

DISCUSSION PAPER SERIES

IZA DP No. 15792

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## ABSTRACT

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### **Do Immigrants Ever Oppose Immigration?\***

This paper analyses immigrants' views about immigration, filling an important void in the immigration literature. In particular, it explores the role of statistical discrimination as a cause of possible opposition to immigration in absence of stringent immigration policies and large volumes of undocumented immigration. We test this hypothesis using US data from the 7th wave of the World Value Survey finding that successful immigrants in the US – i.e. those in the highest socio-economic group – have negative views about immigration especially with respect to its contribution to unemployment, crime, and the risk of a terrorist attack. This effect does not arise in the case of host countries that apply stricter controls on immigration, like Australia, Canada and New Zealand, or do not attract large volumes of undocumented immigrants. We interpret these results as evidence that undocumented or uncontrolled immigration negatively affects the standing of existing high socio-economic status immigrants by lowering it in the eyes of US natives, hence triggering an anti-immigration view as a response.

**JEL Classification:** D1, D89, D90, F22, J15

**Keywords:** immigration, beliefs, attitudes, behaviors

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## **1. Introduction**

After the 2020 US presidential election, many analysts were surprised by the high volume of immigrants from Latin America who voted for President Trump despite his strong stance against open immigration (Ostfeld, 2019; Corral and Leal, 2020; Cadava, 2021; Russonello and Mazzei, 2021; Garcia, 2021). Such political support has re-emerged in the campaign for the mid-term election of November 2022 (Winknews, 2022). Immigration is indeed a hot political topic in the US and other immigration countries. Supporters highlight its role in alleviating critical skill shortages and making a positive contribution to the host country's economy and growth. Detractors emphasise its potential negative effects on the competition for jobs and housing, delinquency, and the dilution of the sense of national identity.

These contrasting images of immigration reflect its influence on both labour demand and supply, and the mixed evidence about the empirical effects found so far. In theory, new immigrants should affect natives with identical characteristics because they increase the supply of labour with those features. In practice, immigrants are employed below their actual skill level, as measured by qualifications and work experience, and so they do not work in the same occupations as natives. As a result, the comparison of immigrants and natives within given job sets yields inconclusive results. Furthermore, natives tend to move 'horizontally' by specialising in jobs relying on language skills on which immigrants cannot compete. This makes it unlikely to find statistically significant effects even when the observed employment outcomes of immigrants and natives are better matched.

Aside from the analysis of its economic impact, a recent and growing literature has focused on natives' attitudes towards immigration as a key factor of influence underpinning voting

preferences (e.g. Hainmueller and Hopkins, 2014; Levinson et al., 2010; O’rourke and Sinnott, 2006; Valentino et al., 2013). This literature has pointed out that natives’ resentment towards immigration arises in several areas, which include the perception that immigrants ‘steal jobs’ from natives (Niyimbanira and Madzivhandila, 2016), worsen security and raise crime (Ousey and Kubrin, 2018), and even contribute to an increased fear of a terrorist attack, especially after the World Trade Center destruction on September 11<sup>th</sup>, 2001 (Choi, 2021). Such resentment is likely undesirable and costly as it works against social cohesion, cooperation, and upward mobility. It may also help harboring extreme political views and preferences hindering societal betterments. The literature tends to explain these negative attitudes with the poor education of respondents, and the associated higher likelihood of misinformation from ‘fake news’ spread through social media (Wright et al., 2021). To combat such misinformation and extremism, this line of research recommends, more or less implicitly, supporting educational and ‘factchecks’ initiatives.

Notwithstanding the above, very little research exists on how immigrants already settled in a host country feel about other immigrants. A priori, one would expect all immigrants to support immigration, as it reinforces group identity, solidarity and networks. But this is not the case, as the Latinos’ voting support for President Trump in the 2020 US presidential election has shown. While this evidence signals that it is possible for immigrants to oppose immigration, research on this topic is almost completely absent. Some insights are offered by studies highlighting that immigrants are a heterogeneous group (Garcia-Rios et al, 2019), and as such they may differently respond to certain challenges like the perception of relative deprivation (Berry et al, 2022).

However, overall, immigrants’ attitudes towards immigration remain grossly under-researched:

is being an immigrant insufficient to generate only positive attitudes to immigration? Can or should new immigrants be able automatically rely on other immigrants in the host country for assistance and support in their journey towards resettlement and socio-economic integration? Or do some immigrants, upon settling in the destination country, try to ‘forget’ and hide their origins by taking a strong anti-immigration stance? If so, why?

We aim to address these questions by offering an explanation based on rationality and economic incentives. In particular, we develop a theoretical model to investigate the role of statistical discrimination as a possible cause of opposition to immigration among a well-defined group of existing immigrants – those who have been most successful in the host country. This outcome builds on two preconditions. First, the existence of a feedback loop linking immigrants’ wellbeing to natives’ views of immigration. In other words, the better natives view immigrants the more existing immigrants benefit in terms of access to good, services, opportunities and amenities in the host country. Second, the existence of statistical discrimination, which affects natives’, but not existing immigrants’, ability to ‘see through’ the potential contribution of each new immigrant. These two conditions yield novel testable propositions about immigrants’ views on immigration, including the anti-immigration support vote expressed by the Latinos in the 2020 US Presidential election. We verify such hypotheses with data sourced from the World Value Survey (WVS) for the US as well as other countries.

We find that differences in immigrants’ types and background create incentives for successful immigrants, at the high end of the socio-economic distribution in the host country, to oppose immigration and associate to it negative views such as its contribution to unemployment, crime, and the risk of terrorism. We also show that this result is positively associated with income and human capital inequality in the countries of origin of immigrant respondents, and negatively

associated with the presence of selective immigration policies in the host country where they now live. Immigrants' anti-immigration views disappear when host countries screen immigrants like Canada, New Zealand, and Australia but become stronger in presence of large inflows of undocumented immigration like in the US.

The results are consistent with the hypothesis of statistical discrimination affecting the native population, and highlight the relevance of developing tools and mechanisms to address it such as through the certification of foreign qualifications, the availability of training in partnership with local education providers and prospective employers, and mentoring support from professional and licensing associations to ease newcomers' entry in the labour market.

The rest of the paper is organized as follows: in Section 2 we review existing literature on attitudes towards immigration. In Section 3, we develop a simple model of statistical discrimination. Section 4 focuses on data and methodology, while Section 5 presents the results. Section 6 concludes.

## **2. Literature**

The United States is known as a prime example of an immigration country, as less than two percent of its citizens have native ancestors. However, perceptions about immigrants among the local population vary significantly. A person's perception is formed by the cognitive interaction with his/her surroundings (Efron, 1969), and information and beliefs about immigrants form the perception about them as well as attitudes towards them, regardless of whether or not these are consciously held.

In the history of immigrants in the US there is contradictory view about immigration (Mears, 2001). Historically, anti-immigration attitudes, driven by both economic (Timmer and Williams,

1998) and cultural factors (O’rourke and Sinnott, 2006) have pre-dated restrictive immigration policy such as the Chinese Exclusion Act in the US, for example. Notwithstanding that most people respond not to hold discriminatory attitudes towards people from different races and nationalities when directly asked in surveys, unconscious bias is likely. This may occur, as people tend to focus on individual features when looking at the members of an in-group but they fail to notice these details in out-group people (Levinson et al., 2010). Hence negative perceptions about immigrants not only persist, but they prevent the realisation of similar levels of empathy for natives among adults and children (Winkler, 2009; Rutland et al., 2005).

Research suggests that immigration attitudes are partly rooted in self-interest (Hainmueller and Hopkins, 2014), such as to protect one from labor market competition brought by immigrants. Although immigration tends to raise natives’ wages (Niyimbanira and Madzivhandila, 2016), native workers are more likely to oppose immigrants across similar skill levels (Scheve and Slaughter, 2001; Facchini and Mayda, 2012) while they favour immigrants with complementary characteristics (Mayda, 2006; Facchini and Mayda, 2012).

Immigration policy preferences are also influenced by non-economic variables, like upholding natives’ traditions and customs (Facchini and Mayda, 2012) and disregard for crime (Mears, 2001; Sampson, 2008; Bianchi et al., 2012) and terrorism (Helbling and Meierrieks, 2020), while attitudes towards immigration differ according to demographic and socioeconomic status. In the US, it is found that native whites have more negative views about immigration and refugees than from people of other backgrounds (Bodvarsson and Van den Berg, 2013; McKeever et al., 2012; Valentino et al., 2013). As for gender differences, women have more positive attitudes towards immigration than men (Rocha et al., 2015; Watson and Riffe, 2013), and republican and conservative ideologies tend to be associated with negative views towards immigrants (Gil de

Zúñiga et al., 2012). People in occupations where the immigrants ratio is high are more likely to oppose immigration (Mayda, 2006).

Despite the large volume of studies on immigration, most focus on the views held by natives with no distinction for those with non-native ancestry. Furthermore, there is very little research on existing immigrants' attitudes towards other immigrants and immigration more broadly. The few existing studies reflect the complexity described by Anderson (2015) whereby immigrants' attitudes towards immigration are shaped by two competing motivations first one is kinship, solidarity, and shared experiences with other immigrants which lead to positive attitudes towards immigration and another one is allegiances to their host societies which creates opposite effect (Just and Anderson, 2015). We aim to contribute to the scant literature by developing a model that reconciles these two competing forces.

### **3. Model**

#### *Intuition*

To frame the potential role of statistical discrimination in determining varying views to immigration among some immigrant groups, we develop a standard utility-maximizing model where immigrants' wellbeing depends on natives' views of immigration. These in turn reflect only the 'average immigrant' as a consequence of natives' statistical discrimination towards immigration: by not having a full understanding of a prospective new immigrant, natives' support for immigration is guided by the features of the 'average immigrant'. These are drawn from existing immigrants and the prospective newcomers. As long as new immigrants make a positive economic contribution, natives will support immigration. This is not the case of immigrants, who can fully understand whether the new immigrant will raise or reduce the

‘average immigrant’ view held by natives. Using an analogy from finance, natives will be happy to add a new security (i.e. an immigrant) to their portfolio (native and immigrant population) as long as its return is positive. Immigrants will be willing to add a new security only if it improves the existing average risk-adjusted return. A positive return is not enough.

This construction innovates on existing models of immigration, as it avoids forcing the introduction of a priori preferences for or against immigration while creating a unity-maximising mechanism entirely based the incentive of whether a new immigrant will add or lower the perception of the average immigrant based on his/her human capital and potential productivity. By voting for or against immigration, existing immigrants effectively become a ‘screen’ for new immigrants and replace more formal institutional mechanisms, which are typically enacted by immigration policy. This theoretical setup yields several relevant and testable propositions.

### *Theoretical setup*

Consider an immigrant  $i$  whose utility in the host country (e.g. the US) depends on his/her individual characteristics as well as US natives’ views about immigration – that is the combination of awareness and perceptions about immigrants’ contribution to the US economy and society based on beliefs, stereotypes, and observations from experience of existing immigrants. This feedback loop is crucial to explain immigrants’ reaction to immigration.

For simplicity we assume that immigrants from all over the world are continuum in terms of abilities and productivity and that they can ‘understand’ other immigrants’ types, so they can see their quality and productivity. Existing US immigrants are by assumption endowed with the ability to understand the type of new immigrants arriving and gauge whether or not they will enhance or reduce US natives’ perception of all (existing and new) immigrants. In contrast, US

natives do not to have this ability and *statistically discriminate* new immigrants by associating a prospective immigrant's type with the average characteristics and behaviours of immigrants already in the US. This set of assumptions are essential to develop the reaction of existing immigrants to new immigration. Thanks to the link with natives' perception of immigrants, existing immigrants will rationally decide whether or not to oppose immigration based on the quality of a prospective immigrant: this will directly affect natives' perception of immigration, and the flow of goods and services that existing immigrants enjoy. The better natives view the average immigrant – e.g. as good citizens, law-abiding, productive workers - the better/more goods and services existing immigrants will enjoy, and vice-versa.

The utility of an existing immigrant  $i$  living in the US can be thus summarised by:

$$U(i) = f(y, X_i)$$

where  $f$  is a function with  $f' > 0$  and  $f'' < 0$ ,  $y$  is US natives' average perception of existing US immigrants (a group indicator of average type), and  $X$  is a set of individual  $i$ 's observed characteristics. These include gender, age, English language skills, marital status, prior education and work experience, to name a few.

By definition,  $y$  affects the wellbeing of existing immigrants. However, for US natives, the variable  $y$  is an imperfect indicator of immigrant type, as they observe:

$$y = q + u$$

where  $q$  is the immigrant's true type (e.g. productivity) and  $u$  is a normally distributed error term with mean zero and constant variance. In contrast, existing immigrants view  $y = q$ .

This difference in understanding the type of prospective immigrants has important consequences. For US natives new immigrants are welcome as long as  $E(q) \geq 0$  – that is as long as their expected contribution to the US economy is positive. But the relevant discriminating variable for existing US immigrants is instead  $E(q|y)$ : the type of immigrant  $q$  *conditional* on the imperfect signal  $y$ .  $E(q|y)$  arises from the regression equation (Aigner and Cain, 1977):

$$E(q|y) = \bar{q} + (y - \bar{q})\beta = \bar{q}(1 - \beta) + \beta y$$

where  $\bar{q}$  is the group (i.e. average) indicator of the immigrant type, and  $\beta$  measures the reliability of the perceived immigrant type, which depends on the distribution of  $q$  and the noise  $u$ , i.e.:

$$\beta = \frac{\text{var}(q)}{\text{var}(q) + \text{var}(u)}$$

As  $\frac{\partial E(q|y)}{\partial q} > 0$  it follows that  $\frac{\partial U(\cdot)}{\partial q} = \frac{\partial U(\cdot)}{\partial E(q|y)} \cdot \frac{\partial E(q|y)}{\partial q} > 0$ . In other words, the utility of an existing immigrant  $i$  depends positively on natives' perceptions of immigrants and the new immigrant's type relative to his/her own, as discussed below.

### *Predictions*

Consider the utility of a high- $q$  existing immigrant, and his/her reaction to the immigration of an identical high- $q$  immigrant from the same country. The existing immigrant recognises the actual type  $q$  of the prospective immigrant. S/he also knows that even if US natives only observe the imperfect signal  $y$ , the new immigrant with  $q$  similar or higher than the  $q$  of the existing immigrant will raise  $\bar{q}$  and  $E(q|y)$ . Should existing immigrant  $i$  welcome or oppose the arrival of

a similarly- $q$  immigrant? The model predicts welcoming, as noting with  $\neg q$  the type of newcomer, if  $\neg q \geq q$  then  $\frac{\partial U(\cdot)}{\partial E(q|y)} \cdot \frac{\partial E(q|y)}{\partial q} > 0$ .

Consider instead the case of an existing immigrant facing the prospect of a new immigrant with a lower  $q$ , i.e.  $\neg q < q$ . In this case, the existing immigrant's utility is negatively affected by the new arrival, as immigration will reduce  $\bar{q}$  - the group indicator of immigrant types in the US. The existing immigrant will therefore strongly oppose immigration, as  $\neg q < q$  and  $\frac{\partial E(q|y)}{\partial \neg q} < 0$ .

The model also predicts that existing immigrants will oppose immigration the higher the distance between their type and that (lower) of new prospective immigrants.

Opposition to immigration will also be strong if the reliability of information about the newcomers is poor – in other words, if US natives have a very poor understanding of the distinction between immigrant types (i.e. if  $var(u)$  is large). This would be the case for countries of origin that are culturally, linguistically and organisationally very different from the US, and do not share the way in which US economy and society are organised and operate.

This simple application of statistical discrimination also predicts that opposition to immigration can diminish if host countries control undocumented immigration or introduce a selective immigration policy, as that reduces the distances between immigrant types and improves the reliability of  $\beta$ . For example, high immigration countries like Australia, Canada and New Zealand restrict permanent immigration to particular types of immigrant by giving higher weight to graduate and postgraduate education as well as work experience in jobs that are in high demand. Screening migrants reduces uncertainty about  $q$  and  $u$ , and results in a lower  $\beta$ . In contrast, large differences between immigrant types and statistical discrimination, which are

more likely when host countries admit immigrants from places of origin with which they have little in common and do not select them on the basis of their qualifications and skills, are predicted to generate strong opposition to immigration from existing immigrants that have achieved above average success in the host country – i.e. those with the highest  $q$ .

### *Testable hypotheses*

This simple application of statistical discrimination about immigrants' quality in the host country produces some remarkably sharp hypotheses:

H(ypothesis) 1: high quality immigrants will oppose new immigration if there is a sufficiently high likelihood that new immigrants are of low- $q$  regardless of whether or not immigrants are documented or undocumented. The opposite occurs for low- $q$  immigrants;

H2: anti-immigration reactions will be stronger in the case of places of origin where the distribution of  $q$  in the local population is highly dispersed;

H3: anti-immigration reactions among high- $q$  immigrants will be stronger in the case of host countries that do not screen immigrants, have large inflows of undocumented immigrants, or admit immigrants from countries with which they have little in common;

H4: the strongest opposition to immigration will originate from immigrants that have achieved above average success in the host country.

## **4. Data**

We test H1-H4 by studying the responses of immigrants of different socio-economic status in the US using data from the World Value Survey (WVS). The WVS is a research project run globally to understand people's values and beliefs and how they change over time using an identical questionnaire, which is internationally comparable. WVSs started in 1981, and it collects data every five years. To date, seven waves of the surveys have been carried out covering 120 countries. The seventh wave (WVS7) contains specific questions related to immigration attitudes, and Table 1 presents the summary statistics of some of these questions for the US and other regions of the world. Statistically significant differences with US responses, obtained from a Welch's t-test of mean differences, are indicated with \*, \*\*, and \*\*\* depending on whether the corresponding p-values of the tests are  $<.1$ ,  $<.05$ , and  $<.01$ .

As clear from that table, WVS's answers for the US differ on average from the answers collected in the rest of the world (column 2 of the table) also when this is broken down in individual countries (Canada, Australia and New Zealand in columns 3-5, respectively) or major regions (Africa, Europe, Asia-Pacific, and Central and Latin America in columns 6-9). US respondents are relatively older (by about 1 year), predominantly males (WVS respondents are mostly females), and middle class. They are amongst the most educated respondents, with an average corresponding to post-secondary non-tertiary education and tend to be married with a child. About 10% of the sample has immigrant origins, but about 15% has an immigrant lineage as either a parent or both were born abroad.

US respondents score the highest average on questions related to the usefulness of immigration but have mixed views about immigrants' influence on crime rates, terrorism, unemployment, and social conflict in general as their average is higher than in other high immigration English-

speaking countries (and lower than in remaining parts of the world): we focus on Canada, Australia, and New Zealand as they take part in the WVS.

Table 2 focuses on the key characteristics of US respondents, by immigrant status. Natives tend to be older, have fewer years of education and are more likely to live in rural centres than immigrants. Natives' views about immigration are less favourable than immigrants', especially with reference to immigrants' possible influence on crime, unemployment and terrorism. When data are further dissected by socio-economic status, some of natives' concerns about immigration arise also in the wealthier immigrant group. In particular, immigrants that self-report as belonging to the highest socio-economic group have the strongest opinions against immigration: notwithstanding its economic contribution, they do not view immigrants as useful (average: .25 vs. natives' .783), and are concerned that immigration brings other socio-economic problems, such as terrorism (average: .625 vs. natives' .521), crime (.75 vs. .478).

Those results give some preliminary support to the hypotheses emerging from the model: notably that natives statistically discriminate immigrants and their benefits, but this does not apply (at least to the same extent) to immigrants already in the US, for whom the arrival of additional immigrants, especially if very different from them in terms of education, attitudes, and beliefs may represent a threat to their general perception in the host country.

H1-H4 are tested using only the 7<sup>th</sup> wave of WVS, which, for the US, was collected in 2017. H1 suggests that immigrants in higher socio-economic groups oppose immigration relative to those in lower socio-economic groups, while H4 suggests that the strongest opposition should arise from those in the highest SOE. H2 is tested by studying the sign of the relationship between the SOE of immigrants in the US and the income of human capital dispersion of their respective

countries of origin. H2 suggests that immigrants of countries with the greatest income disparity or human capital dispersion should hold the strongest views against immigration. Finally, H3 is tested by comparing the dispersion of the education acquired by natives and immigrants in the US with that of three English-speaking countries that instead formally screen immigrants as part of the immigration process: namely, Canada, Australia, and New Zealand.

## 5. Empirical specification and results

H1 and H4 are tested from the same regression model, which applies Ordinary Least Squares (OLS) to the functional form:

$$y_i = \alpha + X_i\beta + \gamma I_i + \delta SOE_i + \theta I_i SOE_i + \varepsilon_i \quad (1)$$

where  $y$  is the for/against attitude of respondent  $i$  towards immigration (reference: for),  $X$  is a vector of demographic, employment, and characteristics such as age, education, labor force status, marital status, state of residence....  $I$  is a dichotomous variable capturing the immigration status of the respondent (immigrant/native),  $SOE$  is a self-reported measure the respondent's socio-economic status (upper, high, average, below-average and low income), and  $\varepsilon_i$  is an error term. The coefficients of interest are  $\gamma$ , the link between the immigration status of the respondent and outcome variable  $y$  relative to a comparable native, and  $\theta$ , the coefficients of the interaction between immigrant and socio-economic status (ref: low socio-economic status).

Since the US attracts immigrants from both ends of the skill distribution (top: H-1 visas; bottom, more common: family reunification and undocumented immigrants), H1 advances that existing immigrants of higher SOE will oppose additional immigration to the US believing that new unqualified foreign labour may worsen US natives' perception of *all* immigrants in the country.

We use five outcome binary indicators: namely, whether respondents believe that immigrants (i) are useful to economic development in the US; (ii) raise crime; (iii) increase the risk of a terrorist attack; (iv) increase the unemployment rate; and (v) lead to social conflicts.

Table 3 presents the baseline results across the five indicators. Prior to discuss the variables of interest it is worth noting that women have a more benign view of immigration than men (negative and statistically significant coefficients), as do highly educated respondents. In contrast, opposition to immigration is higher in rural centres and towns with smaller population size. Singles have less opposition to immigration while those with family, and especially with a large number of children, tend to oppose new immigrant arrivals – perhaps for fear of competition for jobs and housing for them and especially for their children (the indicator for singles is statistically no different from zero).

With respect to the variables of interest, the coefficients for the immigrant dummy variable are statistically no different from zero, implying that natives and immigrants share similar views about the effects of immigration, on average. The indicators of socio-economic status also indicate relatively little differences across social groups. Respondents in the higher socio-economic status view immigrants as contributors to raise the crime rate, though the coefficient is statistically significant only at the 10% level. Respondents in the lower socio-economic groups are less likely to suggest that immigrants carry out useful jobs and raise social conflicts in the US.

However, when immigrant and socio-economic status are interacted, very strong results in support of H1 emerge. Strongest opposition arises in the case of immigrants in the highest socio-economic status, in line with H4. For those respondents, immigrants positively contribute to raise crime, the likelihood of a terrorist attack, and the unemployment rate. The coefficients are all

statistically significant at the 1% level and their magnitude is very large. In fact, the coefficient  $\theta$  is the largest among all explanatory factors, suggesting that such views are strongly and uniformly shared among immigrants in the highest socio-economic group. Interestingly there is no such view on questions about the economic effect of immigration or the contribution to social unrest in the US, revealing that the opposition of immigrants to immigration is limited to specific areas: those that perhaps most directly affect the perception of immigrants held by US natives: crime, terrorism, unemployment.

To verify whether US immigrants in the highest SOE are from countries with high dispersion of income or human capital while overcoming the challenge of H2, we first present descriptive results using two distinct inequality indicators in Table 4a: (i) the dispersion of economic opportunity, as measured by the share of income accruing to the poorest 10% of the population of their respective countries of origin; and (ii) the human capital of the population of their countries of origin, as measured by the Human Capital Index. This measures “the contributions of health and education to worker productivity. The final index score ranges from zero to one and measures the productivity as a future worker of child born today relative to the benchmark of full health and complete education”. Both indicators (i) and (ii) are sourced from the World Bank’s World Development Indicators database.

The results presented in Table 4a and 4b suggest the existence of a positive relationship between immigrants’ socio-economic group and inequality in income and human capital in their respective countries of origin. In Table 4a US-based immigrant respondents in the highest SOE are from countries with the lowest average share of income going to the poorest 10% of the population or the lowest human capital index.

Table 4b presents more formal evidence obtained by regressing each of the five immigration-related questions of the WVS on the socio-economic status of immigrant respondents interacted with the inequality indicator. The regression follows the statistical model:

$$y_i = b_0 + X_i b_1 + b_2 INEQ_i + b_3 SOE_i + b_4 INEQ_i * SOE_i + e_i \quad (2)$$

where  $y_i$  and SOE are defined as in (1) and INEQ is the share of income going to the poorest 10% of the population. The resulting coefficient of the interaction term is positive and statistically significant only for the highest SOE group. A similar result arises when INEQ is replaced by the human capital index.

The results from Tables 4a and 4b support the hypothesis that stronger opposition to immigration arises in the case of immigrants from countries of origin characterized by severe domestic inequality in income and human capital development.

To assess whether the results obtained are specific to the case of the US, and test H3, we run model (1) on various countries and compare the coefficients of the key interaction variables obtained for the US with those of the three other English-speaking immigration-screening countries as well as other regional groups. The results are reported in Table 5. The rows show the countries while the columns report the coefficients of interest: namely, immigrant status ( $\gamma$ ), socio-economic status ( $\delta$ ), and their interaction ( $\theta$ ). As shown,  $\theta$ , the coefficient identifying the responses of immigrants in the high socio-economic group, is positive and statistically significantly different from zero only in the case of the US. In fact, in no other English-speaking country immigrants of higher SOE oppose immigration to the same extent as immigrants living in the US. A similar result applies when the regression is performed on other regional country groups.

H3 interprets these results as a consequence of the high skill dispersion of immigrants resettling into the US relative to the three other English-speaking countries covered by the WVS, which apply more selective immigration policies. As highlighted by the theoretical model, the lack of institutional screening of immigrants entering the US, and the presence of undocumented immigration, creates incentives for high SOE immigrants to signal their quality and differences (to US natives) relative to other immigrants from the same countries of origin through strong opposition to immigration especially from those places of origin. Supporting evidence for this interpretation is reported in Table 6, which shows the average dispersion of education completed among natives and immigrants by main country of destination. In particular, it shows that such dispersion is wider among immigrants than natives in the US – a possible incentive for immigrants of higher education (and SOE) to signal their quality to US natives relative to less educated immigrants from the same country of origin.

### *Robustness*

As these baseline results are obtained on cross-sectional data, they may be affected by omitted variable bias. To test for this possibility, we apply Oster (2019) method to test the stability of the coefficient when control variables are progressively added in a regression under the assumptions that (i) the relationship between treatment and unobservables can be recovered from that between treatment and observables, and (ii) the hypothetical model that includes treatment, observables, and unobserved variables produces a  $R_{\max}$  that can be less than unity – e.g. because of measurement error. We apply Oster’s model to calculate the ratio of unobserved/observed selection (‘delta’) required to nullify the statistical significance of the coefficient  $\theta$ , the estimate

of the interaction between immigrant and socio-economic status, reported in Table 3. Robustness to omitted variable bias occur if delta is greater than 1 (the benchmark).

The results of this calculation, reported in Table 7, indicate robustness to omitted variable bias, as the values of delta in the case of  $R_{\max} = 1.3 \times R^2$ , the benchmark suggested by Oster, range from 7.14 (do immigrants raise crime) to 15.21 (do immigrants increase unemployment?). These values imply that selection on unobservables should be 7.14 and 15.21 times the selection of observables, respectively – a very unlikely scenario (Oster suggests a benchmark ratio of 1). As a result, it is unlikely that the results presented suffer from severe omitted variable bias. Overall, the results of the robustness tests make the point estimates reported in Table 3 credible.

### *Heterogeneity*

To check if the results obtained for the US apply to other high immigration countries, the model is run on pooled data restricted on responding immigrants only. The results, displayed on Table 8a, focus on the five questions of interests and report the coefficient of the interaction term between the highest SOE and the country where WVS data were collected. The model applied is analogous to that specified in equation (1) but the immigrant indicator is replaced by an indicator of host country using Europe as a reference group. The regression is performed on observations restricted to immigrant respondents only. The coefficients clearly point to a statistically significant opposition of immigrants towards immigration only in the case of the US. For every other case, namely Canada, Australia, New Zealand as well as regions (Africa, Americas, and Asia-Pacific), immigrants in the highest SOE group appear to be supportive or at least indifferent to immigration as the coefficients are either negative and statistically significant or statistically equivalent to zero.

To verify whether the US case is symptomatic of a country-specific effect or else we carry out a complementary regression identical to that presented in Table 8a with the exception of restricting the observations to native respondents only. The results are summarized in Table 8b and reveal that US natives do not have different views towards immigrants relative to most other countries and regions of the world. The coefficients are mostly statistically no different from zero. The one exception is represented by Canada, whose natives display a strong opposition to immigration: most coefficients to questions about immigrants' contribution to unemployment, crime, and terrorism are positive and statistically significant, and point to strong negative views and perceptions about immigration.

Immigrants in the US hence emerge as a unique group opposing additional immigration. While the hypotheses developed by the theoretical model are tested by means of correlational analysis, the estimates are consistent with the view that immigrants' opposition to further immigration stems from natives' inability to discern legal and undocumented immigrants' quality and contribution to the host country's economy and social compact.

These results are consistent with the hypothesis that when faced by statistical discrimination immigrants respond by acting as screens for new immigration via their support/opposition to it. This is especially the case when the host country has no institutionalized form of population management or large inflows of undocumented immigrants as is the case in the US.

The results raise important policy questions about the role of immigration policy in enhancing immigrants' integration in the host country, including their acceptance and support from existing immigrants. They support efforts to control undocumented immigration as a way to ensure orderly population management and gain support, especially among natives. The results also support the use of screening tools to limit the dispersion of skills distribution supplied by

immigrants, or at least their tighter control to prevent the possible raise of statistical discrimination towards immigrants (operated by natives) and anti-immigration stances among existing immigrants themselves.

## **6. Conclusions**

This paper fills an important role in the immigration literature by studying the role of statistical discrimination as a cause for (some) immigrants' opposition to immigration in cases where immigrants are not screened or there is a large volume of undocumented immigration. The results support this hypothesis for the case of the US, which stands out among other immigration country. In the US, immigrants in the highest socio-economic group strongly oppose immigration, as shown during the most recent presidential elections, against the expectations of immigration researchers and policy-makers. Rather than an emotional response or a preference we argue that such behavioural response is consistent with a rational utility-maximising decision when new immigrants may compromise existing immigrants' acceptance in the host society.

**Table 1 – Descriptive statistics**

|                               | US             | World ex US       | Canada            | Australia         | New Zealand       | Africa            | Europe            | Asia-Pacific      | Americas          |
|-------------------------------|----------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Gender                        | .464<br>(.499) | .523***<br>(.500) | .488*<br>(.500)   | .609***<br>(.488) | .574***<br>(.495) | .498***<br>(.500) | .549***<br>(.498) | .522***<br>(.500) | .515***<br>(.500) |
| Age                           | 43.4<br>(16.3) | 42.6**<br>(16.5)  | 46.6***<br>(16.9) | 54.3***<br>(17.4) | 57.8***<br>(16.5) | 36.3***<br>(14.1) | 48.4***<br>(17.8) | 42.5**<br>(15.7)  | 41.0***<br>(16.8) |
| Socioeconomic status          | 3.06<br>(.93)  | 3.28***<br>(.98)  | 2.87***<br>(.90)  | 2.97***<br>(.90)  | 2.98***<br>(.91)  | 3.38***<br>(1.11) | 3.17***<br>(.90)  | 3.24***<br>(.966) | 3.41***<br>(1.00) |
| ISCED                         | 4.88<br>(1.58) | 3.44***<br>(2.03) | 4.89***<br>(1.59) | 4.66***<br>(1.73) | 4.44***<br>(1.68) | 2.44***<br>(1.81) | 4.04***<br>(2.08) | 3.31***<br>(2.00) | 3.69***<br>(1.95) |
| Nr children                   | 1.48<br>(1.46) | 1.73***<br>(1.53) | 1.07***<br>(1.21) | 1.79***<br>(1.36) | 2.02<br>(1.40)    | 1.91***<br>(1.83) | 1.31<br>(1.17)    | 1.90***<br>(1.54) | 1.58***<br>(1.55) |
| Living rural town             | .11<br>(.31)   | .34***<br>(.47)   | .23***<br>(.42)   | .19***<br>(.39)   | .10<br>(.30)      | .56***<br>(.49)   | .29***<br>(.45)   | .38***<br>(.48)   | .22***<br>(.42)   |
| Immigrant status              | .106<br>(.307) | .057***<br>(.232) | .179***<br>(.383) | .072***<br>(.258) | .223***<br>(.419) | .020***<br>(.139) | .124***<br>(.329) | .047***<br>(.212) | .043***<br>(.204) |
| Mother immigrant              | .153<br>(.360) | .094***<br>(.291) | .303***<br>(.459) | N/A               | .163<br>(.369)    | .029**<br>(.167)  | .135***<br>(.341) | .097***<br>(.296) | .088***<br>(.203) |
| Father immigrant              | .144<br>(.351) | .095***<br>(.293) | .322***<br>(.467) | N/A               | .170*<br>(.376)   | .029*<br>(.168)   | .130***<br>(.336) | .099***<br>(.299) | .091***<br>(.288) |
| Immigrants are useful         | .604<br>(.489) | .464***<br>(.499) | .585<br>(.493)    | .480***<br>(.499) | .566**<br>(.496)  | .394***<br>(.489) | .486***<br>(.500) | .464***<br>(.499) | .476***<br>(.499) |
| Immigrants raise crime        | .301<br>(.459) | .447***<br>(.497) | .202***<br>(.402) | .318<br>(.466)    | .132***<br>(.339) | .457***<br>(.498) | .556***<br>(.497) | .419***<br>(.493) | .447***<br>(.497) |
| Immigrants raise terrorism    | .397<br>(.489) | .443***<br>(.497) | .201***<br>(.401) | .392<br>(.488)    | .240***<br>(.427) | .501***<br>(.500) | .579<br>(.494)    | .405***<br>(.491) | .435***<br>(.496) |
| Immigrants raise unemployment | .321<br>(.467) | .491***<br>(.500) | .217***<br>(.413) | .312<br>(.463)    | .202***<br>(.402) | .593***<br>(.491) | .526***<br>(.499) | .454***<br>(.498) | .519***<br>(.500) |
| Immigrants raise conflict     | .425<br>(.494) | .481***<br>(.500) | .318***<br>(.466) | .407<br>(.491)    | .250***<br>(.433) | .485***<br>(.500) | .606***<br>(.489) | .427***<br>(.495) | .536***<br>(.499) |
| Survey year                   | 2017           | various           | 2020              | 2018              | 2020              | various           | various           | various           | various           |
| N                             | 2,596          | 108,665           | 4,018             | 1,799             | 1,034             | 12,498            | 20,746            | 53,727            | 21,694            |

Source: World Value Survey, 7<sup>th</sup> wave, various years. Averages with standard deviations in parentheses. The stars indicate statistically different means vs. US equivalent reported in the first row with p-value < .01 (\*\*\*), p-value < .05 (\*\*), and p-value < .1 (\*).

**Table 2 – Descriptive statistics: US data by immigrant status**

|                               | Natives        | Immigrants     |
|-------------------------------|----------------|----------------|
| Gender                        | .466<br>(.498) | .451<br>(.498) |
| Age                           | 43.8<br>(16.4) | 41.5<br>(15.2) |
| Socioeconomic status          | 3.07<br>(.93)  | 3.00<br>(.93)  |
| ISCED                         | 4.85<br>(1.55) | 5.30<br>(1.65) |
| Nr children                   | 1.50<br>(1.47) | 1.34<br>(1.33) |
| Living rural town             | .12<br>(.33)   | .02<br>(.15)   |
| Mother immigrant              | .087<br>(.281) | .913<br>(.281) |
| Father immigrant              | .087<br>(.281) | .868<br>(.340) |
| Immigrants are useful         | .601<br>(.490) | .665<br>(.472) |
| Immigrants raise crime        | .314<br>(.464) | .225<br>(.418) |
| Immigrants raise terrorism    | .407<br>(.491) | .335<br>(.473) |
| Immigrants raise unemployment | .332<br>(.471) | .234<br>(.424) |
| Immigrants raise conflict     | .440<br>(.496) | .330<br>(.471) |
| N                             | 2,268          | 268            |

Source: World Value Survey – US sample, 7<sup>th</sup> wave, 2017. Averages with standard deviations in parentheses. Immigrants are defined as foreign-born.

**Table 3 – Results: baseline**

|                            | Immigrants.....     |                        |                            |                          |                            |
|----------------------------|---------------------|------------------------|----------------------------|--------------------------|----------------------------|
|                            | ...fill useful jobs | ...increase crime rate | ...increase terrorism risk | ...increase unemployment | ...lead to social conflict |
| Immigrant                  | 0.0102              | -0.0484                | 0.0319                     | 0.0144                   | 0.0510                     |
|                            | [0.0592]            | [0.0549]               | [0.0645]                   | [0.0622]                 | [0.0749]                   |
| SOE – 1 <sup>st</sup> q    | 0.105               | 0.201*                 | 0.163                      | 0.0960                   | 0.0762                     |
|                            | [0.0887]            | [0.118]                | [0.116]                    | [0.109]                  | [0.113]                    |
| SOE – 2 <sup>nd</sup> q    | 0.0231              | 0.0262                 | 0.0193                     | 0.0495**                 | 0.0326                     |
|                            | [0.0246]            | [0.0245]               | [0.0257]                   | [0.0251]                 | [0.0271]                   |
| SOE – 4 <sup>th</sup> q    | -0.0508*            | 0.0470*                | 0.0378                     | 0.0578**                 | 0.0348                     |
|                            | [0.0278]            | [0.0264]               | [0.0274]                   | [0.0269]                 | [0.0285]                   |
| SOE – 5 <sup>th</sup> q    | -0.109**            | 0.0220                 | 0.0201                     | 0.0306                   | -0.0824*                   |
|                            | [0.0435]            | [0.0426]               | [0.0467]                   | [0.0452]                 | [0.0449]                   |
| Im x SOE 1 <sup>st</sup> q | -0.246              | 0.593***               | 0.577***                   | 0.687***                 | 0.143                      |
|                            | [0.311]             | [0.131]                | [0.133]                    | [0.123]                  | [0.311]                    |
| Im x SOE 2 <sup>nd</sup> q | -0.0973             | 0.0120                 | 0.100                      | -0.0169                  | -0.202**                   |
|                            | [0.0762]            | [0.0762]               | [0.0895]                   | [0.0812]                 | [0.0923]                   |
| Im x SOE 4 <sup>th</sup> q | 0.0516              | 0.0237                 | 0.0229                     | -0.0693                  | -0.114                     |
|                            | [0.0901]            | [0.0825]               | [0.0939]                   | [0.0832]                 | [0.101]                    |
| Im x SOE 5 <sup>th</sup> q | -0.0420             | 0.199                  | 0.0901                     | 0.105                    | 0.214                      |
|                            | [0.181]             | [0.176]                | [0.180]                    | [0.178]                  | [0.196]                    |
| Female                     | -0.0565**           | -0.0698***             | -0.0238                    | -0.0561**                | -0.0720**                  |
|                            | [0.0206]            | [0.0201]               | [0.0212]                   | [0.0206]                 | [0.0220]                   |
| Mother immi                | 0.0581              | -0.0109                | -0.0513                    | -0.0138                  | -0.0612                    |
|                            | [0.0439]            | [0.0417]               | [0.0467]                   | [0.0442]                 | [0.0479]                   |
| Father immi                | 0.0717*             | -0.0751*               | -0.108**                   | -0.0914**                | -0.0188                    |
|                            | [0.0418]            | [0.0396]               | [0.0446]                   | [0.0425]                 | [0.0464]                   |
| Not married                | 0.0103              | -0.101***              | -0.0567*                   | -0.00800                 | 0.00502                    |
|                            | [0.0297]            | [0.0275]               | [0.0295]                   | [0.0285]                 | [0.0310]                   |
| Nr children                | -0.0192**           | -0.00891               | 0.0144*                    | 0.0119                   | 0.000301                   |
|                            | [0.00813]           | [0.00783]              | [0.00833]                  | [0.00804]                | [0.00836]                  |
| Educ BA+                   | 0.263***            | -0.109***              | -0.142***                  | -0.105***                | 0.0006                     |
|                            | [0.0214]            | [0.0207]               | [0.0221]                   | [0.0213]                 | [0.0233]                   |

|                         |           |             |            |             |            |
|-------------------------|-----------|-------------|------------|-------------|------------|
| Rural                   | -0.0419   | 0.0506      | 0.0507     | 0.0374      | 0.00122    |
|                         | [0.0316]  | [0.0326]    | [0.0335]   | [0.0327]    | [0.0334]   |
|                         |           |             |            |             |            |
| Pop size                | 0.00208   | -0.00941*** | -0.0118*** | -0.00983*** | -0.0164*** |
|                         | [0.00327] | [0.00321]   | [0.00335]  | [0.00327]   | [0.00349]  |
|                         |           |             |            |             |            |
| Constant                | 0.787***  | 0.230**     | 0.289***   | 0.310***    | 0.463***   |
|                         | [0.101]   | [0.0964]    | [0.103]    | [0.101]     | [0.107]    |
|                         |           |             |            |             |            |
| LF status               | Yes       | Yes         | Yes        | Yes         | Yes        |
| Adjusted R <sup>2</sup> | 0.124     | 0.053       | 0.071      | 0.046       | 0.021      |
| N                       | 2,281     | 2,283       | 2,282      | 2,279       | 2,278      |

Source: World Value Survey – US sample, 7<sup>th</sup> wave, 2017. Baseline results based on model (1) in the main text.

**Table 4a – Average income and human capital indicators of countries of origin, by immigrant respondents’ socio-economic status in the US**

|   | SOE – 1 <sup>st</sup> q | SOE – 2 <sup>nd</sup> q | SOR – 3 <sup>rd</sup> q | SOE – 4 <sup>th</sup> q | SOE – 5 <sup>th</sup> q |
|---|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| Share of income of poorest 10% population | 5.77                    | 6.60                    | 6.17                    | 5.96                    | 6.23                    |
| Human capital index                       | .619                    | .642                    | .630                    | .622                    | .656                    |

Notes: Socio-economic status is based on 5-self-reported categories and is sourced from the World Value Survey – US sample, 7<sup>th</sup> wave, 2017. The two indicators of income and human capital development reflect indicator averages of the corresponding countries of birth and are sourced from the World Bank’s World Development Indicators database.

**Table 4b – Regression results by US immigrants’ socio-economic status.**

|                            | Immigrants.....     |                        |                            |                          |                            |
|----------------------------|---------------------|------------------------|----------------------------|--------------------------|----------------------------|
|                            | ...fill useful jobs | ...increase crime rate | ...increase terrorism risk | ...increase unemployment | ...lead to social conflict |
| Inequality                 | 0.0190              | -0.0121                | 0.0400                     | 0.0022                   | -0.0245                    |
|                            | [0.0346]            | [0.0265]               | [0.0317]                   | [0.0304]                 | [0.0339]                   |
| SOE – 1 <sup>st</sup> q    | -2.291***           | -0.842                 | -0.635                     | -0.768                   | -2.202***                  |
|                            | [0.385]             | [0.708]                | [0.714]                    | [0.712]                  | [0.384]                    |
| SOE – 2 <sup>nd</sup> q    | -0.364              | 0.0777                 | 0.352                      | 0.0981                   | -0.236                     |
|                            | [0.338]             | [0.249]                | [0.338]                    | [0.283]                  | [0.304]                    |
| SOE – 4 <sup>th</sup> q    | 0.244               | 0.0139                 | 0.0687                     | 0.165                    | 0.0648                     |
|                            | [0.388]             | [0.257]                | [0.346]                    | [0.277]                  | [0.337]                    |
| SOE – 5 <sup>th</sup> q    | 1.011*              | 0.540                  | -0.453                     | 0.274                    | 0.284                      |
|                            | [0.498]             | [0.489]                | [0.475]                    | [0.524]                  | [0.558]                    |
| In x SOE 1 <sup>st</sup> q | 0.334***            | 0.230**                | 0.178*                     | 0.216**                  | 0.377***                   |
|                            | [0.0699]            | [0.102]                | [0.104]                    | [0.103]                  | [0.0696]                   |
| In x SOE 2 <sup>nd</sup> q | 0.0573              | -0.0107                | -0.0464                    | -0.0165                  | 0.0278                     |
|                            | [0.0494]            | [0.0360]               | [0.0513]                   | [0.0426]                 | [0.0456]                   |
| In x SOE 4 <sup>th</sup> q | -0.0484             | 0.00106                | -0.0120                    | -0.0229                  | -0.0136                    |
|                            | [0.0628]            | [0.0394]               | [0.0573]                   | [0.0429]                 | [0.0516]                   |
| In x SOE 5 <sup>th</sup> q | -0.202**            | -0.0562                | 0.0832                     | -0.0164                  | -0.0284                    |
|                            | [0.0689]            | [0.0660]               | [0.0722]                   | [0.0779]                 | [0.0790]                   |
| Constant                   | 0.591***            | 0.252                  | 0.0446                     | 0.179                    | 0.502**                    |
|                            | [0.221]             | [0.173]                | [0.196]                    | [0.191]                  | [0.221]                    |
| Adjusted R <sup>2</sup>    | 0.060               | 0.025                  | 0.005                      | 0.015                    | -0.007                     |
| N                          | 213                 | 213                    | 211                        | 211                      | 210                        |

Notes: Regression based on model (2). Socio-economic status is based on 5-self-reported categories and is sourced from the World Value Survey – US sample, 7<sup>th</sup> wave, 2017. Inequality is based on the share of income going to the poorest 10% of the population in the country of origin of the US-based immigrant respondents. This indicator is sourced from the World Bank’s World Development Indicators database.

**Table 5 – Regression results by country or region of destination and socio-economic status**

|                  | Immigrants increase terrorism |                    |                    |                   |                    |
|------------------|-------------------------------|--------------------|--------------------|-------------------|--------------------|
|                  | Immigrant                     | SOE - high         | SOE - low          | Imm x SOE high    | Imm x SOE low      |
| US               | -.034<br>(.063)               | .166<br>(.113)     | .015<br>(.047)     | .606***<br>(.133) | .105<br>(.186)     |
| Canada           | -.005<br>(.038)               | .074<br>(.057)     | .110***<br>(.036)  | .006<br>(.146)    | -.265***<br>(.045) |
| Australia        | .017<br>(.080)                | -.116<br>(.114)    | .067<br>(.079)     | -.304**<br>(.143) | -.567***<br>(.117) |
| New Zealand      | -.076<br>(.052)               | .128<br>(.158)     | .279**<br>(.127)   | .225<br>(.406)    | -.269<br>(.198)    |
| World (ref: USA) | -.034**<br>(.013)             | -.015<br>(.015)    | -.005<br>(.007)    | .022<br>(.087)    | .038<br>(.030)     |
| Africa           | -.007<br>(.153)               | -.005<br>(.049)    | -.036**<br>(.018)  | -.389**<br>(.156) | -.147<br>(.244)    |
| Europe           | .024<br>(.034)                | -.052<br>(.051)    | -.022<br>(.023)    | .039<br>(.207)    | .074<br>(.073)     |
| Asia-Pacific     | -.072***<br>(.021)            | -.079***<br>(.020) | -.032***<br>(.010) | .124<br>(.180)    | .172***<br>(.143)  |
| Americas         | -.070***<br>(.025)            | .013<br>(.034)     | -.007<br>(.013)    | .051<br>(.117)    | -.106*<br>(.072)   |

Notes: Regression based on model (1) separately performed on various countries and regions. Socio-economic status is based on 5-self-reported categories and is sourced from the World Value Survey. Only some of the coefficients estimated are reported. Full results available from the authors.

**Table 6 - Dispersion of educational qualifications in the home country population**

|               | Natives | Immigrants | Difference |
|---------------|---------|------------|------------|
| United States | 1.55    | 1.65       | -0.10      |
| Australia     | 1.73    | 1.58       | 0.15       |
| Canada        | 1.58    | 1.48       | 0.10       |
| New Zealand   | 1.63    | 1.63       | 0.00       |
| Africa        | 1.78    | 1.73       | 0.05       |
| Europe        | 2.43    | 1.90       | 0.53       |
| Asia-Pacific  | 1.96    | 1.74       | 0.22       |
| Americas      | 1.83    | 1.79       | 0.04       |
| World ex-US   |         |            |            |
|               |         |            |            |
| Cyprus        | 2.43    | 1.91       | 0.52       |
| Taiwan RoC    | 2.01    | 1.69       | 0.32       |
| Greece        | 1.92    | 1.65       | 0.27       |
| South Korea   | 1.61    | 1.44       | 0.17       |
| Ukraine       | 1.72    | 1.57       | 0.15       |
| Kazakhstan    | 1.70    | 1.61       | 0.09       |
| Kyrgyzstan    | 1.72    | 1.66       | 0.06       |
| Tunisia       | 1.78    | 1.73       | 0.05       |
| Serbia        | 2.07    | 2.05       | 0.02       |
| Brazil        | 1.68    | 1.69       | -0.01      |
| Russia        | 1.79    | 1.81       | -0.02      |
| Macau         | 1.79    | 1.82       | -0.03      |
| Guatemala     | 2.30    | 2.35       | -0.05      |
| Jordan        | 1.73    | 1.79       | -0.06      |
| Chile         | 1.59    | 1.66       | -0.07      |
| Japan         | 1.47    | 1.57       | -0.10      |
| Argentina     | 1.46    | 1.57       | -0.11      |
| Hong Kong     | 1.80    | 1.93       | -0.13      |
| Malaysia      | 1.71    | 1.85       | -0.14      |
| Puerto Rico   | 1.83    | 1.97       | -0.14      |
| Singapore     | 1.93    | 2.10       | -0.17      |
| Andorra       | 1.76    | 1.98       | -0.22      |
| Colombia      | 1.79    | 2.02       | -0.23      |
| Portugal      | 1.91    | 2.21       | -0.30      |
| Germany       | 1.73    | 2.06       | -0.33      |
| Ecuador       | 1.77    | 2.19       | -0.42      |

Notes: Standard deviation of average education of the immigrant US population, by country of origin. Source: World Value Survey – US sample, 7<sup>th</sup> wave, 2017.

**Table 7 – Robustness to omitted variable bias – Tests (delta) based on Oster (2019).**

|                             | Immigrants             |                            |                          |
|-----------------------------|------------------------|----------------------------|--------------------------|
|                             | ...increase crime rate | ...increase terrorism risk | ...increase unemployment |
| $R_{\max} = 1.0 \times R^2$ | 79.57                  | 193.15                     | 122.74                   |
| $R_{\max} = 1.3 \times R^2$ | 7.14                   | 11.87                      | 15.21                    |
| $R_{\max} = 2.0 \times R^2$ | 2.29                   | 3.73                       | 5.00                     |

For a description of the methodology see the main text as well as Oster (2019). Test applied on the interaction term between the top socio-economic group and immigrant status. Data sourced from the World Value Survey – US sample, 7<sup>th</sup> wave, 2017.

**Table 8a – Heterogeneity by main country/region of residence. Immigrant respondents**

|                                      | Immigrants.....     |                        |                            |                          |                            |
|--------------------------------------|---------------------|------------------------|----------------------------|--------------------------|----------------------------|
|                                      | ...fill useful jobs | ...increase crime rate | ...increase terrorism risk | ...increase unemployment | ...lead to social conflict |
| SOE 1 <sup>st</sup> q x US           | -0.503**            | 0.440**                | 0.364*                     | 0.468**                  | -0.0715                    |
|                                      | [0.209]             | [0.215]                | [0.220]                    | [0.227]                  | [0.223]                    |
| SOE 1 <sup>st</sup> q x Africa       | -0.395**            | -0.700***              | -0.566***                  | -0.732***                | -0.278                     |
|                                      | [0.188]             | [0.187]                | [0.187]                    | [0.194]                  | [0.331]                    |
| SOE 1 <sup>st</sup> q x Asia-Pacific | -0.134              | -0.274                 | -0.0512                    | 0.284                    | -0.380*                    |
|                                      | [0.238]             | [0.235]                | [0.239]                    | [0.193]                  | [0.195]                    |
| SOE 1 <sup>st</sup> q x Americas     | 0.0018              | 0.281                  | 0.005                      | 0.191                    | -0.0239                    |
|                                      | [0.388]             | [0.257]                | [0.346]                    | [0.277]                  | [0.337]                    |
| SOE 1 <sup>st</sup> q x Canada       | -0.207              | 0.101                  | 0.0513                     | 0.0770                   | -0.0144                    |
|                                      | [0.192]             | [0.192]                | [0.183]                    | [0.186]                  | [0.171]                    |
| SOE 1 <sup>st</sup> q x Australia    | 0.375**             | -0.422***              | -0.568***                  | -0.338**                 | -0.353**                   |
|                                      | [0.147]             | [0.140]                | [0.147]                    | [0.144]                  | [0.150]                    |
| SOE 1 <sup>st</sup> q x New Zealand  | 0.286**             | 0.236                  | 0.205                      | -0.265*                  | -0.275**                   |
|                                      | [0.136]             | [0.345]                | [0.422]                    | [0.139]                  | [0.136]                    |
| Adjusted R <sup>2</sup>              | 0.009               | 0.102                  | 0.062                      | 0.090                    | 0.072                      |
| N                                    | 4,107               | 4,115                  | 4,089                      | 4,126                    | 4,107                      |

Notes: Regression based on model (1) replacing immigrant status with the country or region of residence. This specification is performed on observations restricted to immigrant respondents only. The region of reference is Europe. Socio-economic status is based on 5-self-reported categories and is sourced from the World Value Survey. Only some of the coefficients estimated are reported. Full results available from the authors.

**Table 8b - Heterogeneity by main country/region of residence. Native respondents**

|                                      | Immigrants.....     |                        |                            |                          |                            |
|--------------------------------------|---------------------|------------------------|----------------------------|--------------------------|----------------------------|
|                                      | ...fill useful jobs | ...increase crime rate | ...increase terrorism risk | ...increase unemployment | ...lead to social conflict |
| SOE 1 <sup>st</sup> q x US           | 0.156               | 0.359***               | 0.194                      | 0.177                    | 0.170                      |
|                                      | [0.101]             | [0.118]                | [0.118]                    | [0.114]                  | [0.117]                    |
| SOE 1 <sup>st</sup> q x Africa       | 0.0759              | 0.107                  | 0.0303                     | -0.130*                  | -0.0515                    |
|                                      | [0.0718]            | [0.0712]               | [0.0719]                   | [0.0714]                 | [0.0709]                   |
| SOE 1 <sup>st</sup> q x Asia-Pacific | 0.0005              | 0.0734                 | -0.0191                    | -0.0424                  | -0.0277                    |
|                                      | [0.0563]            | [0.0556]               | [0.0555]                   | [0.0553]                 | [0.0551]                   |
| SOE 1 <sup>st</sup> q x Americas     | 0.0657              | 0.104                  | 0.0099                     | 0.0393                   | 0.0315                     |
|                                      | [0.0649]            | [0.0647]               | [0.0650]                   | [0.0641]                 | [0.0641]                   |
| SOE 1 <sup>st</sup> q x Canada       | -0.0731             | 0.245***               | 0.150*                     | 0.141*                   | 0.0782                     |
|                                      | [0.0836]            | [0.0783]               | [0.0785]                   | [0.0782]                 | [0.0810]                   |
| SOE 1 <sup>st</sup> q x Australia    | -0.148              | 0.008                  | -0.164                     | -0.159*                  | -0.171                     |
|                                      | [0.146]             | [0.119]                | [0.120]                    | [0.0942]                 | [0.121]                    |
| SOE 1 <sup>st</sup> q x New Zealand  | 0.107               | 0.262*                 | 0.154                      | -0.0092                  | -0.0608                    |
|                                      | [0.168]             | [0.148]                | [0.165]                    | [0.118]                  | [0.121]                    |
| Adjusted R <sup>2</sup>              | 0.012               | 0.040                  | 0.039                      | 0.050                    | 0.039                      |
| N                                    | 65115               | 65082                  | 64857                      | 65455                    | 65058                      |

Notes: Regression based on model (1) replacing immigrant status with the country or region of residence. This specification is performed observations restricted to native respondents only. The region of reference is Europe. Socio-economic status is based on 5-self-reported categories and is sourced from the World Value Survey. Only some of the coefficients estimated are reported. Full results available from the authors.

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