-based improvements for inference with clustered errors," *The Review of Economics and Statistics*, 2008, *90* (3), 414–427.

Card, David, "The impact of the Mariel Boatlift on the Miami Labor mMrket," *Industrial and Labor Relations Review*, 1990, *43* (2), 245–257.

Choi, Jung-Kyoo and Samuel Bowles, "The coevolution of parochial altruism and war," *Science*, 2007, *318* (5850), 636–640.

Clemens, Michael A, "Economics and Emigration: Trillion-dollar Bills on the Sidewalk?," *Journal of Economic Perspectives*, 2011, *25* (3), 83–106.

Corneo, Giacomo and Frank Neher, "Income inequality and self-reported values," *The Journal of Economic Inequality*, 2014, *12* (1), 49–71.

Cotofan, Maria, Lea Cassar, Robert Dur, and Stephan Meier, "Macroeconomic Conditions When Young Shape Job Preferences for Life," *The Review of Economics and Statistics*, 2023, *105* (2), 467–473.

Dustmann, Christian, Uta Schönberg, and Jan Stuhler, "The impact of immigration: Why do studies reach such different results?," *Journal of Economic Perspectives*, 2016, *30* (4), 31–56.

Emmenegger, Patrick and Robert Klemmensen, "What motivates you? The relationship between preferences for redistribution and attitudes toward immigration," *Comparative Politics*, 2013, *45* (2), 227–246.

Enke, Benjamin, Ricardo Rodríguez-Padilla, and Florian Zimmermann, "Moral universalism: Measurement and economic relevance," *Management Science*, 2022, *68* (5), 3590–3603.

Esses, Victoria M, Lynne M Jackson, and Tamara L Armstrong, "Intergroup competition and attitudes toward immigrants and immigration: An instrumental model of group conflict," *Journal of Social Issues*, 1998, *54* (4), 699–724.

Facchini, Giovanni and Anna Maria Mayda, "Does the welfare state affect individual attitudes toward immigrants? Evidence across countries," *The Review of Economics and Statistics*, 2009, *91* (2), 295–314.

Falk, Armin and Johannes Hermle, "Relationship of gender differences in preferences to economic development and gender equality," *Science*, 2018, *362* (6412).

Fisman, Raymond, Pamela Jakiela, and Shachar Kariv, "How did distributional preferences change during the great recession?," *Journal of Public Economics*, 2015, *128*, 84–95.

Foged, Mette and Giovanni Peri, "Immigrants' effect on native workers: New analysis on longitudinal data," *American Economic Journal: Applied Economics*, 2016, *8* (2), 1–34.

Friedman, Benjamin M, "Moral Consequences of Economic Growth: The John R. Commons Lecture, 2006," *The American Economist*, 2006, *50* (2), 3–8.

Fuchs-Schündeln, Nicola and Matthias Schündeln, "On the endogeneity of political preferences: Evidence from individual experience with democracy," *Science*, 2015, *347* (6226), 1145–1148.

Giuliano, Paola and Antonio Spilimbergo, "Growing up in a Recession," *Review of Economic Studies*, 2014, *81* (2), 787–817.

Goette, Lorenz, David Huffman, Stephan Meier, and Matthias Sutter, "Competition between organizational groups: Its impact on altruistic and antisocial motivations," *Management Science*, 2012, *58* (5), 948–960.

Green, Donald P, Jack Glaser, and Andrew Rich, "From lynching to gay bashing: the elusive connection between economic conditions and hate crime.," *Journal of Personality and Social Psychology*, 1998, *75* (1), 82.

Haaland, Ingar and Christopher Roth, "Labor Market Concerns and Support for Immigration," *Journal of Public Economics*, 2020, *191: 104256.*

Hainmueller, Jens and Daniel J Hopkins, "Public attitudes toward immigration," *Annual Review of Political Science*, 2014, *17*, 225–249.

______ **, Michael J Hiscox, and Yotam Margalit**, "Do concerns about labor market competition shape attitudes toward immigration? New evidence," *Journal of International Economics*, 2015, *97* (1), 193–207.

Hatton, Timothy J, "Immigration, Public Opinion and the Recession in Europe," *Economic Policy*, 2016, *31* (86), 205–246.

Inglehart, Ronald, "The silent revolution in Europe: Intergenerational change in post-industrial societies," *American Political Science Review*, 1971, *65* (4), 991–1017.

Kahn, Lisa B, "The long-term labor market consequences of graduating from college in a bad economy," *Labour Economics*, 2010, *17* (2), 303–316.

Krosnick, Jon A and Duane F Alwin, "Aging and susceptibility to attitude change," *Journal of Personality and Social Psychology*, 1989, *57* (3), 416.

Laudenbach, Christine, Ulrike Malmendier, and Alexandra Niessen-Ruenzi, "Emotional tagging and belief formation-The long-lasting effects of experiencing communism," *American Economic Review*, 2019, *109* (May), 567–571.

Malmendier, Ulrike and Stefan Nagel, "Depression babies: do macroeconomic experiences affect risk taking?," *The Quarterly Journal of Economics*, 2011, *126* (1), 373–416.

_____ and _____ , "Learning from inflation experiences," *The Quarterly Journal of Economics*, 2015, *131* (1), 53–87.

Mayda, Anna Maria, "Who is against immigration? A cross-country investigation of individual attitudes toward immigrants," *The Review of Economics and Statistics*, 2006, *88* (3), 510–530.

McLaren, Lauren M, "Immigration and the new politics of inclusion and exclusion in the European Union: The effect of elites and the EU on individual-level opinions regarding European and non-European immigrants," *European Journal of Political Research*, 2001, *39* (1), 81–108.

Meer, Jonathan and Benjamin A Priday, "Generosity Across the Income and Wealth Distributions," *National Tax Journal*, 2021, *74*, 655–687.

O'Rourke, Kevin, "Heckscher-Ohlin theory and individual attitudes towards globalization," in R. Henriksson H. Lindgren Findlay, R. and M. Lundahl, eds., *International Trade, and Economic History*, MIT Press, 2006, pp. 107–138.

Ottaviano, Gianmarco IP and Giovanni Peri, "Rethinking the effect of immigration on wages," *Journal of the European Economic Association*, 2012, *10* (1), 152–197.

Peri, Giovanni, "Do immigrant workers depress the wages of native workers?," *IZA World of Labor*, 2014.

Piff, Paul K and Angela R Robinson, "Social class and prosocial behavior: Current evidence, caveats, and questions," *Current Opinion in Psychology*, 2017, *18*, 6–10.

Posner, Daniel N, "The political salience of cultural difference: Why Chewas and Tumbukas are allies in Zambia and adversaries in Malawi," *American Political Science Review*, 2004, *98* (4), 529–545.

Quillian, Lincoln, "Prejudice as a response to perceived group threat: Population composition and anti-immigrant and racial prejudice in Europe," *American Sociological Review*, 1995, pp. 586–611.

Roodman, David, Morten Arregaard Nielsen, James G. MacKinnon, and Matthew D. Webb, "Fast and wild: Bootstrap inference in Stata using boottest," *The Stata Journal*, 2019, *19* (1), 4–60.

Scheve, Kenneth F and Matthew J Slaughter, "Labor market competition and individual preferences over immigration policy," *Review of Economics and Statistics*, 2001, *83* (1), 133–145.

Schwandt, Hannes and Till Von Wachter, "Unlucky cohorts: Estimating the long-term effects of entering the labor market in a recession in large cross-sectional data sets," *Journal of Labor Economics*, 2019, *37* (S1), S161–S198.

Sherif, M, "Group conflict and cooperation: The Robber's cave experiment," 1966.

Slotwinski, Michaela and Alois Stutzer, "Women Leaving the Playpen: The Emancipating Role of Female Suffrage," *Working Paper*, 2018.

Webb, Matthew D, "Reworking wild bootstrap based inference for clustered errors," *Queen's Economics Department Working Paper, No. 1315*, 2013.