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Does growing up in a recession increase compassion? The case of attitudes towards immigration

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Abstract
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 experienced during young adulthood affect attitudes towards immigration. Using data from the General Social Survey and the World Value Survey, we find strong evidence that bad macroeconomic circumstances during young adulthood strengthen attitudes against immigration for the rest of people's lives. In addition, growing up in difficult macroeconomic times increases parochialism, i.e. people become more outgroup hostile --- not just against 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 ingroup.

Key words: immigration, attitudes, social preferences, Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Migration Policy Institute (MPI), Maddison Project Database
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; Von Wachter, 2020), it also shapes critical political and economic preferences for the rest of people's lives (e.g. Giuliano and Spilimbergo, 2014; Cotofan et al., 2020). These findings are consistent with an extensive literature in political science and psychology showing that experiences during the impressionable years (between 18 and 25 years old) play an important role in the formation of people's attitudes and worldviews (e.g. Inglehart, 1971; Krosnick and Alwin, 1989; Bianchi, 2013, 2014). 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; Hansen and Stutzer, 2021).

In a highly influential paper, Giuliano and Spilimbergo (2014) examine how macroeconomic conditions shape preferences for redistribution. They show that people who grow up in a recession more strongly favor government redistribution and assistance to the poor during the rest of their lives. A recession during young adulthood also makes people believe that poverty is more likely due to bad luck than to a lack of effort, which is 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 underwent 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 the interests of one's ingroup, then we predict support for immigration to decrease, as less immigration may reduce competition for jobs and benefits, something which may be particularly valuable during a recession when jobs and benefits are scarce (Hatton, 2016).[1]

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 bad macroeconomic times significantly lowers acceptance of immigration.[2] The size of this effect is comparable to the size of the effect on redistribution preferences found by Giuliano and Spilimbergo (2014). We also find that people who grow up in bad macroeconomic conditions 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 bad macroeconomic conditions or recessions do not lead to a universal increase in compassion towards the poor. The positive effect 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 ingroup, 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 several of 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

[1] While this view about the impact of immigration on natives is not necessarily consistent with empirical studies (compare 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).

[2] Different from Giuliano and Spilimbergo (2014), we use experienced income per capita at the regional level as the main independent variable (as in Cotofan et al., 2020). This allows us to more flexibly look at different macroeconomic conditions. However, we show that our results are robust to using a recession indicator akin to Giuliano and Spilimbergo (2014) or national unemployment rates.

[3] In the same spirit, Cotofan et al. (2020) find that people who grew up in a recession put more priority on earnings and less on meaning when choosing jobs.

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., 2018).

Our empirical approach (closely related to Giuliano and Spilimbergo (2014)) exploits variation in macroeconomic experiences not only over time but also across regions. This allows us to control for national shocks, both when people are young and at the time of the survey, such as immigrant inflows or changes to national immigration policies. These factors have been shown to influence immigration attitudes, see among others Dustmann et al. (2019); Tabellini (2020); Rozo and Urbina (2020). In a number of robustness tests, we also control for experienced immigrant inflows during young adulthood. We find that this shapes anti-immigration attitudes for life, with higher experienced inflows leading to stronger anti-immigration attitudes, but it does not explain the effect of experienced macroeconomic conditions.

Our key prediction is based on research about how *concurrent* macroeconomic conditions affect attitudes towards immigrants. First, previous research theorizes that recessions intensify competition between immigrants and native workers for jobs and government transfers, leading to an increase in negative attitudes towards immigrants and immigration, e.g. Esses et al. (1998); Scheve and Slaughter (2001); Mayda (2006). Especially unskilled workers in richer countries will be opposed to immigration, as they may be most impacted by the inflow of unskilled immigrants (e.g. O'Rourke, 2006; Mayda, 2006). Existing empirical results on the effect of labor market competition on mass attitudes towards immigration are, however, mixed (see Hainmueller and Hopkins, 2014). While Mayda (2006) finds evidence consistent with the labor market competition theory, others do not find strong support (e.g. Hainmueller et al., 2015). Indeed, there is large unexplained individual heterogeneity in pro-immigration attitudes.

Second, another large literature investigates a related question: how competition and economic downturns affect outgroup hostility or parochialism — going back to Sherif's famous Robbers Cave experiment (Sherif, 1966). Parochialism is an omnipresent and important aspect of human interaction. A number of studies in multiple disciplines show that competition increases group conflict and outgroup 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 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). We test how macroeconomic conditions during young adulthood affect outgroup bias using several measures from the World Value Survey data. We find evidence that growing up in a recession increases outgroup bias against people of a different race, people of a different religion, and immigrants or foreign workers. Hence, experiencing different macroeconomic conditions during young adulthood shape parochialism for the rest of one's life. Past research showed that attitudes towards immigrants depend, among others, on the cultural similarity between natives and immigrant population (Tabellini, 2020). Our results indicate that this might be due to a general increase in outgroup bias along particular identity lines such as religion or race.

In contrast to these existing literatures, we do not focus on the effect of current macroeconomic conditions but analyze the lifelong consequences of people's experience of macroeconomic conditions during young adulthood. Hence, our study stresses that attitudes towards immigration and ingroup bias are shaped much earlier and are more persistent than implied by previous research. While a substantial literature exists investigating the development of prosocial behavior and parochialism in children (e.g. Fehr et al., 2008; Warneken and Tomasello, 2009), we focus on the effect of macroeconomic experiences during young adulthood. Our results suggest that current macroeconomic downturns will 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 during young adulthood has "moral consequences" as proposed by Friedman (2005) who stated that times of growth allow people to be more tolerant and prosocial. Our results support this conjecture in terms of experiencing good macroeconomic conditions when young. Differences in experiences during the impressionable years can thus explain part of the significant heterogeneity in ingroup bias and moral universalism (documented for example by Enke et al., 2019).

Our paper is closely related to a small but growing number of studies outside of economics

[4] A related literature looks at income and prosocial behavior in general (see, e.g. Piff and Robinson, 2017; Meer and Priday, 2020) and ingroup bias in particular (Aksoy and Palma, 2019; Boonmanunt and Meier, 2020).

analyzing the effect of cohorts, i.e. shared macro-level experiences, on attitudes towards immigration (e.g. Wilkes and Corrigall-Brown (2011) using Canadian data and McLaren et al. (2020) using British data). In addition to several macroeconomic factors, McLaren et al. (2020) shows that experienced immigration inflows when young affects immigration attitudes (and part of the cohort effects), similar to our robustness tests. Coenders and Scheepers (1998, 2008) using Dutch and German data and Laaker (2020) using the European Social Survey find similar results to our finding that experienced high unemployment rates when young increases anti-immgration attitudes. Our paper is the first to study this question on a global scale and we use much more comprehensive datasets (the General Social Survey and the World Value Study), which allows us to better disentangle the effects of national and global shocks in immigration flows and policies from the effects of macroeconomic conditions. In the General Social Survey data we do so by using regional variation in macroeconomic conditions, while in the World Value Study we use data from close to one hundred countries. Furthermore, our study is the first to show that these attitudes are not just directed towards immigrants but rather reflect broader parochial views among natives.

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 the formation of attitudes against immigration in the US. We use data from the General Social Survey (GSS), which is a repeated cross-section survey of the US population that has been running since 1972 and currently contains 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. The next subsection further describes the data and provides some summary statistics. Next, we present the results of our analysis in three steps: Subsection 2.2 presents the main results, Subsection 2.3 discusses a series of robustness tests, and Subsection 2.4 assesses heterogeneous effects.

2.1 Data

We use the 10 waves of the GSS, between 1994 and 2016, in which over 13,000 respondents gave 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 "Can't choose", 9 "No answer", 0 "Not applicable"

(iii) In 2004, 2006, 2008, 2010, 2012, 2014, and 2016 the exact same question was asked: "Do you think the number of immigrants to America nowadays should be ...", but answer category 8 was phrased in a slightly different manner:

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"[5]

We create one variable which pools the answers across all ten waves. In Table A5 (Column 6) in the Appendix we 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 scale where a higher number means a more negative attitude towards the number of immigrants in the US (1 is "immigration should be increased a lot", and 5 is "immigration should be reduced a lot").

[5]A very small number of respondents in 2004 and 2014 answered both question (ii) and (iii). For these respondents, we used their answer to question (iii).

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 greater detail. Attitudes towards immigration have become more favorable over time in the US. While in 1994 almost two-thirds of the respondents were in favor of reductions in immigration, in 2016 this percentage had shrunk to slightly more than 40%. A similar percentage think in 2016 that the number of immigrants should remain the same, while the remaining 20% are in favor of increased immigration.

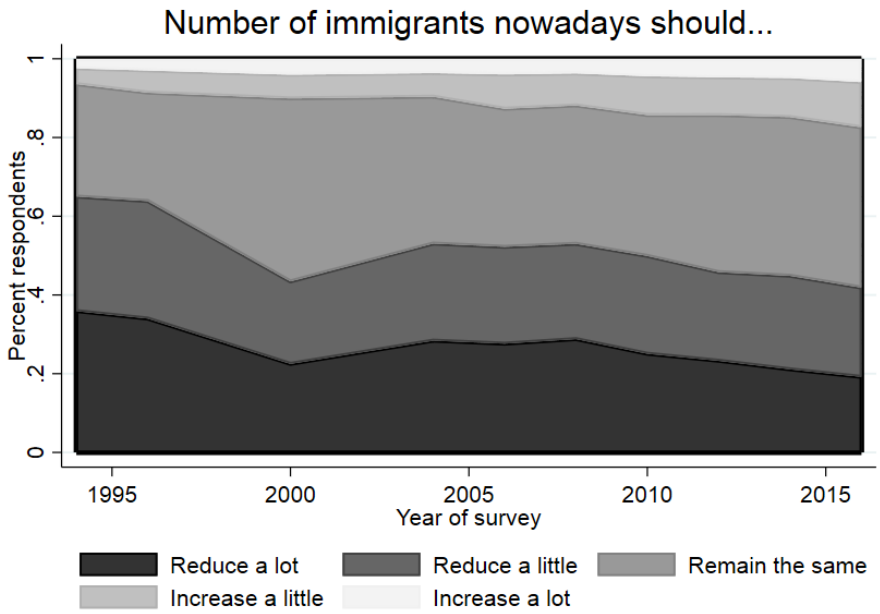

Figure 1: Attitudes towards immigration in the US (Source: General Social Survey, multiple waves)

Our key explanatory variable is experienced macroeconomic conditions during the "impressionable years," where impressionable years are defined as the years during which the respondent 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 macroeconomic experiences during other life stages in Subsection 2.3. 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 such as technology shocks, immigration policy changes, or national immigrants inflows. The data distinguish nine different regions across the US.[6] The GSS provides information on the region in which respondents resided both at the time of the survey and when they were at age 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 of the geographical location of each respondent during their impressionable years. 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 (see Subsection 2.3), suggesting that selection effects due to respondents moving across regions are not a major concern in our setting. We exclude from our sample those who moved to the US after the age of 16 (coded as "foreigners"; 5.4%), as we do not know where they resided during young adulthood.

We construct our measure of experienced macroeconomic conditions using annual state-level income data from the Bureau of Economic Analysis (BEA), which are available for each year since 1929 (SAINC1 Personal Income Summary: Personal Income, Population, Per Capita Personal Income). Our main explanatory variable $IncomeLevel^{18-25}$ is the logarithm of the average of the regional income levels when the respondent was between the ages of 18 and 25 in the region in which he/she resided at age 16. 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:

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

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 in region r at time t ($PopS_{i,t}$) 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:

[6] The nine regions are described in the "Description of the GSS" section of the Appendix.

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

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

Finally, using the year of the survey and the age of each respondent at the time of the survey, we identify the years in which the individual was between 18 and 25 years old. The log of the average experienced regional income of individual i during the impressionable years is then defined as:

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

where $IncomeLevel_i^{18-25}$ 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 age 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.

In addition to our key explanatory variable, we include a rich set of control variables in our regressions. Table 1 provides the summary statistics of all variables used in the analysis, which are described in detail in the Description of the GSS Data in the Appendix.

Table 1: Descriptive Statistics of the GSS Data

	Mean	Standard deviation	N
Attitudes and preferences			
Immigration should be reduced (5-point scale)	3.68	1.06	11,860
Socio-Demographics			
% Female	54	50	11,860
Years of education	13.69	2.65	11,860
Age	43.24	15.20	11,860
Birth year	1963.23	16.43	11,860
Household income (1986US$)	37,935.05	34,877.63	10,754
Household size	2.86	1.45	11,860
Number of children	1.72	1.59	11,860
% Married	54	50	11,860
% White	79	40	11,860
% Full-time employed	54	50	11,860
% Part-time employed	12	33	11,860
% Temporarily not working	2	15	11,860
% Unemployed	4	20	11,860
% Retired	10	30	11,860
% In school	4	20	11,860
% Keeping house	10	30	11,860
% Both parents born in the US	87	34	11,860
Mother's years of education	12.04	3.24	10,604
Father's years of education	11.94	3.86	8,829
Household income at age 16 (5-point scale)	2.80	0.90	8,862
Experiences between age 18 and 25			
National unemployment rate	6.04	1.14	11,860
Regional income (2017US$)	33,506.43	9,338.82	11,860
National income (2017US$)	33,597.88	8,531.79	11,860
Immigrant inflow (% of the population)	0.269	0.088	11,860

2.2 Main Results

To assess the effect of experienced macroeconomic conditions during the impressionable years on attitudes towards immigration, we estimate the following equation:

$$Att_i = \beta_0 + \beta_1 IncomeLevel_i^{18-25} + \beta_2 X_i + \tau_i + \rho_i + \rho_i^{age16} + \epsilon_i \tag{4}$$

where Att_i is the attitude towards immigration of respondent i. $IncomeLevel_i^{18-25}$ is the logarithm of the average experienced regional income level during the impressionable years of respondent i. We carefully control for time fixed effects τ_i, region of residence at the time of the survey fixed effects ρ_i, and region of residence at age 16 fixed effects ρ_i^{age16}.

X_i 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, logarithm of household income, logarithm of household income at the age of 16, work status, decade-of-birth dummies, and immigrant status of the parents. 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 birth year on attitudes towards immigration is the same for all individuals born within the same decade. In Subsection 2.3 we show that our findings are robust to various alternative and flexible specifications controlling for age, birth and year effects. The standard errors ϵ_i are clustered at the level of the region in which a respondent resided at age 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 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.

Table 2 reports the results from estimating equation (4), using OLS.[7] 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: a log-point increase in regional income during the impressionable years results in a downward shift of 0.4 points on the 5-point anti-immigration scale. Note that this shift is equivalent to 40% of the population moving a full point on the 5-point scale. To put the coefficient into perspective, we compare it with the coefficients for several of the control variables in the regression. A log-point change in experienced regional income during the impressionable

[7] Table A5 in the Appendix shows the results from estimating equation (4) using an ordered probit model instead. The results are very similar to those in Table 2.

years has a much larger effect on attitudes than a log-point change in household income (0.013 points on a 5-point scale) or than the effect of being unemployed (-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). Regional levels of income vary substantially over time and across regions (for details see Figure A5 in Cotofan et al., 2020). Importantly, there is substantial variation across different areas, with differences across regions of up to 105% in income levels.

The second column in Table 2 estimates equation (4) without controls for education, household income at the time of the survey, and labor market status — variables that are affected by graduating during a recession (e.g. Kahn, 2010; Schwandt and Von Wachter, 2019). The very similar coefficients in columns (1) and (2) indicate that experienced regional income levels during the impressionable years do not appear to partly work through these channels. Therefore, we will control for education, household income at the time of the survey, and labor market status in all subsequent tables.

In an additional step, we ask whether the impact of experienced macroeconomic conditions during the impressionable years decays over time, or is persistent throughout the life cycle. In the third column of Table 2 we include interaction terms between $IncomeLevel_i^{18-25}$ 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 in a permanent shift in attitudes towards immigration.

Table 2: Experienced regional income during the impressionable years and attitudes towards immigration

	(1)	(2)	(3)
Dependent Variable:	**Anti Immigration**		
Income level 18-25	-0.404**	-0.410**	-0.413**
	(0.215)	(0.216)	(0.215)
	[0.039]	[0.040]	[0.043]
Income level 18-25 * 26-50 age grp			-0.006
			(0.006)
			[0.530]
Income level 18-25 * 51-75 age grp			0.004
			(0.007)
			[0.537]
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	11,860
R^2	0.11	0.09	0.11

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, race, father"s and mother's education, marital status, number of children, household size (squared), logarithm of household income at the age of 16, and 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 5,000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

2.3 Robustness Tests

In this subsection, we report the results of a number of empirical tests to check the robustness of our main result.

Variance of Experienced Income Level. First, in column (1) of Table A1 in the Appendix, we study whether not only the level but also the volatility in regional income levels during the impressionable years impacts attitudes towards immigration. We therefore additionally control for the standard deviation of experienced regional income levels during the impressionable years. Clearly, the standard deviation of income levels does not appear to predict immigration attitudes, nor does it change our key conclusions regarding the effect of the level of regional income during the impressionable years in any important way.

Current Income at the Regional Level. Next, in column (2) of Table A1 in the Appendix, we check how our results are affected if we additionally control for the regional income level at the time of the survey. The results suggest that current income matters as well and in the same way as experienced income during the impressionable years. While the coefficient is not statistically significant, it suggests that attitudes towards immigration change over the business cycle. In more prosperous times, people are more in favor of immigration, while economic hardship is associated with more negative attitudes. Importantly, the inclusion of current income levels does not change our result regarding the effect of *experienced* regional income levels on immigration attitudes. The coefficient is very close to the one reported in Table 2.

Recession Indicator. In column (3) of Table A1 in the Appendix, we more closely follow the approach in Giuliano and Spilimbergo (2014) and replace experienced income levels during the impressionable years with a binary indicator which takes the value 1 if a respondent experienced a recession during the impressionable years, i.e. 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 this recession indicator are somewhat more noisy (p-value = 0.10), they are consistent with our main estimate using the log of experienced regional income levels and do not change our conclusion overall. It is also interesting to note that the size of our coefficient is quite comparable to the key coefficients in Giuliano and Spilimbergo (2014). For instance, the positive effect of recessions on the support for helping the poor found by Giuliano and Spilimbergo (2014) is of about equal size to the negative effect we find of recessions on support for immigration.

National Unemployment. Instead of regional income levels we can 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 from 1976 onward, implying that we can reconstruct macroeconomic experiences for only a small subset of the sample. Instead, we construct a measure of experienced *national* unemployment. The result in column (4) of Table A1 in the Appendix are consistent with the result using regional income levels:

experiencing higher unemployment rates during the impressionable years leads to more negative views of immigration. However, since regional variation is lacking, these results rely only on variation in age at the time of the survey.

Immigration Flows. Next, in Table A2 in the Appendix, we add experienced immigration inflows during the impressionable years to our main regression. A growing literature shows that immigration inflow affects attitudes towards immigrants and immigration (Dustmann et al., 2019; Tabellini, 2020; Rozo and Urbina, 2020). Not controlling for this variable may affect our key result if macroeconomic conditions and immigrant inflows are corrrelated. We construct a measure of experienced national immigration inflows during the impressionable years by ranking respondents' experienced inflows and creating dummies for the upper three quartiles. Table A2 in the Appendix shows that, while experiencing higher immigration inflows when entering the labor market leads to more negative attitudes towards migrants (mimicking the results for concurrent immigrants inflow and immigration attitudes), our main results hold and remain equally strong even after controlling for these experiences.

Impressionable Years vs. Other Years. An important question is whether only the macroeconomic conditions experienced during the impressionable years (ages 18-25) affect immigration attitudes or whether experiences during other phases of life matter too. In Tables A3 and A4 in the Appendix we investigate the effects of experienced regional income levels 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). Recall that we only have information about a respondent's location at age 16 and at the time of the survey. When studying the effect of macroeconomic experiences during various age ranges, 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. Giuliano and Spilimbergo (2014) follow the same approach. The underlying assumption is that location at age 16 is a relatively good proxy for the location at other ages for this subsample.

We present three tests: first, we estimate equation (4) separately for each of the five different age intervals. Second, we add to experienced income during the different age intervals the experienced income during the impressionable years (ages 18-25). The results of those two tests are shown in Table A3 in the Appendix. Generally, experiences during other age ranges 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 explaining attitudes towards immigration.

To assess the effect of experiences during all of these age ranges on attitudes towards immigration using one single regression restricts the sample size to quite some extent, as all individuals in the sample must be at least 42 years old (the youngest age of the highest age range). Yet, Table A4 shows that, indeed, experiences during the impressionable years remain the most important, even after controlling for all other macro-economic conditions experienced at different ages.

Additional robustness tests. The final set of robustness tests is reported in Table A5. The first two columns show that our results are robust to several specifications of the time of birth and age categories. The third and fourth columns show that our results remain the same when using Ordered Probit instead of OLS. In column (5), we restrict the sample to people who reside at the same location at age 16 and at the time of the survey. As discussed above, for this subsample we expect location at age 16 to be a relatively strong proxy for location at age 18-25. In line with this, we find a slightly larger effect size for this subsample, along with slightly larger standard errors (probably due to the smaller sample size). Last, in column (6) we excluded from the sample those respondents who answered a slightly differently phrased question (that is, we used only the respondents to question (iii) in Subsection 2.1). The results are slightly stronger than those in Table 2.

2.4 Heterogeneous Effects

Our main result shows that experiencing bad macroeconomic conditions during the impressionable years increases attitudes against immigration. In this section, we explore heterogeneity in the effect. 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 on the composition of both 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 face competition from low-skilled migrants in the labor market. Our paper further explores this question by asking whether macroeconomic conditions when entering the labor market shape the attitudes of low-skilled workers towards immigrants more strongly than the attitudes of high-skilled workers.

In our sample, the median respondent has completed 13 years of education and 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 the median hold a more negative attitude towards immigration (0.27 points on a 5-point 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 is below the median is 0.20 points on a 5-point scale higher (about 20% of a standard deviation) than those whose fathers are more educated.

Table 3 explores the heterogeneity in the effect of experienced macroeconomic conditions by estimating equation (4) 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, columns (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 of education, respectively. While the lower number of observations affects the power of our tests, the results indicate that the findings in Table 2 are clearly mostly driven by respondents who are less educated and whose fathers are less educated.

A log-point increase in regional income during the impressionable years prompts less-educated respondents to be 0.770 points more positive towards immigration on a 5-point scale. On the other hand, highly educated respondents are only 0.119 points more positive towards immigration on a 5-point scale. The p-value from testing whether the difference between the two coefficients is statistically significant is 0.131. Similarly, in response to a log-point increase in regional income, respondents with less-educated fathers are 0.567 points more positive towards immigration, as compared to 0.263 points for respondents whose fathers were more highly educated. The p-value from testing whether the difference between the two coefficients is statistically significant is 0.486. While the differences between the two groups with less or more (own or father) education are not statistically significant, the point estimates suggest that less-educated respondents who grow up in comparatively difficult times are more likely to harbor anti-immigration attitudes for the rest of their lives.

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

	(1)	(2)	(3)	(4)
Dependent Variable		**Anti Immigration**		
Subgroup	**Less educ.**	**Highly educ.**	**Father less educ.**	**Father highly 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
R^2	0.12	0.10	0.13	0.10

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, race, father's and mother's education, marital status, number of children, household size (squared), logarithm of household income at the age of 16, and 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 5,000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

Summarizing, the results from the GSS show that experiencing bad macroeconomic conditions during young adulthood negatively affects attitudes towards immigration for the rest of people's lives. Growing up in bad macroeconomic conditions leads people to be less in favor of immigration — an effect that is particularly pronounced for low-skilled workers. In the following section, we examine how universal this effect is around the world, whether it depends on the development level of the country, and whether growing up in a recession affects outgroup bias more broadly than just with regard to immigrants.

3 Evidence using the World Value Survey

In this section we present cross-country evidence on the impact of macroeconomic experiences during young adulthood on attitudes towards immigration. We use data from the World Value Survey (WVS), a repeated cross-section survey which has been conducted in approximately 100 developed and developing economies in six waves since 1981. The WVS contains data on a rich set of background variables as well as the social, economic, and political preferences of a representative sample of respondents across the participating countries. The survey is conducted mostly through face-to-face and phone interviews and covers respondents ages 18 and older.

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: 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 a group of 15 economically highly developed and a group of more than 80 economically less developed countries. We classify as highly developed countries those countries which belonged to the OECD already before the 1980s, with the exception of Turkey.[8] For the exact classification of countries into the two groups, see Table A6 in the Appendix.

This section is structured as follows. In the next subsection, we provide some more information about the data. Next, we present our method and main results in Subsection 3.2. Subsection 3.3 discusses a number of robustness checks and Subsection 3.4 considers heterogeneity of the effect across developed and less developed countries as well as across education level of the respondents. Last, in Subsection 3.6, we study the effect of experienced macroeconomic conditions on attitudes towards outgroups beyond immigrants. In most of our analysis, we follow the same approach as in the previous section.

[8]We exclude Turkey (which became a member in 1961) because it 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.

3.1 Data

For our main results, we make use of a question asked in the WVS to measure attitudes towards immigration. The question asks respondents to state their views regarding immigration policy within their country:

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

Possible answers on a 4-point scale are (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 code the variable "Immigration Restriction" such that it takes the value 1 for the most lenient attitudes towards immigration and the value 4 for the strongest anti-immigration views. The question is asked in three out of the five WVS waves: in 1994-1998, 1999-2004, 2005-2009. The average score is in between the second and third categories, both for the 15 most developed countries and for the rest of the sample. There is substantial variation in the responses; the standard deviation is about 0.8. See Table 4 for summary statistics.

In addition, we use a question about prioritizing natives over immigrants for jobs:

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

The question was asked in the five most recent waves. We re-code the variable into a binary indicator, 'Native Priority', which takes the value 1 if the respondent agrees with the statement and 0 otherwise. About half of the respondents in developed countries and more than three quarters in developing countries favor giving priority to natives.

Additionally we use questions in the WVS to measure attitudes towards immigrants and outgroup members in general:

"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 and covers various groups of people. For our purposes, the most relevant groups are "Immigrants/Foreign workers", "People of a different race", and

"People of a different religion". We construct for each of these three groups a binary indicator which takes the value 1 if the category was chosen, and 0 otherwise. For each group, approximately one out of five respondents indicate they would not like to have people from that group as neighbors. The fraction is substantially lower in developed countries (about one out of ten).

To construct a measure of experienced macroeconomic conditions, we make use of the Maddison database compiled by Angus Maddison. More specifically, we use the recently updated and improved estimates by Inklaar et al. (2018) who provide two measures of GDP. We focus on the measure most appropriate for studying income levels across countries (*cgdppc*).[9] 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 dataset provides historical data on income levels for 97 countries that are also surveyed in the World Value Survey. Because of 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 the impressionable years for all respondents, for a small number of developing economies only younger respondents will be included in our sample.

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 the impressionable years:

$$IncomeLevel_i^{18-25} = \log\left(\frac{\sum_{t=1}^{T} IncCap_{c,t}^{2011\text{US\$}}}{T}\right) \tag{5}$$

where $IncomeLevel_i^{18-25}$ is the log of the average national income level that respondent i experienced between age 18 and 25, expressed in 2011 US$. As in the GSS data, we lack data on where people resided between age 18 and 25. Therefore, when available, we use information on

[9] In additional robustness checks we have also used the other measure of GDP which is constructed by tracking the real growth rate of GDP per capita reported in national accounts (*rgdpnapc*). Our results are similar across both measures. The results using *rgdpnapc* are available upon request.

citizenship and country of birth to restrict the sample to those respondents who were born in the country in which they are currently residing.[10]

In addition to our key explanatory variable, we include a number of control variables in our analysis that are described in detail in the Description of the WVS Data in the Appendix. Table 4 lists them and provides summary statistics.

Table 4: Descriptive statistics (WVS)

	Mean			**SD**			**N**	
	All	Rich	Rest	All	Rich	Rest	Rich	Rest
Attitudes								
Immigration Restriction (4-point scale)	2.47	2.41	2.49	0.85	0.68	0.88	24,291	115,269
Native Priority (binary)	0.72	0.50	0.77	0.45	0.50	0.42	37,211	182,570
No immigrants (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)	0.21	0.08	0.23	0.40	0.26	0.42	23,764	135,810
Socio-Demographics								
% Female	51	52	51	50	50	50	59,466	271,365
Education category (9-point scale)	4.39	4.90	4.29	2.42	2.22	2.44	49,548	255,491
Age	39.76	44.44	38.77	14.92	15.77	14.54	55,807	264,922
Birth year	1962.15	1954.46	1963.91	17.59	18.53	16.88	59,262	259,731
Household income (decile)	4.60	5.17	4.48	2.33	2.62	2.25	51,528	251,351
No. children	1.92	1.65	1.98	1.84	1.48	1.91	58,938	266,389
% Married	57	56	58	50	50	49	60,523	275,030
% Full-time employed	34	41	32	47	49	47	60,523	275,030
% Part-time employed	8	11	7	27	31	25	60,523	275,030
% Self-employed	11	6	12	31	23	33	60,523	275,030
% Retired	11	18	10	31	39	29	60,523	275,030
% Housewife	15	10	16	35	30	36	60,523	275,030
% Students	7	5	8	26	21	27	60,523	275,030
% Unemployed	9	5	10	29	25	30	60,523	275,030
Experiences between age 18 and 25								
National income (2011US$)	10,354	21,347	7,933	10,684	10,316	9,130	55,807	253,579

3.2 Main Results

Our main regression equation reads:

[10] The question on citizenship is asked in only three of the five WVS waves. In a robustness check (available upon request), when data on citizenship was not available, we instead excluded respondents whose parents were immigrants, as they are more likely to be immigrants themselves. Our results are robust to this alternative check.

$$Att_i = \beta_0 + \beta_1 IncomeLevel_i^{18-25} + \beta_2 X_i + \tau_i + \rho_i + \epsilon_i \tag{6}$$

where Att_i captures the attitude of respondent i as defined in the previous subsection. $IncomeLevel_i^{18-25}$ represents the experienced national income level per capita during the impressionable years by respondent i. X_i 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. τ_i is a year-of-survey fixed effect, ρ_i is a country fixed effect, and the standard error ϵ_i is clustered at the country level. We avoid perfect collinearity between birth year, age, and year of the survey by controlling for birth decade instead of birth year. WVS country-specific weights are used in the regression analysis, in order to ensure that the sample is representative of each country's population.[11]

The first and third columns of Table 5 present the results from estimating equation (6). In the first column, the dependent variable is attitudes towards immigration ("Immigration Restriction"). In the second column, the dependent variable is the response to the question about whether employers should give priority to natives over immigrants when jobs are scarce ("Native Priority"). The evidence appears to be consistent with the findings for the US in Section 2. An increase in experienced national income levels during the impressionable years results in a more positive attitude towards immigration. Again, the coefficient is both statistically and economically significant. The effect of a log-point increase in national income during the impressionable years is equivalent to the effect of moving from the lowest to the seventh decile in the country-level household income distribution for the "Immigration Restriction" question and to the fifth decile for the "Native Priority" question. Globally, the logarithm of experienced income during the impressionable years exhibits substantial variation across countries, with a standard deviation of 1, and ranging between 6.1 and 12.3 in the sample.

In the second and fourth columns of Table 5 we investigate whether shocks to immigration attitudes caused by macroeconomic experiences during the impressionable years persist throughout the life cycle, or whether they tend to decay over time. We estimate interactions between $IncomeLevel_i^{18-25}$ and age groups, where the baseline category is composed of the experienced

[11] We get almost identical coefficients and the same (or stronger) significance when we do not apply these weights.

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 for both outcome variables, suggesting that these shocks to attitudes are permanent.

Table 5: Experienced national income during the impressionable years and attitudes towards immigration (WVS)

	(1)	(2)	(3)	(4)
Dependent Variable:	**"Immigration Restriction"**		**"Native Priority"**	
Income level 18-25	-0.064***	-0.071***	-0.024**	-0.025***
	(0.016)	(0.016)	(0.007)	(0.009)
Income level 18-25 * age 26-50		0.013		-0.002
		(0.009)		(0.006)
Income level 18-25 * age 51-75		0.012		0.012
		(0.012)		(0.009)
Household income decile	✓	✓	✓	✓
Education category	✓	✓	✓	✓
Labor market status	✓	✓	✓	✓
Demographic variables	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Decade of birth FE	✓	✓	✓	✓
N	139,560	139,560	219,781	219,781
R-squared	0.12	0.12	0.13	0.13

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

3.3 Robustness Tests

In this subsection, we check the robustness of our main results in a variety of ways.

First, similar to the results using the GSS data, our results using the WVS data are robust to controlling for two additional (experienced) income indicators. The first and third columns of Table A7 in the Appendix control for the standard deviation of income during the impressionable years. This measure is meant to capture the fact that some individuals have experienced more volatile macroeconomic circumstances 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 the second and fourth columns of Table A7 in the Appendix show that current income plays a much smaller role, and that it does not impact our main result on the effect of macroeconomic experiences during the impressionable years.

We also explore how experiences during years other than the impressionable years impact attitudes towards immigration. Like the analysis for the GSS, we run several regressions, adding experiences during another age category to the main regression equation (6). The results in Table A8 in the Appendix show quite consistently that the effect of experiences during the impressionable years is robust to controlling for experiences in other years. Moreover, it appears that almost without exception the experiences during the impressionable years matter more than experiences in other years.

Additionally, 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 (see the first four columns in Table A9). Last, we also show the results using the WVS data when we only include the observations from the US. The estimates in the fifth and sixth columns of Table A9 are largely consistent with the conclusions from the analysis of the GSS data in the previous section but are estimated less precisely due to the lower number of observations.

3.4 Heterogeneous Effects

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

Table 6 estimates equation (6) for both the subsample of developed economies and the remaining countries. Since the number of rich countries in columns (1) and (3) 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 immigration are more responsive to variation in macroeconomic conditions during the impressionable years than in less developed countries. For both outcome variables, the point estimate in developed countries are much larger than in the rest of the world.

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

	(1)	(2)	(3)	(4)
Dependent Variable:	**"Immigration Restriction"**		**"Native Priority"**	
Subgroups:	(Rich)	(Rest)	(Rich)	(Rest)
Income level 18-25	-0.170	-0.056**	-0.132**	-0.019**
	(0.061)	(0.017)	(0.027)	(0.008)
	[0.148]		[0.011]	
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	37,211	182,570
R-squared	0.08	0.13	0.10	0.08

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, marital status, and number of children at home. In parentheses, heteroskedasticity robust standard errors are reported. In all columns, standard errors are clusterred at the country level. In columns (1) and (3), since the number of clusters is small, p-values are reported in brackets, estimated using the wild bootstrap procedure suggested by Cameron et al. (2008) and the more conservative Webb weights are used (Webb, 2013). The wild bootstrap procedure is implemented using the boottest estimator developed by Roodman et al. (2019), with 5,000 replications. In columns (2) 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.

Following a similar procedure as in the analysis using the GSS, we next investigate heterogeneous treatment effects between highly and less educated workers in more and less developed countries. The median respondent in our sample has completed some form of secondary education such as technical or vocational schooling. We therefore define those with secondary education or less as less educated and those with additional education as highly educated. Table A10 in the Appendix shows the descriptive statistics of the dependent variables by education level and country development. Clearly, in rich countries, less educated workers hold more negative attitudes towards immigration and immigrants than highly educated workers. In contrast, in poorer countries, the difference in attitudes between highly and less educated workers is very small. It is also important to note that in less developed countries, people tend to be more negative about immigration and much more strongly feel that natives should get priority in the labor market over immigrants.

Table 7 shows how highly and less educated workers' attitudes relate to economic conditions during young adulthood in the 15 richest and in the other countries, respectively. Consistent with our findings for the US in Section 2, we find for "Immigration restriction" 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. For "Immigration restriction", 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. For "Native Priority", we find the opposite result. For this variable, highly educated workers tend to be more responsive to macroeconomic conditions during young adulthood as compared to less educated workers. The p-value from testing whether the difference between the two coefficients is statistically significant is 0.027 in rich countries and 0.553 in the rest of the world.

Table 7: Experienced national income during the impressionable years and attitudes towards immigration in the WVS: effects in rich countries and the rest of the world, by education (LE means less educated, HE means highly educated)

Dependent Variable	Immigration Restriction				Native Priority			
	LE (Rich)	HE (Rich)	LE (Rest)	HE (Rest)	LE (Rich)	HE (Rich)	LE (Rest)	HE (Rest)
Income level 18-25	-0.185**	-0.167	-0.076***	-0.024	-0.094**	-0.164***	-0.016	-0.022**
	(0.052)	(0.062)	(0.021)	(0.018)	(0.034)	(0.028)	(0.010)	(0.010)
	[0.026]	[0.226]			[0.046]	[0.010]		
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	16,578	20,633	97,206	85,364
R-squared	0.06	0.08	0.13	0.13	0.06	0.11	0.08	0.08

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, marital status, and number of children at home. In parentheses, heteroskedasticity robust standard errors are reported. In all columns, standard errors are clustered at the country level. In columns 1, 2, 5, and 6, since the number of clusters is small, p-values are reported in brackets, estimated using the wild bootstrap procedure suggested by Cameron et al. (2008) and the more conservative Webb weights are used (Webb, 2013). The wild bootstrap procedure is implemented using the boottest estimator developed by Roodman et al. (2019), with 5,000 replications. In columns 3, 4, 7, and 8, 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: *** $p<.01$, ** $p<.05$, * $p<.1$.

Summarizing, our results provide some indication for heterogeneity in how experience of macroeconomic conditions shapes immigration preferences. There is clear evidence that macroeconomic conditions during young adulthood are a more important determinant of attitudes towards immigrants in highly developed countries than in less developed countries. Regarding the difference between less educated and highly educated workers, the results are less clear and more dependent on the exact question. All groups are responsive to macroeconomic conditions during young adulthood, but less educated workers tend to respond more strongly to one indicator ("Immigration restriction") and less strongly to the other ("Native Priority"). We find this pattern both in highly developed and in less developed countries. The evidence from the WVS thus reflects the mixed results in the literature about concurrent effects of labor market conditions on less and highly educated workers (Hainmueller and Hopkins, 2014).

3.5 Ingroup mentality

In this final subsection, we test whether experiencing different macroeconomic conditions during the impressionable years not only affects attitudes towards immigration and immigrants, but affects attitudes towards other outgroups more generally. Parochialism, i.e. the tendency to favor one's own group, is universal and argued to be particularly pronounced in competitive environments (e.g. Choi and Bowles, 2007; Goette et al., 2012; Bianchi et al., 2018). Difficult macroeconomic times increase competition for jobs and government transfers. We test whether those times have a long-lasting effect on outgroup hostility.

The World Value Survey provides a number of questions which are appropriate for measuring such outgroup bias. Specifically, we use responses to a question asked in every wave which asks individuals to name "groups of people they would not like as neighbours". In addition to the group of "Immigrants or foreign workers", we focus on answers to two other groups: "People of a different race" and "People of a different religion". We create three binary indicators (one for each group) which take value 1 if the respondent mentioned the group, and 0 otherwise. Table 4 provides the descriptive statistics.

Table 8 reports the results of estimating equation (6), where the dependent variable is replaced by attitudes towards people of a different race ("No other race") in the first column, attitudes towards people of a different religion ("No other religion") in the second column, and attitudes towards immigrants ("No immigrants") in the third column. The estimated coefficients are close to those in Table 5. In Panel A we show the results for the full sample. A log-point increase in experienced income level during the impressionable years results in respondents being 3.2 percentage points less likely to not want people of a different race as neighbours, 1.3 percentage points less likely to not want people of a different religion as neighbours, and 2.4 percentage points less likely to not want immigrants as neighbors.

In Panel B and Panel C we split the sample between developed economies and the rest of the world. In line with the results in the previous section, the estimated coefficients are much larger in developed economies, even though they are significant as well in less developed countries. The estimation results thus clearly suggest that positive macroeconomic conditions during the 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.

It is interesting to compare the coefficients in Table 8 with those in Table 6. Arguably, the coefficients in Table 8 capture a broader attitude towards immigrants than the coefficients in the third and fourth columns of Table 6, which are much more focused on immigrants as competitors for jobs in the labor market. In line with a theory of labor market competition, the coefficients in Table 6 are much larger than those in Table 8. In rich countries, a log-point increase in national income during the impressionable years results in respondents being 4.4 percentage points less likely to mention that they would not want immigrants as neighbours, but 13.2 percentage points less likely to think that employers should prioritize jobs for natives. In poorer countries, these effects are much smaller and very close to each other, but both are statistically significant.

In sum, our results show that experiencing different macroeconomic conditions during the impressionable years not only affects attitudes towards immigration and immigrants but against outgroup members more generally. Parochialism is shaped by experienced macroeconomic conditions during young adulthood and not just concurrent competition, as shown by, e.g., Choi and Bowles (2007); Bornstein et al. (2002); Goette et al. (2012).

The results also suggest that part of the attitudes against immigration and immigrants might be more deeply rooted in parochialism more generally. Past research showed that attitudes against immigrants depend on their cultural background. For example, Tabellini (2020) shows that attitudes against immigrants were historically limited to immigrants with different religious backgrounds. Our results indicate that early experiences in a person's life can shape those attitudes against certain outgroups.

Table 8: Experienced regional income during the impressionable years and ingroup mentality in the WVS

Panel A: Full sample	**No other race**	**No other relig.**	**No immigrants**
Income level 18-25	-0.032**	-0.013*	-0.024**
	(0.013)	(0.007)	(0.008)
N	226,193	159,574	224,959
R-squared	0.10	0.12	0.11
Panel B: Rich	**No other race**	**No other relig.**	**No immigrants**
Income level 18-25	-0.079***	-0.045**	-0.044***
	(0.015)	(0.015)	(0.014)
	[0.002]	[0.034]	[0.001]
N	36,482	23,764	37,068
R-squared	0.05	0.11	0.08
Panel C: Rest	**No other race**	**No other relig.**	**No immigrants**
Income level 18-25	-0.030**	-0.012*	-0.023***
	(0.014)	(0.007)	(0.008)
N	189,711	135,810	187,891
R-squared	0.09	0.10	0.10
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 gender, marital status, and number of children at home. In parentheses, heteroskedasticity robust standard errors are reported. In all panels, standard errors are clustered at the country level. In Panel B since the number of clusters is small, p-values are reported in brackets, estimated using the wild bootstrap procedure suggested by Cameron et al. (2008) and the more conservative Webb weights are used (Webb, 2013). The wild bootstrap procedure is implemented using the boottest estimator developed by Roodman et al. (2019), with 5,000 replications. 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 Summary and Conclusion

This paper has investigated how experiencing different macroeconomic conditions during young adulthood affects attitudes towards immigration. Our results provide a framework for reconciling two seemingly contradictory results from the literature. On the one hand, research has shown that people who grew up in recessions more strongly favor redistribution and seem more compassionate towards the poor (Giuliano and Spilimbergo, 2014). On the other hand, hard economic conditions during young adulthood have been shown to increase a focus on one's own income (Cotofan et al., 2020).

Our results indicate that increases in compassion due to experiencing bad macroeconomic conditions are not indiscriminately directed towards all poor. In fact, we show that growing up in bad macroeconomic conditions increases anti-immigration attitudes, despite the fact that immigration tends to reduce global poverty. As such, the seminal finding that growing up in a recession increases preferences for redistribution (Giuliano and Spilimbergo, 2014) can be better understood as a self-interested response to a perceived weakening of one's economic position. A growing body of research shows that attitudes towards redistribution are closely linked to attitudes towards immigration (see, e.g. Alesina et al., 2018). Our paper shows that those attitudes are partly shaped by macroeconomic conditions experienced in young adulthood and that they persist well into old age.

We have documented how anti-immigration attitudes are shaped by early macroeconomic experiences in both the US and in 100 developed and developing economies. Bad macroeconomic conditions increase anti-immigration attitudes on a global scale, and this result is particularly strong for low-skilled workers in rich countries. In line with theories of labor market competition, this group is most likely to directly compete for jobs and social benefits with immigrants.

In addition, we have shown that our findings are not restricted to anti-immigration attitudes. Experienced macroeconomic conditions during young adulthood shape a broad set of attitudes towards members of outgroups. We find that those who grew up in bad economic times are significantly less likely to want immigrants, people of a different race, and people of a different religion as neighbors. We document these attitudes globally but show that they are stronger in rich countries. Parochialism is an important aspect of human beings and has been argued to be affected by competition. While an extensive literature has investigated the development of parochialism in children, little is known about why and how parochialism is shaped in young adults. Our paper shows that experiencing increased labour market competition during young adulthood makes natives more parochial for the rest of their lives.

Immigration is one of the most controversial issues of our times. It is of vital importance to study the origins of people's attitudes towards immigrants and immigration — not only to get a better understanding of the dynamics in political decision making, but also because there are important economic and social repercussions of changing immigration attitudes, both for the countries receiving immigrants and, particularly, for immigrants themselves (see, e.g. Esses, 2021). Our study of how immigration attitudes are formed during young adulthood by macroeconomic conditions adds a piece to the puzzle, but much work remains to be done. One issue we have not addressed is whether the effects we find are mainly due to personal economic experiences (e.g. of low income and unemployment) or arise more broadly and independently of personal experiences (e.g. out of general fear or out of solidarity with people of the same cohort). To study this issue one would need richer data than we have, including personal economic histories over a long period of time. It would also be interesting to study the interaction between macroeconomic experiences and the prevailing policies and institutions in a country, as in Hansen and Stutzer (2021). Another interesting next step would be to go beyond attitudes and beliefs and study behavioral consequences of different attitudes. One of our results shows that people develop stronger outgroup bias when facing hard economic times during young adulthood. It is likely that these changes in attitudes also result in important changes in behavior, for instance regarding whom to vote for, whom to marry, whom to work with, or whom to hire. With an extremely severe economic crisis happening globally right now, there is all the more reason to get a better understanding of the long-run impacts of macroeconomic conditions on attitudes, beliefs, and behavior.

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Appendix

Contents

Description of the GSS Data

This section describes the control variables from the GSS data in more detail.

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.

Parental 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.

Regions. The nine different regions in the data are: 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), and 9. Pacific

(Washington, Oregon, California, Alaska, Hawaii).

National unemployment. 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.

Immigrant inflow. The Migration Policy Institute (MPI) provides annual figures on the number of new legal permanent residents to the US. The data allows us to calculate immigrant inflow on the national level from 1929 onward by adjusting the percentage of legal immigrants each years by the US population. We then calculate the average inflows each person experienced during their impressionable years. For each responder, we define where their experienced immigrant inflow lays in the entire distribution of immigrant inflow. That is we define four quantiles based on the distribution of experiences.

Additional Tables for GSS Analysis

Table A1: Various Experienced Income Indicators

Table A1: Different Experienced Income Indicators

	(1)	(2)	(3)	(4)
Dependent Variable:	**Anti Immigration**			
Income level 18-25	-0.399**	-0.396**		
	(0.217)	(0.215)		
	[0.046]	[0.046]		
S.D. of income 18-25	-0.004			
	(0.027)			
	[0.803]			
Income level at survey		-0.321		
		(0.436)		
		[0.376]		
Recession indicator			0.027	
			(0.029)	
			[0.100]	
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	11,806	11,860	11,860	11,860
R^2	0.11	0.11	0.11	0.11

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, race, father and mother education, marital status, number of children, household size (squared), the logarithm of household income at the age of 16, and the immigrant status of the parents. In column (1) we additionally control for the standard deviation of "Income level 18-25", as a measure of the dispersion of income during the impressionable years. In column (2) we add the logarithm of the regional income level at the time of the survey as a control variable. In column (3) we replace experienced income levels during the impressionable years with a binary indicator which takes value 1 if during their impressionable years 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 US regions from 1929 to 2016. In column (4) we control for the national unemployment rate during a respondent's impressionable years. 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 5,000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** p<.01, ** p<.05, * p<.1.

Table A2: Immigration inflows

Table A2: 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
R^2	0.11

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, race, father and mother education, marital status, number of children, household size (squared), the logarithm of household income at the age of 16, 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 5,000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

Tables A3 and A4: Impressionable years vs. other age groups in the GSS

Table A3: 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
R^2	0.11	0.11
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
R^2	0.11	0.11
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
R^2	0.11	0.11
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
R^2	0.10	0.10
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
R^2	0.10	0.10

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, race, father and mother education, marital status, number of children, household size (squared), the logarithm of household income at the age of 16, and the immigrant status of the parents. As per usual, we also control for education, the logarithm of household income, work status, age polynomials, decade-of-birth dummies, and the region of residence at age 16. At the time of the survey, all respondents live in the same region as they did at age 16. 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 5,000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

Table A4: 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
R^2	0.10

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, race, father and mother education, marital status, number of children, household size (squared), the logarithm of household income at the age of 16, and the immigrant status of the parents. As per usual, we also control for education, the logarithm of household income, work status, age polynomials, decade-of-birth dummies, region of residence, and the region of residence at age 16. In parentheses, heteroskedasticity robust standard errors are reported. 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 5,000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** $p<.01$, ** $p<.05$, * $p<.1$.

Table A5: Additional Robustness Tests

Table A5: Robustness Tests (GSS)

Dependent Variable:	Anti Immigration					
Robustness:	Birth/Age	Birth/Age	Ord. Probit	Ord. Probit	Non-Movers	Non-pooled DV
	(1)	(2)	(3)	(4)	(5)	(6)
Income level 18-25	-0.305***	-0.411***	-0.486**	-0.493**	-0.462**	-0.473***
	(0.236)	(0.244)	(0.237)	(0.235)	(0.242)	(0.295)
	[0.009]	[0.003]			[0.011]	[0.003]
Household income	✓	✓	✓	X	✓	✓
Years of education	✓	✓	✓	X	✓	✓
Labor market status	✓	✓	✓	X	✓	✓
Demographic variables	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region at 16 FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	X	✓
Age polynomials	X	X	✓	✓	✓	✓
Age FE	✓	X	X	X	X	X
Decade of birth FE	X	✓	✓	✓	✓	✓
Age groups (intervals of 5)	X	✓	X	X	X	X
Years of birth groups (intervals of 5)	✓	X	X	X	X	X
N	11,860	11,860	11,860	11,860	9,251	8,507
R^2	0.12	0.12	0.04	0.03	0.11	0.11

Notes: Regressions in columns (1), (2), (5), and (6) are estimated using OLS. Regressions in columns (3) and (4) are estimated using Ordered Probit, and at the bottom of the table we report the Pseudo R^2 instead. Demographic variables include controls for gender, race, father and mother education, marital status, number of children, household size (squared), the logarithm of household income at the age of 16, and the immigrant status of the parents. In columns (1) and (2) we use alternative specifications for "age" and for "decade of birth". In column (5) we restrict the analysis to those who never moved region, such that at the time of the survey, all respondents live in the same region as they did at age 16. In column (6), the dependent variable is not pooled across waves in which the question text changed. In parentheses, heteroskedasticity robust standard errors are reported. 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 5,000 replications. Sample re-weighted using the *wtssall* population weights in the GSS. Significance levels: *** p<.01, ** p<.05, * p<.1.

Description of the WVS Data

This section describes the control variables used in the analysis of the WVS data in more detail.

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 (income deciles).

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.

Additional Tables for WVS Analysis

Table A6: List and classification of countries in the WVS

Table A6: List and classification of countries in the WVS

“Rich” countries	Australia, Canada, Finland, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Spain, Switzerland, the United Kingdom, and the United States.
“Rest”	Albania, Algeria, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Bosnia and Herzegovina, Brazil, Bulgaria, Burkina Faso, Chile, China, China - Hong Kong SAR, Colombia, Croatia, Cyprus, Czech Republic, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Georgia, Ghana, Guatemala, Haiti, Hungary, India, Indonesia, Iran (Islamic Republic of), Iraq, Israel, Jordan, Kazakhstan, Kuwait, Kyrgyzstan, Latvia, Lebanon, Libya, Lithuania, Malaysia, Mali, Mexico, Montenegro, Morocco, Nigeria, Pakistan, Peru, Philippines, Poland, Puerto Rico, Qatar, Republic of Korea, Republic of Moldova, Romania, Russian Federation, Rwanda, Saudi Arabia, Serbia, Singapore, Slovakia, Slovenia, South Africa, State of Palestine, TFYR of Macedonia, Taiwan, Thailand, Trinidad and Tobago, Tunisia, Turkey, U.R. of Tanzania: Mainland, Uganda, Ukraine, Uruguay, Uzbekistan, Venezuela (Bolivarian Republic of), Viet Nam, Yemen, Zambia, Zimbabwe

Notes: Countries in the WVS are classified as ‘rich’ if they were a member of the OECD already before the 1980s, with the exception of Turkey. Turkey, which became a member in 1961, is excluded as it 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.

Table A7: Different Experienced Income Indicators

Table A7: Different Experienced Income Indicators

	(1)	(2)	(3)	(4)
Dependent Variable:	**Immigration**	**Restriction**	**Native**	**Priority**
Income level 18-25	-0.069***	-0.064***	-0.026***	-0.026***
	(0.018)	(0.015)	(0.007)	(0.007)
Standard deviation of income 18-25	-0.000		0.000	
	(0.000)		(0.000)	
Income level at survey		0.001		0.037
		(0.157)		(0.026)
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	134,479	139,560	212,068	219,781
R^2	0.12	0.12	0.13	0.13

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, marital status, and the number of children at home. In columns (1) and (3) we additionally control for the standard deviation of "Income level 18-25", as a measure of the dispersion of income during Impression-able years. In columns (2) and (4) we add the log of the national income level in each country at the time of the survey as a control variable. In parentheses, heteroskedasticity robust standard errors are reported. In all columns, standard errors are clusterred at the country level. Sample re-weighted using the population weights in the WVS. Significance levels: *** p<.01, ** p<.05, * p<.1.

Table A8: Impressionable years vs. other time periods in the WVS

Table A8: Experienced national income during other years and attitudes towards immigration in the WVS

	(1)	(2)	(3)	(4)
Dependent Variable:	Immigration Restriction		Native Priority	
Panel A: Ages 0-9				
Income level 0-9	-0.063***	-0.038**	-0.020**	-0.013
	(0.019)	(0.016)	(0.010)	(0.009)
Income level 18-25		-0.059***		-0.019**
		(0.018)		(0.007)
N	130,041	130,015	205,894	205,870
R^2	0.12	0.12	0.13	0.13
Panel B: Ages 10-17				
Income level 10-17	-0.073***	-0.045*	-0.025***	-0.014
	(0.018)	(0.024)	(0.009)	(0.009)
Income level 18-25		-0.036*		-0.015**
		(0.022)		(0.007)
N	135,557	135,534	214,076	214,055
R^2	0.12	0.12	0.13	0.13
Panel C: Ages 26-33				
Income level 26-33	-0.038**	-0.008	-0.012	0.005
	(0.018)	(0.020)	(0.007)	(0.008)
Income level 18-25		-0.056***		-0.024***
		(0.021)		(0.008)
N	113,038	110,992	178,748	175,882
R^2	0.12	0.12	0.13	0.13
Panel D: Ages 34-41				
Income level 34-41	-0.023	-0.013	-0.004	0.005
	(0.020)	(0.018)	(0.010)	(0.009)
Income level 18-25		-0.065***		-0.019**
		(0.021)		(0.008)
N	85,817	82,008	136,232	131,286
R^2	0.12	0.12	0.13	0.14
Panel E: Ages 42-49				
Income level 42-49	-0.018	-0.045*	-0.006	0.007
	(0.022)	(0.027)	(0.010)	(0.012)
Income level 18-25		-0.056**		-0.021
		(0.025)		(0.014)
N	60,105	55,438	96,474	90,672
R^2	0.12	0.12	0.14	0.14

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, marital status, and the number of children at home. As per usual, we also control for household income decile, education category, labor market status, year fixed effects, country fixed effects, age fixed effects, and decade of birth fixed effects. In parentheses, heteroskedasticity robust standard errors are reported. In all regressions, standard errors are clusterred at the country level. Sample re-weighted using the population weights in the WVS. Significance levels: *** p<.01, ** p<.05, * p<.1.

Table A9: Additional Robustness Tests

Table A9: Robustness Tests (WVS)

Dependent Variable:	**Immigration Restriction**		**Native Priority**		**Immigration Restriction**	**Native Priority**
Robustness:	Birth/Age	Birth/Age	Birth/Age	Birth/Age	US only	US only
	(1)	(2)	(3)	(4)	(5)	(6)
Income level 18-25	-0.064***	-0.064***	-0.025***	-0.024***	-0.034	-0.484
	(0.016)	(0.016)	(0.008)	(0.007)	(1.475)	(0.633)
Household income decile	✓	✓	✓	✓	✓	✓
Education category	✓	✓	✓	✓	✓	✓
Labor market status	✓	✓	✓	✓	✓	✓
Demographic variables	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	X	X
Age FE	✓	X	✓	X	✓	✓
Decade of birth FE	X	✓	X	✓	✓	✓
Age (intervals of 5)	X	✓	X	✓	X	X
Decade of birth (intervals of 5)	✓	X	✓	X	X	X
N	139,560	139,560	219,781	219,781	2,167	3,985
R-squared	0.12	0.12	0.13	0.13	0.14	0.06

Notes: Regressions are estimated using OLS. Demographic variables include controls for gender, marital status, and the number of children at home. In columns (1), (2), (3), and (4) we use alternative specifications for "age" and for "decade of birth". In columns (5) and (6) we restrict the analysis to the US only to compare the results to those obtained when using the GSS instead. In parentheses, heteroskedasticity robust standard errors are reported. In columns (1) to (4), standard errors are clusterred at the country level. Sample re-weighted using the population weights in the WVS. Significance levels: *** p<.01, ** p<.05, * p<.1.

Table A10: Descriptive Statistics for Dependent Variables for developed and less developed countries and by education level

Table A10: Descriptive Statistics for the Dependent Variables for developed and less developed countries and by education level (LE means less educated, HE means highly educated)

	Rich HE	**Rich LE**	**Rest HE**	**Rest LE**
Immigration Restriction				
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
Native Priority				
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
No immigrants				
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 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

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