How Immigrants and Racial Segregation Affect Immigration Attitudes

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Abstract

Do immigrant presence and racial segregation affect different individuals' attitudes toward immigration? There is a controversy in previous literature about whether more immigrants lead to more or less anti-immigration attitudes. I argue that the disagreement is because they ignore the degree to which the immigrants (and other minorities) are segregated. In the U.S. context, I hypothesize that for conservatives, higher immigrant/racial segregation is related to more pro-immigration attitudes because a lack of intergroup communication functions as a "shield" against more salient group membership and substantial prejudice against the outgroups. With data covering five presidential elections in 2008-2024 from the U.S. Census, American Community Survey, and Cooperative Election Study, I use Bayesian multilevel linear regressions with immigration attitudes as DV. Most results support the hypothesis. This paper contributes to immigration politics by comparing the different effects of immigrant presence and racial segregation interacting with ideology and providing a modified version of the threat theory in explaining the divergent effects of racial segregation on liberals' and conservatives' immigration attitudes.

Keywords: Trump, segregation, immigration, populism

1 Introduction

While Trump's campaign raised the alarms about immigration, he did not win an overwhelming share of votes in some counties with large immigrant population. For instance, Trump received only 38% of the votes in 2020 in Webb County, Texas, where the proportion of immigrants was high[1]. One possible answer to this puzzle is that traditional political science studies suggest that contact with "others" can reduce fear and prejudice (e.g. Schmid et al. 2008; Semyonov and Glikman 2009). Webb County's high level of integration, then, could add to the explanation for the low level of Trump's support. However, even holding the percentage of immigrants constant, counties differ greatly in terms of the level of segregation. In some counties with a high proportion, the segregation level could also be very high. Translating these issues to the current political environment, to what degree do a country's immigrant population and the level of segregation increase voters' antipathy toward immigration?

Most extant work on immigration attitudes can be classified into contact and threat theories (e.g. Jolly and DiGiusto 2014; Green and Kadoya 2015). They have different theoretical foundations and predict opposite effects of immigration on immigration attitudes. Although most scholars agree that more contact with immigrants can produce a more pro-immigration attitude, some have different findings, which suggest that not all voters perceive the same immigration threats, even if their neighborhoods have the same proportions. The disagreement in this literature is that they ignore the degree to which immigrants (and other minorities) are segregated in their communities.

Derived from the social identity theory, the "shield theory" proposed in this paper hypothesizes that higher immigrant or racial segregation shields conservatives from threats posed by immigrants or other races. For conservatives, a lack of intergroup encounter or communication functions as a "shield" against more salient group membership and substantial prejudice against the outgroups. They will feel safe as long as this shield exists and safer when this shield gets stronger. This theory also expects that this shield has a stronger effect in places with a high proportion of immigrants or other races than in places with a low proportion.

With data from the 2010 and 2020 U.S. Censuses, American Community Survey (5-year estimates, 2010, 2012, 2016, 2020, and 2023), and Cooperative Election Study (2010, 2012, 2016, 2020, and 2024), I first run unidimensional 2PL IRT models to generate a single variable immigration attitude and then run Bayesian multilevel linear regressions with immigration attitude as DV. I first focus on 2020 and then compare the results from all years. Most results support my theory and hypothesis. I find that in counties with a high immigrant proportion, higher immigrant segregation is associated with a more friendly attitude toward immigrants among conservatives. Moreover, this effect holds if the proportion and segregation are about Hispanics and Latinos. The comparison over time shows that my findings remain robust and that this effect is the strongest in 2020.

This paper is organized as follows. Section 2 reviews the previous literature on immigration attitudes, focusing on the contact theory and threat theory, and then introduces social identity theory. Section 3 develops the "shield theory" based on social identity theory and derives the hypothesis. Section 4 introduces data, variables, and methods. Section 5 introduces descriptive statistics of immigrant presence and racial segregation. Section 6 discusses the statistical results and robustness check, most of

[1]The immigrant proportion is 17.89%. The segregation value (from tract to county) is 0.16, the lowest among all counties with a population greater than 100,000. Data is from the 2020 Census.

which support the hypothesis. Section 7 discusses the empirical findings, theoretical implications, and limitations.

2 Previous Literature

2.1 Immigration Attitudes

There are two major schools of theories about the effects of immigration and attitudes toward immigrants: contact and threat (Jolly and DiGiusto 2014; Green and Kadoya 2015). The contact theory, based on Allport (1954), argues that more contact with immigrants should decrease prejudice against immigrants. A substantial literature finds that contact with immigrants can diminish the perceived threat posed by immigrants. Green and Kadoya (2015) find that in Japan, individuals with better English conversation skills view immigrants more positively, which supports contact theory. Clayton et al. (2021) find that French non-immigrants with frequent contact with immigrants care less about immigrants' nationality than those with less contact in terms of what type of immigrants is preferable. The effect of contact with immigrants may also depend on the type of contact. While superficial contact with, or mere exposure to, immigrants can lead to increased support for anti-immigrant parties (Steinmayr 2021; Valdez 2014), intimate or positive contact can reduce non-immigrants' willingness to expel immigrants and vote for the anti-immigrant parties (McLaren 2003; Green et al. 2016; Steinmayr 2021).

On the other hand, the threat theory argues that more contact with immigrants makes the majority group feel threatened in terms of competition over resources and thus have stronger anti-immigration attitudes (Green and Kadoya 2015; Blumer 1958; Buckler et al. 2009). Enos (2014) even finds that a minor change in the demographic context can lead to "strong exclusionary reactions" (p. 3699).

Moreover, threats could be generated by contact with some specific types of immigrants. Newman et al. (2012) find that in the U.S., contact with immigrants who speak Spanish or do not speak English reinforces Americans' feeling of threats posed by immigrants and their anti-immigration attitudes. Additionally, such threats posed by contact with immigrants may only exist within part of voters, depending on their predispositions. Karreth et al. (2015) find that a more diverse immigration context is associated with a more negative attitude toward immigrants only among those on the political right who are more sensitive to these threats than those on the political left. Homola and Tavits's (2018) study on Germany and the United States reveals that contact reduces threats related to immigration only among leftist voters, whereas it actually increases threats or has no effect among rightist voters. Despite these inconsistent conclusions, some meta-analyses find that the contact theory is usually tenable (Pettigrew and Tropp 2006; Paluck et al. 2019). Both theories have been repeatedly tested and compared in different contexts, and the argument continues.

Voters' attitudes toward immigrants were found to be among the most critical factors in voting for Trump in the 2016 and 2020 U.S. presidential elections, with a presumption about the supposed threat increasing his support. Scholars have found that many individual-level predispositions related to immigration have substantial effects on their support for Trump, such as voters' policy preferences on the immigration issue, populist attitudes, anti-Muslim sentiment, anti-trade attitudes, authoritarian dispositions, xenophobia, racial resentment, and animus toward groups associated with the Democratic Party in 2011 (Rudolph 2021; Tucker et al. 2019; Buyuker et al. 2021; Mason et al. 2021; Lajevardi and Abrajano 2019; Smith and Hanley 2018; Hinojosa Ojeda and Telles 2021; Hooghe and Dassonneville 2018). Yet, it remains unclear how other aspects of immigration, such as segregation, can affect immigration attitudes and what consequences they may have on elections[2]. Nor do we know how racial segregation and immigrant presence can have different interactive effects with ideology.

2.2 Social Identity Theory

Identity is "any social category in which an individual is eligible to be a member" (Chandra 2006, p. 400). Social identity theory argues that individuals belonging to different groups favor the in-group and discriminate against the out-group, even when the social categorization is the only difference between them (Tajfel and Turner 1979). Social categorization creates and defines a social identity, i.e., "those aspects of an individual's self-image that derive from the social categories to which he perceives himself as belonging," for each of them (p. 40). Moreover, their need for a positive social identity motivates them to compare with the out-group and reinforce the positive distinctiveness of their own group, which is also referred to as "the sequence of social categorization-social identity-social comparison-positive ingroup distinctiveness" (Tajfel and Turner 1979; Tajfel 1979; Turner and Onorato 1999, p. 18; Turner 1999, p. 8).

As a close relative of social identity theory, "self-categorization" theory argues that an individual may be defined as a unique person displaying a personal identity different from others, or as a member of a certain group displaying one of the collective identities (Turner and Onorato 1999; Klandermans 2014). When a collective identity is shared by the group and individuals more strongly identify with the group, a social identity becomes salient (Klandermans 2014). In the process of "self-categorization," individuals perceive more intragroup similarities and intergroup distinctions in terms of the salient social categories. The different ways of viewing the ingroup and the outgroup turn to stereotypes which keep being enhanced. When social identity is more salient than personal identity, individuals consider themselves more as "similar, prototypical representatives of their ingroup category" than as unique persons (Turner and Onorato 1999, p. 21), which is called a "depersonalization of the self" (Turner 1984, p. 528; 1999, p. 11). Salience of group membership can thus be "defined as a psychological process which implies the depersonalization of self-perception" (Lorenzi-Cioldi and Doise 1990, p. 72). Now that individuals' self-perception becomes more similar to other ingroups, their behavior will become more homogeneous. From this perspective, social identity is "the process which transforms interpersonal into intergroup behavior" (Turner 1999, p. 11).

From the specific contact with one or some outgroups, individuals update their attitudes and feelings toward their group as a whole, which is termed "*contact*

[2] De Kadt and Sands (2021) find that in South Africa, whites in a more isolated area are more likely to vote along the racial line. Yet, it remains to be seen whether a similar effect applies to the segregation of immigrants from non-immigrants.

generalization" (Paolini et al. 2010; Al Ramiah and Hewstone 2013, p. 529). The generalization is greater among individuals with salient group membership than among those without, as the psychological awareness of their own group membership makes them more likely to view outgroups as "representatives of their groups rather than as individuals" (Paolini et al. 2010, p. 1724). Furthermore, negative intergroup contact leads to higher category salience and is more influential on intergroup relationships than positive one (Graf et al. 2014; Barlow et al. 2012; Paolini et al. 2010).

Some studies have already applied social identity theory to immigration politics. For example, Mangum and Block (2018) build five dimensions of American identity based on social identity theory and argue that all of these dimensions "lead to opposition to legal immigration" (p. 1). Bloom et al. (2015) differentiate religious social identity from religious belief and find that the former increases opposition to immigrants of other religions or ethnicities, whereas the latter produces a favorable attitude toward immigrants of the same religion and ethnicity. However, none of these studies considers how segregation could affect attitudes toward immigration.

3 "Shield" Theory and Hypotheses

The mixed findings of previous studies on immigration attitudes suggest that not all voters perceive the same immigration threats, even when their neighborhoods have the same proportions of immigrants. Moreover, the immigration situation may vary across areas if we consider more than just the proportion. In an area with a high immigrant proportion, but with most immigrants concentrated in a small subarea and barely interacting or being seen by voters, voters ought not perceive the same immigration threat as those who reside in an area where immigrants and non-immigrants are highly mixed. As a modified version of the traditional threat theory, this paper proposes the "shield" theory that takes the segregation of immigrants from non-immigrants into consideration.

The traditional wisdom is that segregation leads to prejudices against outgroups and that integration contributes to eliminating related inequalities (Semyonov and Glikman 2009; Enos 2017; Enos and Celaya 2018). The reality, however, is that communities numerically dominated by a particular ethnic group (also called "ethnic enclaves" in Qadeer and Kumar 2006 and Edin et al. 2003), such as Chinatown and Little Italy, have vibrant cultural activities and ethnic economies with many positive effects on inter-ethnic relations (Qadeer and Kumar 2006). Ethnic tension is actually weaker within ethnic communities than outside. New immigrants, faced with (presumed) racism and language and cultural barriers, have better economic opportunities and resources in a homogeneous community with their own people (Zhou 1992). The shelter and support provided by such a community could protect them from labor-market discrimination that they would suffer outside and help them better transition into American society (Logan et al. 2002). Successful immigrants (and their descendants) are more likely and better able to exit the ethnic enclave and integrate into white neighborhoods in the future than new arrivals. As a result, immigrants with disadvantaged socioeconomic status tend to be concentrated in segregated communities which function as a magnet, while those dispersed into the broad country may be more advantaged. The political consequence is that the segregated communities prevent the general public's attitudes toward immigration from becoming more negative than in a highly integrated situation where disadvantaged immigrants flood into all voters' neighborhoods.

The "shield" theory is mainly built on "self-categorization" and "contact generalization" from the social identity theory[3]. In the early stages of communication with immigrants or other races, individuals begin to perceive that they belong to different groups without knowing more differences between them. When the racial or immigrant group shares a collective identity and individuals more strongly identify with the group, the social identity regarding race or immigrant becomes salient (Klandermans 2014). In the process of "self-categorization," individuals from a racial or immigrant group perceive greater similarities within their own group and greater distinctions from other groups, which can evolve into stereotypes. Furthermore, based on the specific communication with an outgroup, individuals update their attitudes and feelings toward the outgroup as a whole (i.e., "contact generalization"), which is particularly efficient among individuals with salient group membership (Paolini et al. 2010).

Although the processes of "self-categorization" and "contact generalization" apply to both liberals and conservatives, we cannot assume that they feel threatened by immigrants or other races/ethnicities equally (Thomsen and Rafiqi 2019; Northcutt Bohmert and DeMaris 2015; Skipworth et al. 2010; Dyck and Pearson-Merkowitz 2014; Danckert et al. 2017). First, whereas both perceive more intergroup distinctions than intragroup ones, the level of intergroup distinctions perceived by conservatives tends to be higher than that perceived by liberals. Second, "contact generalization" is more efficient among conservatives than among liberals.

In a more racially segregated[4] area, there are fewer encounters and less communication between races (Danzer and Yaman 2013), which "shields" conservatives from threats from other races. No matter how big the actual population size of other races is, they should feel safe as long as this shield exists and safer when this shield gets stronger. As in the previous example of ethnic enclaves, the shelter provided by these segregated communities can shield disadvantaged immigrants from various types of discrimination and barriers outside the communities (Damm 2009). Meanwhile, outsiders need not face superfluous exposure to or communication with these disadvantaged immigrants, thanks to the magnet role of ethnic communities. Where the shield is weak, more interaction with other races resulting from high integration should enhance the salience of their own racial identity and thus make them more antagonistic toward the outgroups. In contrast, greater intergroup exposure or interaction should lead liberals to form even more favorable attitudes toward outgroups.

I do not deny that intergroup communication may increase or decrease prejudice against the outgroups as previous literature shows, but the focus of this study is

[3]In this paper, the social category is either a race/ethnicity or a group of immigrants, despite that all individuals possess multiple social categories (Hamidou-Schmidt and Mayer 2021). Although outgroups are not necessarily immigrants, the attitudes toward outgroups should also apply to immigrants because immigrants are outgroups. Therefore, the "shield" theory applies to both racial/ethnic segregation and immigrant segregation.

[4]Segregation in this paper only refers to residential segregation because it is more important than other types of segregation, such as workplace segregation and school segregation. Although usually positively correlated, residential segregation is more extreme than workplace segregation, and the former strongly affects the latter (Hu et al. 2022). See the Research Design section for details.

not whether the communication is positive or negative. Instead, my theory suggests that for conservatives, a lack of intergroup communication functions as a "**shield**" against more salient group membership and substantial prejudice against the outgroups. More communication, either good or bad, may cause them to realize the intergroup distinctions more strongly.

Table 1: Comparison of Conservatives in Four Hypothetical Areas

	High Proportion	Low Proportion
High Segregation	**Area A**: Pro-immigration (++)	**Area B**: Pro-immigration (+)
Low Segregation	**Area C**: Pro-immigration (−)	**Area D**: Pro-immigration (−)

Note: The number of +/− indicates the strength of pro-immigration attitudes.

Table 1 presents the theoretical expectations about conservatives' attitudes toward immigrants. Areas in the top row have high segregation, while those in the bottom row have low segregation. Likewise, areas in the left column have high proportions, whereas those in the right column have low proportions. The proportion of immigrants and the level of segregation predict the level of immigrant presence in opposite directions. In Area A where the immigrant proportion is high and immigrants are highly segregated from non-immigrants, conservatives perceive a strong shield from threats posed by immigrants. In contrast, in Area C where the proportion is also high but the segregation is low, the shield is weak because conservatives are expected to feel salient group membership of belonging to non-immigrants and thus have strong prejudice against immigrants.

In Areas A and B where the segregation is high, the theory predicts conservatives in Area A with a high proportion to be more pro-immigration than those in B with a low proportion, since the perceived shield in A is stronger than in B. However, in Areas C and D where immigrants and non-immigrants are highly integrated, a higher proportion is not necessarily related to a more pro-immigration attitude among conservatives because high integration indicates a weak shield regardless of the proportion. The main hypothesis is thus:

Hypothesis: *Conservatives in an area where immigrants/races are more segregated are more pro-immigration than conservatives in an area where they are less segregated.*

The theory proposed here is expected to be more manifest in areas where the proportion of immigrants or racial/ethnic minorities is higher. If the relative size of immigrants or racial/ethnic minorities in an area is small, the strength of this shield should be weak. Assuming individuals perceive the proportion as the size of the threat and the degree of segregation as the distance from the threat, the distance is more crucial in terms of affecting their attitude toward the outgroups when the size is substantial enough than when it is minimal. While this paper does not include an enumerated hypothesis about proportion so as to highlight the importance of segregation, it should not be omitted from the theory and the subsequent analysis because this omission may lead to an underestimation of the real effect of segregation.

4 Research Design

I use data from the U.S. 2010 and 2020 Censuses[5], American Community Survey (5-year estimates, 2010, 2012, 2016, 2020, and 2023)[6], and Cooperative Election Study (2010, 2012, 2016, 2020, and 2024)[7]. The dependent variable is attitude toward immigrants. I focus on the 2020 presidential election first, then compare all presidential elections in 2008-2024. CES (2020) has 61,000 observations covering 2,673 counties. Only respondents living in counties with a population of more than 10,000 are kept. After being cleaned and merged with the 2020 Census, 41,118 observations from 2,009 countries remain[8].

4.1 Independent Variables

4.1.1 Proportion of Immigrants

Data on immigrants in each county is from 5-year estimates of the American Community Survey (ACS). Among the 3,143 counties in the 50 states and the District of Columbia[9], the proportion of immigrants ranged from 0% to 30.8% in 2020. After being merged with the CES data, the maximum proportion in counties with a population of more than 10,000 is 28.9%.

4.1.2 Segregation

Based on Duncan and Duncan (1955), the value of segregation is the index of dissimilarity, which is calculated as

$$ID = 0.5 \times \sum_i \left| \frac{n_{Ai}}{n_{A+}} - \frac{n_{Bi}}{n_{B+}} \right|$$

where n_{Ai} is the size of the population group A in area i, n_{A+} is the total population of A across all areas in the study region ($n_{A+} = \sum_i n_{Ai}$), and n_{B+} is the corresponding value for the population group B. The scaling constant 0.5 means that the range of the

[5]The 2010 Census data is from Summary File 1 (U.S. Census Bureau 2010b), and the 2020 one is from Demographic and Housing Characteristics File (DHC) (U.S. Census Bureau 2020b).

[6]Data of all years except 2012 are accessed via API (U.S. Census Bureau 2010a, 2016, 2020a, 2023b). The 2012 one is from NHGIS (Manson et al. 2024). ACS (5-year estimates, 2024) has not been released yet when this paper is being written.

[7]The datasets are from Kuriwaki (2025), Dagonel (2021), Ansolabehere (2012), Ansolabehere and Schaffner (2013), Ansolabehere and Schaffner (2017), Schaffner et al. (2021), and Schaffner et al. (2025). The 2008 dataset of CES does not include questions about attitudes toward immigration. The 2010 one includes questions about such attitudes and vote choice in 2008. The 2010 Census data is matched with CES 2010.

[8]This number is 44,769 in 2010, 43,153 in 2012, 51,971 in 2016, and 49,112 in 2024. PID is not considered in this calculation.

[9]The 2020 Census does not have data about immigrants, while ACS (5-year estimates) does. No data for Puerto Rico in ACS.

ID is from 0 to 1, with 0 meaning complete integration and 1 complete segregation. The value of ID can be interpreted as the proportion of population group A that needs to move in order to achieve a uniform distribution of the two groups.

In the following models, area i can be county subdivision, tract, or block group, and the study region is each county[10]. For example, if area i refers to county subdivision[11], the value of segregation in each county is based on population composition in all subdivisions of each county. As some scholars note, using more fine-grained data with smaller units will produce a higher segregation value (Wong 2003; Manley 2014). I mainly focus on the lowest level because it provides more information about the population composition. Population data of citizen-noncitizen division is available at the county subdivision and tract levels but not block group level. In contrast, population data of races is available at all three levels. In this study, in addition to citizen-noncitizen segregation, I choose two racial groups to calculate racial segregation: Latinos and Hispanics VS non-Latinos and non-Hispanics. Population data is from the U.S. Census and American Community Survey, which are merged with the Cooperative Election Study.

In the 2020 Census and ACS 5-year estimates (2020), there is a variable with two minimum categories on ethnicity: Hispanic or Latino and Not Hispanic or Latino. The race variable has five minimum categories: White, Black or African American, American Indian or Alaska Native, Asian, and Native Hawaiian or Other Pacific Islander. Although it has been emphasized that "Hispanic origins are not races" because people with a Hispanic, Latino, or Spanish origin can be of any race[12], it is not far-fetched to include them in studies on racial politics if the definition of race is loosened (e.g. Hajnal and Rivera 2014; McClain et al. 2006; Stokes-Brown 2006). In this study, to simplify expressions, *racial segregation covers Latinos and Hispanics from non-Latinos and non-Hispanics.*

This study only considers residential segregation because it is more important than other types of segregation, such as workplace segregation and school segregation. Whites, especially high-income whites, prefer racial residential segregation for the purpose of "hoarding of the best neighborhoods, resources, and opportunities" (Jargowsky 2020, p. 151). One of the most substantial resources is school, as most American children attend schools in the school district where they reside (Frankenberg 2013). When deciding where to live, white parents prefer neighborhoods with schools that mainly serve white students (Owens 2020). These findings suggest that racial residential segregation is an effective, albeit imperfect, measure of overall racial segregation.

4.2 Control Variables

In addition to ideology and partisan identity, this study includes demographic variables (gender, race, and birth year) and socioeconomic variables (family income, education, employment status, evangelical, and religious importance) (see Appendix B in Online

[10] The 2020 data includes 35,628 county subdivisions, 84,208 tracts, and 239,209 block groups.

[11] According to the standard hierarchy of census geographic entities from the Census Bureau, counties are composed of census tracts, which are composed of block groups. Counties are also composed of county subdivisions, which have no further sub-levels.

[12] See U.S. Census Bureau (2023a), p. G-1.

Resource for details). I also include the county-level unemployment rate to control for the effects of the local economy and also city type[13].

4.3 Dependent Variables

The dependent variable is attitude toward immigrants. There are three questions about this attitude in 2010, six in 2012, four in 2016, six in 2020, and five in 2024 (see Appendix C in Online Resource). All of these questions have two options. They are recoded to 1 for pro-immigration and 0 for anti-immigration. To simplify comparison across years, I use unidimensional 2-Parameter Logistic (2PL) Item Response Theory models to evaluate these questions (Paek and Cole 2020). The models assume a single latent trait, i.e., attitudes toward immigration (see Appendix D.2-7 for technical details). An estimate of the latent trait of each respondent is saved as a single variable to be used as the DV in subsequent analysis[14]. A higher value of the latent variable means being more pro-immigration. I also use the sum of the questions each year for a robustness check.

4.4 Methods

The present study employs Bayesian multilevel linear regressions to analyze the association between immigrant/racial segregation and attitudes toward immigrants. By-county varying intercepts and weakly informative priors are included in all models[15].

5 Descriptive Statistics

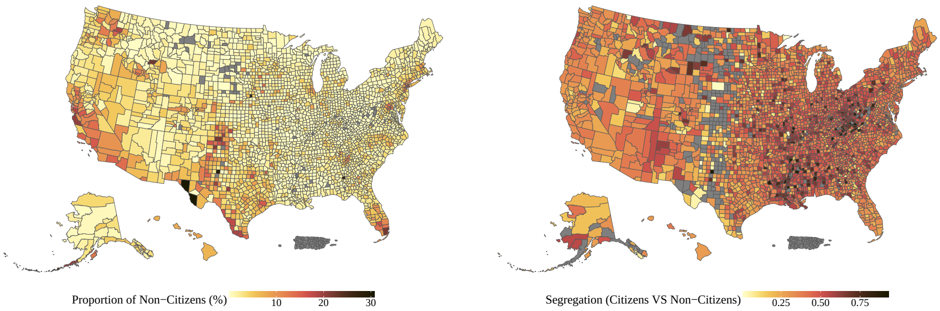
Because the focus of analysis is the 2020 election, descriptive statistics in this part also present immigrant/Hispanic proportion and segregation at the county level in 2020. The differences in these proportions and segregation values between 2008 and 2024 are minimal.

[13] Data are from the website of Local Area Unemployment Statistics of the U.S. Bureau of Labor Statistics and Pollard and Jacobsen's (2021) report.

[14] The DV in this paper is the attitude toward immigrants measured in two ways. However, there is a possibility that individuals' attitude toward immigrants should be the IV. Research on how their immigration attitude affects their housing choice requires a detailed record of their residence locations for at least two years, as well as their attitudes at different locations. The current datasets utilized in this study do not allow exploration of the relationship between their mobility and immigration attitude. A more detailed discussion of the potential endogeneity issue is presented in the final section.

[15] Based on the distribution pattern of the DV, I use the same priors for models across different years: Normal(0, 1) for the intercept, Normal(0, 2) for coefficients, and t(3, 0, 1) for residual standard deviation. More informative and less informative priors have also been tested with the same model specifications, but the results are proven to be insensitive to different priors. Each model has four chains with 4,000 iterations.

5.1 Immigrant Presence



(a) Proportion of Immigrants

(b) Segregation of Citizens VS Non-Citizens (From Tract to County)

Fig. 1: County-Level Immigrant Presence in 2020

5.1.1 Proportion of Immigrants

The left plot in Figure 1 depicts the county-level proportion of immigrants in 2020. In general, counties in the south and west have a higher proportion of immigrants than those in the north and central U.S. Among the 3,144 counties in the 2020 U.S. Census[16], Hudspeth County in Texas has the highest proportion of immigrants (30.77%), and Niobrara County in Wyoming has the lowest (0%). Among counties with a population of at least 100,000 (hereinafter heavily populated counties), the highest proportion is from Miami-Dade County in Florida (22.11%), and the lowest one is from Trumbull County in Ohio (0.30%). Four out of the ten heavily populated counties with the highest proportion are in Texas: Hidalgo (18.54%), Webb (17.89%), Dallas (16.79%), and Harris (15.99%).

5.1.2 Segregation of Citizens From Non-Citizens

The right plots in Figures 1 above and A.1 in Online Resource display the segregation of citizens from non-citizens in 2020. Area i is census tract in Figure 1 and county subdivision in Figure A.1[17]. The distribution pattern of immigrant segregation differs considerably from that of the immigrant proportion. As the right plot in Figure 1 shows, counties in the south and east tend to be more segregated than those in the west. Among the heavily populated counties, Livingston Parish in Louisiana has the highest segregation of citizens from non-citizens (0.68), although its proportion of immigrants is only 1.71%. The lowest segregation is found in Webb County, Texas, where the proportion is as high as 17.89%. The ten heavily populated counties with the highest level of segregation are in Louisiana, Ohio, Pennsylvania, West

[16] Puerto Rico is excluded because no data on immigrants is available.

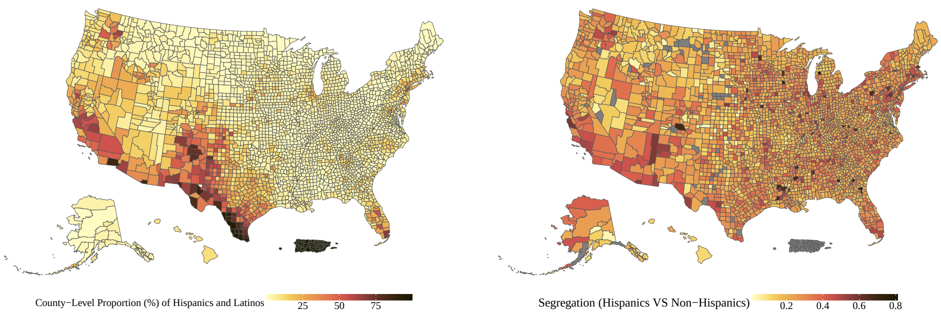
[17] Counties with only one subdivision or census tract are dropped and shown in gray in the plots because the value of segregation cannot be properly calculated in these counties.

Virginia, and Michigan. In the ten counties, the highest proportion of immigrants is only 3.63% (Luzerne County, Pennsylvania). In contrast, seven out of the ten most integrated heavily populated counties have a proportion higher than 10%. Moreover, among counties with a population bigger than 10,000, the segregation values (i = census tract) and the proportion of immigrants are moderately negatively correlated, $r(2400) = -.36$, $p < .01$[18].

Nevertheless, counties with a higher proportion are not always more integrated. In three heavily populated counties (Warren in New Jersey, Bonneville in Idaho, and Matenuska-Susitna Borough in Alaska) where the segregation value is only 0.23, the immigrant proportion is 3.33%, 2.81%, and 1.20% respectively, which implies that in counties where citizens and non-citizens are highly integrated, the immigrant proportion can be very low. In such scenarios, we do not know whether the level of contact with immigrants is high or low.

5.2 Races: Latinos and Hispanics

Figure 2 shows the county-level proportion of Latinos and Hispanics and segregation of Latinos and Hispanics from non-Latinos and non-Hispanics (from block group to county) in 2020[19]. In all graphs of segregation, a darker shade indicates a higher segregation level.



(a) Proportion of Hispanic and Latino Population

(b) Segregation of Hispanics VS Non-Hispanics (From Block Group to County)

Fig. 2: County-Level Hispanic Proportion and Segregation in 2020

The proportion of Hispanics and the segregation of Hispanics from non-Hispanics are moderately positively correlated among counties with a population bigger than 10,000, $r(2407) = .32$, $p < .01$[20]. Counties with the highest proportion of Hispanic and Latino population mainly concentrate in the southeast (see the left of Figure 2). Eight out of the twenty heavily populated counties with the highest proportion are

[18]Counties with an NA for the segregation value or exactly 0% of immigrants are excluded. If limited to heavily populated counties, the two are strongly negatively correlated, $r(601) = -.53$, $p < .01$.

[19]See Figure A.2 in Online Resource for segregation from tract/county subdivision to county.

[20]Counties with an NA for the segregation value or exactly 0% of Hispanics are excluded. If limited to heavily populated counties, the correlation is still positive but slightly stronger, $r(601) = .42$, $p < .01$.

in California, and seven are in Texas. In the right plot of Figure 2, counties in the southwest and northeast tend to be more segregated than those in the central U.S. The most segregated heavily populated county is Essex County in Massachusetts (0.63), whereas the least segregated are Kootenai County in Idaho and Hawaii County in Hawaii (0.11). Among the twenty heavily populated counties with the highest level of segregation, five are from Pennsylvania and four are from California. Monterey County in California is the 4th most segregated heavily populated county (0.58), and its proportion of Hispanics is the 13th highest (60.43%), which indicates that high racial segregation may coexist with a high proportion of the race.

5.3 Trump's Vote Shares in 2020

Because the attitude toward immigrants is measured at the individual level rather than at a geographical level, here I briefly introduce Trump's vote share at the county level in 2020 as a proxy for the overall attitude toward immigrants in a county[21]. Notably, in all the twenty heavily populated counties with the highest proportion of immigrants, Trump's vote share was lower than 50%. In contrast, in all the twenty heavily populated counties with the lowest proportion, Trump received over half of the votes. If segregation refers to citizens VS non-citizens, Trump won in nineteen out of the twenty most segregated heavily populated counties and in only three out of the twenty most integrated ones in 2020, which suggests that Trump was more likely to win in counties with a lower immigrant proportion or a higher level of segregation of citizens from non-citizens. If the proportion and segregation are about Hispanics, Trump won in only five out of the twenty most segregated heavily populated counties, with the highest vote share from Lebanon County, Pennsylvania (65%). Moreover, he won in seven out of the twenty heavily populated counties with the highest Hispanic proportions. Taken together, these data show that at the county level, a higher proportion or segregation is not always related to an electoral victory for Trump.

6 Results

In each of the following models, segregation interacts with both ideology and proportion. There are two sets of segregation values: citizens VS non-citizens, and Latinos and Hispanics VS non-Latinos and non-Hispanics[22]. Visual examination of the trace plots of all models shows they have converged well. Moreover, the range of Rhat values of all models are extremely close to 1. When interpreting the results, the high/low proportion and segregation level are decided by the bivariate graphs in Figure D.1 in Online Resource. For example, the high and low proportions of immigrants are 2% and 10%, and the segregation value of immigrants ranges from 0.1 to 0.7. If the high proportion is changed to 20%, then the segregation to be examined ranges from 0.1 to 0.4. I select these values to ensure that the extreme cases illustrated do exist in reality,

[21] This study recognizes that Trump's vote share at the county level is not a perfect proxy for the overall sentiment about immigrants in a county. But the purpose of this brief introduction is to show that proportion and segregation could be related to Trump's vote share at a county level, which could be an important implication for this study. The data is from MIT Election Data and Science Lab (2025).

[22] In the following text, I use Hispanics to stand for Latinos and Hispanics. See the Research Design section for explanations.

Table 2: Results of 2020 (DV: Attitudes Toward Immigrants)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
ideology	-0.502	0.016	-0.534	-0.470	✓	-0.472	0.009	-0.489	-0.454	✓
segregation	-0.599	0.123	-0.840	-0.359	✓	-0.384	0.108	-0.594	-0.175	✓
proportion	-0.031	0.005	-0.040	-0.021	✓	-0.001	0.002	-0.004	0.002	
seg. × ideo.	0.155	0.034	0.088	0.222	✓	0.174	0.029	0.118	0.231	✓
prop. × ideo.	0.006	0.001	0.005	0.008	✓	0.001	0.000	0.000	0.001	
prop. × seg.	0.048	0.013	0.023	0.073	✓	-0.004	0.004	-0.011	0.004	

Note: The DV is the estimate of the latent trait from IRT models, with a higher value indicating more pro-immigration. PID is not controlled for. If the 95% credible interval of a posterior estimate does not cover 0, checkmark ✓ is used in column "95% *CrI* excl. 0?".

rather than a hypothetical situation where the proportion is 0% but the segregation is 1.0 (see Appendix D.1 for the details).

6.1 The 2020 Presidential Election

Table 2 shows the posterior estimates of the Bayesian multilevel linear regression models of immigration attitudes with 95% credible intervals[23] (see Table D.3 in Online Resource for full results). Segregation and proportion in the two models refer to immigrants and Hispanics, respectively. Figure 3 shows the predicted attitudes toward immigration based on the two models with selected low and high proportions/segregation values. The x axis is the selected level of segregation, and the y axis is the predicted attitudes toward immigration.

Model 1 examines the interactive effects of immigrant segregation/proportion with ideology on attitudes toward immigration. The 95% credible intervals of all variables and interactions included in the table do not cover 0. On the x axis of the first group of plots of Figure 3, the low segregation value of citizens from non-citizens is 0.1, while the high one is 0.7 (also see Figure D.37 in Online Resource for the complete plot where segregation is continuous). The low and high proportions are 2% and 10%.

While liberals are always more pro-immigration than moderates who are also more so than conservatives, a higher segregation value is related to a more pro-immigration attitude among conservatives. Furthermore, for conservatives, the effect of segregation is stronger in high-immigrant-proportion counties than in low-immigrant-proportion ones (from -0.94 to -0.54 in the former and from -0.97 to -0.81 in the latter). This effect holds in counties where the proportion of immigrants reaches 20% (Figure D.38 in Online Resource). In contrast, the effect of segregation on liberals is mixed. Although liberals in a segregated county are more anti-immigration than in an integrated one if the proportion is very low, this effect is not shown where the proportion is high.

The main IV in Model 2 is the segregation of Hispanics from non-Hispanics. The graph for each model consists of two parts: the left for the low Hispanic proportion

[23] To avoid confusion with "confidence intervals" in frequentist statistics, Bayesian statistics usually uses the term "credible intervals" (e.g. Gelman et al. 2020 and Bürkner 2020).

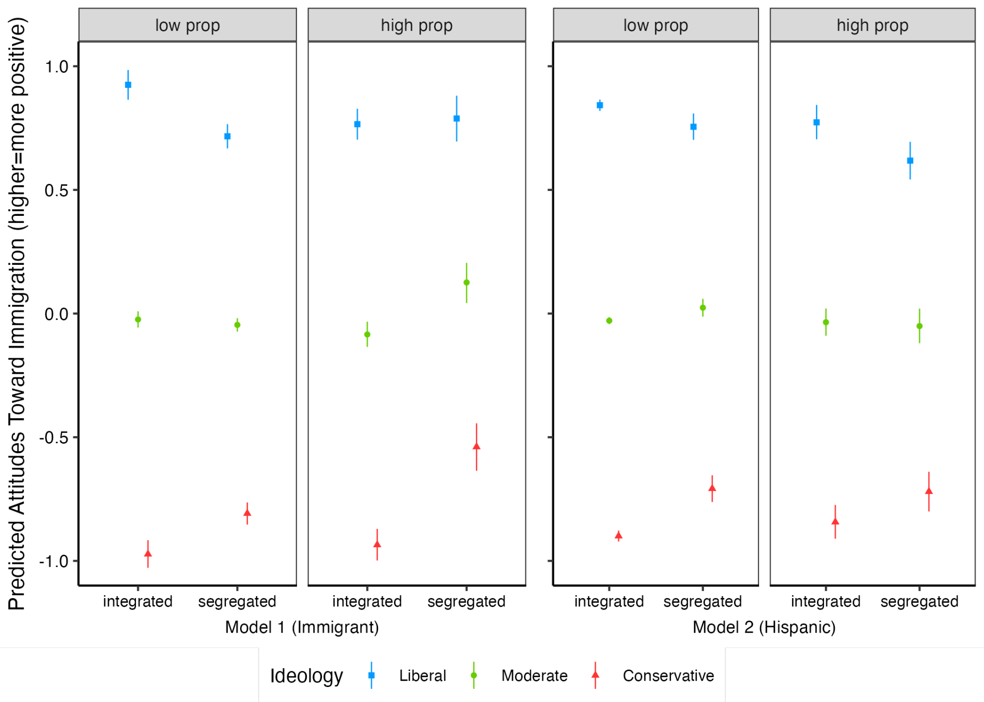


Fig. 3: Predicted Immigration Attitudes (2020)

Note: The DV is the estimate of the latent trait from IRT models. PID is not controlled for.

and the right for the high proportion (see the right group in Figure 3; also see Figure D.39 in Online Resource where segregation is plotted continuously). For Hispanics, the low and high proportions are 2% and 50%, and the low and high segregation values are 0.2 and 0.6.

Where the Hispanic proportion is extremely low (2%), the more segregated a county is, the more anti-immigration liberals are (from 0.84 to 0.76), while conservatives show the opposite trend (from -0.9 to -0.71), which supports my hypothesis. In high-Hispanic-proportion counties (50%), higher segregation is only related to a slightly more friendly attitude toward immigrants among conservatives (from -0.84 to -0.72). This effect is stronger where the proportion is only 25% (Figure D.40).

6.2 Other Presidential Elections Since 2008

Results about other presidential elections since 2008 also corroborate the main hypothesis. In Figure 4, only conservatives in counties with a high immigrant/Hispanic proportion are kept[24] (10% for the proportion of immigrants on the left and 50% for the proportion of Hispanics on the right), and years are represented with different colors

[24] See Figures D.17-19 in Online Resource for the full plots.

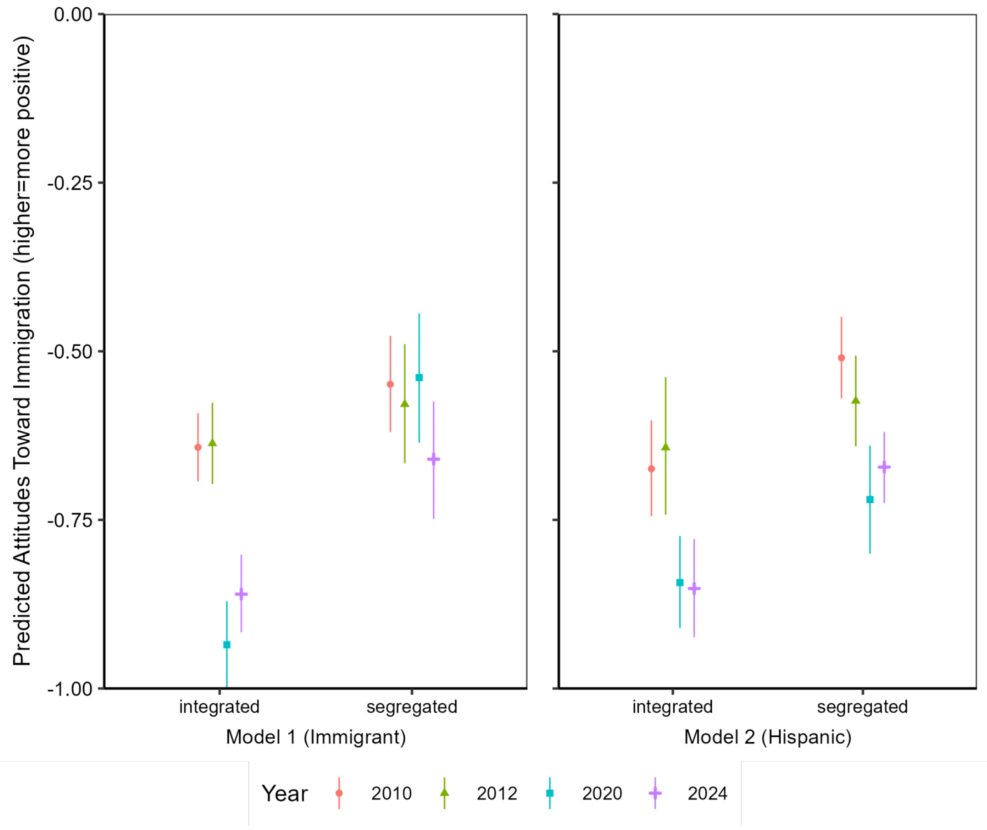


Fig. 4: Predicted Immigration Attitudes (Conservatives in High-Proportion Counties Only)

Note: The DV is the estimate of the latent trait from IRT models. 2010, rather than 2008, is used because the CES 2008 does not include questions about attitudes toward immigrants. 2016 is not included because the IRT model has poor global fitness. PID is not included in all of the models.

and shapes. 2016 is not included here because the IRT model has poor global fitness (but it is included in models where the DV is an index of questions about immigration attitudes in the Robustness Check section). There are two categories on the x-axis in each dimension: "integrated" represents low segregation and "segregated" represents high segregation[25]. In each year, conservatives in a segregated high-proportion county always have a more positive attitude toward immigrants than conservatives in an integrated one. Moreover, the segregation of immigrants has a stronger effect in the 2020 election than in the other three elections.

[25]On the left, the segregation value is 0.1 for "integrated" and 0.7 for "segregated". On the right, the two values are 0.2 and 0.6.

6.3 Robustness Check

To test whether the findings in this paper are sensitive to how immigration attitudes are measured, the models are rerun with an index of these questions. Figure D.23 in Online Resource shows the predicted immigration attitudes in 2020 with the sum of the six questions as the dependent variable. It highly resembles Figure 3, which demonstrates that changing measurements of immigration attitudes does not alter the main findings in this study. Moreover, Figure D.25 shows predicted immigration attitudes of conservatives in high-proportion counties in all presidential elections from 2008 to 2024 with the index as the DV. Because the number of questions about attitudes toward immigration varies across years, the interpretation of this figure should focus on comparing "integrated" and "segregated" within each year rather than on changes over time. It provides further support for the main hypothesis: conservatives in a segregated county are more pro-immigration than those in an integrated one, if the proportion of immigrants/Hispanics is held high.

Another concern is that the ideology variable may also contain some effects of partisanship and cause the problem of multicollinearity. To test whether including partisanship has any effect on the outcomes, all models have been rerun with partisanship controlled for (see Figures D.26-36). The predicted immigration attitude of liberals in models controlling for partisanship is more negative than that in models not including partisanship, while conservatives show the opposite trend. Nevertheless, within voters of the same ideological category, the comparison of those in an integrated county and those in a segregated one is similar to the models not controlling for partisanship.

The theory and hypothesis in this study are not limited to the segregation of immigrants from nonimmigrants and Hispanics from non-Hispanics. To test whether it can generalize to other racial/ethnic categories, the models were replicated with the county-level proportion of blacks and the segregation level of blacks from whites as the major IVs. Figures D.42-43 show that where the proportion of blacks is 60%, conservatives living in a county where blacks and whites are highly segregated (0.8) are more pro-immigration than conservatives in a county where they are integrated (0.1). This effect remains robust across years and is the strongest in 2020.

7 Discussion and Conclusion

This study examines how immigrant presence and racial segregation in a county affect attitudes toward immigrants in the 2008-2024 U.S. presidential elections. I hypothesize that for conservatives, higher immigrant or racial segregation is related to a more pro-immigration attitude.

With data from the U.S. 2010 and 2020 Censusus, American Community Survey (5-year estimates, 2010, 2012, 2016, 2020, and 2023), and Cooperative Election Study (2010, 2012, 2016, 2020, and 2024), I run Bayesian multilevel linear regression with immigration attitudes as DV. Although the 95% CrI of posterior estimates of the interaction of immigrant/racial segregation with ideology do not always exclude 0, most results still support my hypothesis. Model 1 shows that higher immigrant segregation is related to a more friendly attitude toward immigrants among conservatives, especially in counties with a high immigrant proportion. Model 2 also yields a similar result for conservatives in counties with a high proportion of Hispanics. The major findings are robust across years and with different measurements of the DV. Moreover, the theory and hypothesis proposed in this study may generalize to other racial/ethnic categories, such as whites VS blacks. Future research should consider the possibility of extending the "shield" theory to more types of outgroups.

The scholarship on immigration politics has overwhelmingly focused on the proportion rather than on other aspects of immigration, such as composition, density, and segregation. Neither have the similarities of immigration politics and ethnic/racial politics been fully explored. The traditional contact theory and threat theory cannot satisfactorily explain why immigrant/racial segregation has opposite relationships with liberals and conservatives, because it seems over-simplified to argue that one works among liberals and the other among conservatives. In my "shield" theory derived from the social identity theory, higher immigrant/racial segregation shields conservatives from threats from immigrants/other races. They will feel less salient group membership and have weaker prejudice against the outgroups than those in a more integrated area. In contrast, liberals have a weaker perception of their group membership salience and, thus, a weaker need for this shield.

Although previous literature tends to agree that more racial integration and less segregation can reduce racial prejudice and conflicts (Roch and Rushton 2008; Semyonov and Glikman 2009; Stringer et al. 2009; Schmid et al. 2008), this study finds that conservatives in a less racially segregated county may be more anti-immigration. It challenges previous studies that find segregation causes intergroup prejudice and leads to populist right voting (Enos and Celaya 2018; Schmid et al. 2008; Van Der Waal et al. 2013). Whereas it remains to be explored whether this finding can be extended to more contexts, this study implies that the relationship between racial segregation and related attitudes is more complicated than we often assume.

This study contributes to understanding the relationship between immigration/racial segregation and attitudes toward immigration. First, I use both the proportion of immigrants and segregation of immigrants at the county level as indicators of immigrant presence, which mitigates the concern that proportion does not mean contact in many previous studies (Gravelle 2016). Second, by including racial segregation, I demonstrate how this county-level context, seemingly irrelevant to immigration, could be related to individuals' attitudes toward immigration. The internal mechanisms of local immigration and racial context affecting immigration attitudes are not exactly the same but related, which is often neglected in previous scholarship. Third, I provide a modified version of the traditional threat theory to explain the divergent effects of segregation on liberals' and conservatives' immigration attitudes.

This study has some limitations. First, area i in the formula for calculating racial segregation can be block group, tract, or county subdivision, and block group level is not available for calculating segregation of immigrants. This means any racial composition information below the level of block group and any residential information of immigrants below the level of tract are not captured in the segregation values in this study. A neighbor next door from other races or countries could have a more significant effect than immigrant/racial segregation presence in other places within the block group/tract. Unfortunately, the current data availability does not allow me to include such fine-grained racial/immigration information. Second, only residential segregation is considered, while other types of segregation are also important, such as workplace segregation, income segregation, school segregation, and gender segregation. Third, this study does not measure the change in proportion and segregation across time, while some studies have already demonstrated that the short-term shock has a strong effect on voters' attitude toward immigrants (Enos 2014, 2023; Newman and Velez 2014; Kaufmann 2017). Future research should consider how the change in the level of segregation affects voters' attitude toward immigrants or other races and also the extent to which this change starts to trigger changes in their attitude.

Finally, one problem that remains to be addressed is the potential endogeneity. Some studies have already found that neighborhood demographic context or individuals' attitude toward immigrants/other races affects their decision of choosing which place to live in (e.g. Crowder 2000; Boustan et al. 2023). It is possible that those who are anti-immigration are more likely to move to places with fewer immigrants than those who are pro-immigration. However, this reversed causal direction is not suitable for this study because it contradicts the findings presented here. Another possibility is that some characteristics of those living in a segregated area are associated with a more pro-immigration attitude, compared with those in an integrated area. For example, individuals with the ability to relocate to a preferred area may have a higher income than those who are stuck in the same place. A higher income is associated with a higher education level, which in turn is related to a more pro-immigration attitude (Manevska and Achterberg 2013). If this reasoning is valid, it suggests that people who choose to stay away from immigrants may not always be anti-immigration. They can have a pro-immigration attitude as long as immigrants are out of their sight. An ideal approach to test this argument would be to utilize datasets that include information on people's mobility and their attitudes toward immigrants. Future research should consider the possibility of building or using such datasets to further explore the causal direction of the demographic context and immigration attitude.

Supplementary information. The Online Resource file is here: XXX

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- Declaration of Interests. The author has no known competing interests to disclose.
- Ethical Statement. This study conforms to ethical standards of APSA and IRB guidelines. It does not require IRB consent because all datasets used in this study are publicly available and all respondents are unidentifiable.
- Data availability. The CES data are from Harvard Dataverse. The 2020 Census DHC data, the ACS 5-year data (2010, 2016, 2020, 2023), and the 2010 Census data (Summary File 1) are accessed via API from the U.S. Census Bureau. ACS (5-year estimates, 2012) is from NHGIS. The unemployment rate data are from Local Area

Unemployment Statistics of the U.S. Bureau of Labor Statistics. The city type is from the website of Appalachian Regional Commission. The replication code files are available here: https://doi.org/10.7910/DVN/TNHSL2.

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Supplementary Information

How Immigrants and Racial Segregation Affect Immigration Attitudes

(On *Political Behavior*)

January 3, 2026

Contents

Appendices

A Maps

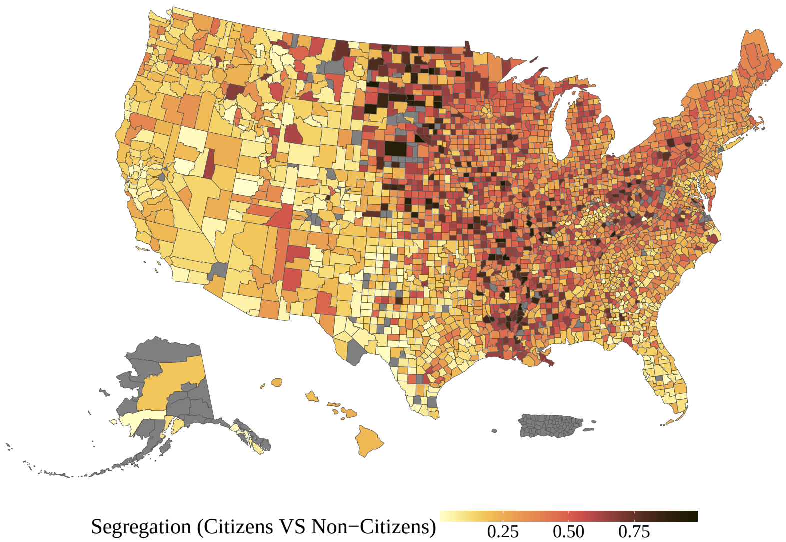
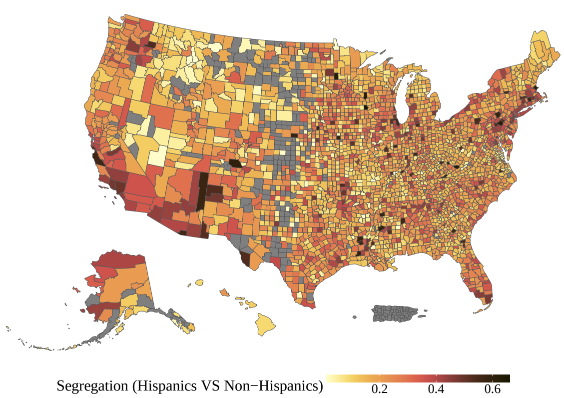
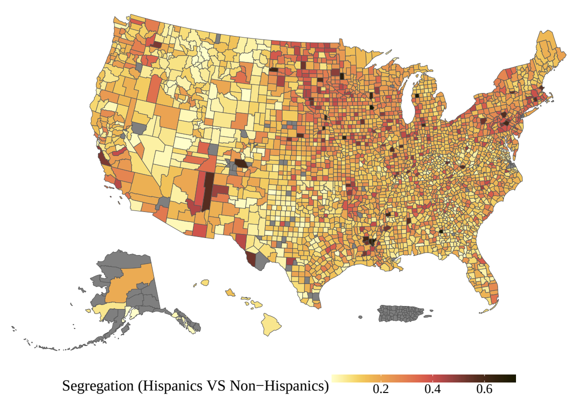


Figure A.1: Segregation of Citizens VS Non-Citizens in 2020 (From County Subdivision to County)



(a) From Tract to County



(b) From County Subdivision to County

Figure A.2: Segregation of Hispanics VS Non-Hispanics in 2020

B Control Variables

- Ideology: on a 1-5 scale, with 1 being very liberal and 5 very conservative.
- Partisan identity: Democratic, Republican, independent, and other.
- Gender: 1 for male and 0 for female.
- Race: based on the question "What racial or ethnic group best describes you?" The options are white, black or African-American, Hispanic or Latino, Asian or Asian-American, Native American, Middle Eastern, Two or more races, and other. It is recoded to 1 for white and 0 for others.
- Family income: the family's annual income over the last year with 16 categories ranging from less than $10,000 to $500,000 or more.
- Education: on a 1-6 scale, with 1 being did not graduate from high school and 6 postgraduate degree. It is treated as a continuous variable.
- Unemployment: based on the question of the current employment status. 1 for being unemployed, and all the other options are recoded to 0.
- Birth year: the year respondents were born.
- Evangelical: based on the question "Would you describe yourself as a 'born-again' or evangelical Christian, or not?" 1 for evangelical and 0 for not.
- Religious importance: on a 1-4 scale, with 1 being very important and 4 not at all important.
- Unemployment rate: county-level unemployment rate on a continuous scale.
- Urban: city type with five categories: large metro, small metro, nonmetro adjacent to large metro, nonmetro adjacent to small metro, and rural. The base category is large metro.

C Questions of Attitudes Toward Immigrants

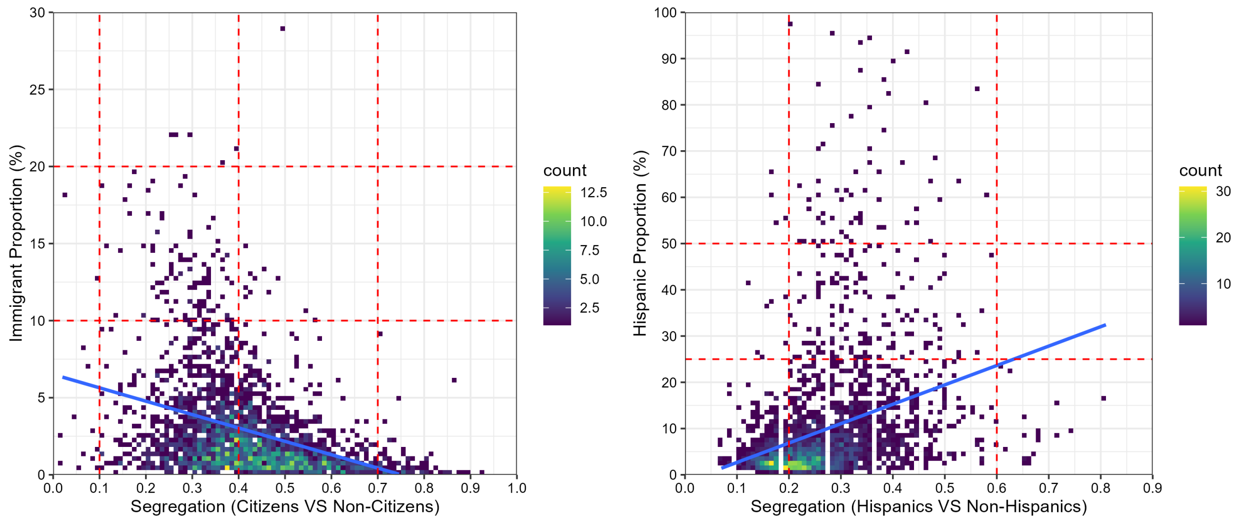
What do you think the U.S. government should do about immigration?

- Grant legal status to all illegal immigrants who have held jobs and paid taxes for at least 3 years, and not been convicted of any felony crimes. (2010, 2012, 2016, 2020, 2024)
- Increase the number of border patrols on the US-Mexican border. (2010, 2012, 2016, 2020, 2024)
- Withhold federal funds from any local police department that does not report to the federal government anyone they identify as an illegal immigrant. (2020)
- Reduce legal immigration by 50 percent over the next 10 years by eliminating the visa lottery and ending family-based migration. (2020)
- Increase spending on border security by $25 billion, including building a wall between the U.S. and Mexico. (2020, 2024)
- Allow police to question anyone they think may be in the country illegally. (2010, 2012)
- Fine US businesses that hire illegal immigrants. (2012)
- Prohibit illegal immigrants from using emergency hospital care and public schools. (2012)
- Identify and deport illegal immigrants. (2016)
- Deny automatic citizenship to American-born children of illegal immigrants. (2012)
- Provide permanent resident status to children of immigrants who were brought to the United States by their parents (also known as Dreamers). Provide these immigrants a pathway to citizenship if they meet the citizenship requirements and have committed no crimes. (2020, 2024)
- Grant legal status to people who were brought to the US illegally as children, but who have graduated from a U.S. high school. (2016, treated as the same question as the previous one)
- Deny access to asylum for immigrants who cross the US-Mexico border illegally. (2024)

Note: If a question was only asked to a small proportion of respondents in a given year, it is not included in this list.

D Supplemental Statistical Results

D.1 Segregation and Proportion



(a) Immigrants **(b)** Hispanics

Figure D.1: Proportion and Segregation of Immigrants (From Census Tract to County) and Hispanics (From Block Group to County) in 2020

Note: Only counties with a population bigger than 10,000 are kept. In each of the two plots, counties with an NA value for segregation or exactly 0% for proportion are omitted.

For immigrants, the following pairs of ranges are selected:
1. proportion $\in [2\%, 10\%]$, segregation $\in [0.1, 0.7]$
2. proportion $\in [2\%, 20\%]$, segregation $\in [0.1, 0.4]$

For Hispanics, the following pairs of ranges are selected:
1. proportion $\in [2\%, 50\%]$, segregation $\in [0.2, 0.6]$
2. proportion $\in [2\%, 25\%]$, segregation $\in [0.1, 0.6]$
3. proportion $\in [2\%, 95\%]$, segregation $\in [0.2, 0.6]$

While this study recognizes that different selections of the proportions and segregation levels could affect how results are plotted, the above values are selected to ensure that the extreme cases presented in the figures do exist in reality, rather than a hypothetical situation where the proportion is 0% but the segregation is 1.0.

D.2 IRT Models of Immigration Attitudes

For each year, I run a unidimensional 2-parameter logistic (2PL) item response theory (IRT) model on the questions about attitudes toward immigrants which are recoded so that 1 means pro-immigration and 0 means anti-immigration. Cases with an NA value in any variable used in the subsequent Bayesian models are dropped. Not all questions are used in all years. immig_dreamer is excluded from 2020 and 2024 because it causes poor global fit. Due to the large sample sizes, the p-values in the fit tests are not reliable. For the IRT models and fit tests listed in the rest of this section, PID is not included in the data. See Section D.6 for an example of interpreting the model results and fit tests.

An estimate of each respondent's latent trait (θ) is saved and used as DV in subsequent Bayesian models. The IRT model of 2016 has poor global fit.

D.3 2010

The options of fining U.S. businesses that hire illegal immigrants and of increasing guest workers were only asked to 2,263 respondents in 2010 and thus dropped. The other three options were asked to 55,400 respondents. 44,769 remain. M2 and item-level goodness of fit statistics do not apply to models with only three items. Discrimination parameters (a) indicate good separation, and the difficulty values (b) cluster around the mid-range. Yen's Q3 residuals show no evidence of local item dependence.

D.3.1 Item Coefficients

```
> coef(irt_model, IRTpars = TRUE, simplify = TRUE)
$items
                    a      b g u
immig_legalize 1.884  0.304 0 1
immig_border   1.658  0.403 0 1
immig_police   3.837 -0.099 0 1
```

Figure D.2: Item Coefficients (2010)

D.3.2 Goodness of Fit

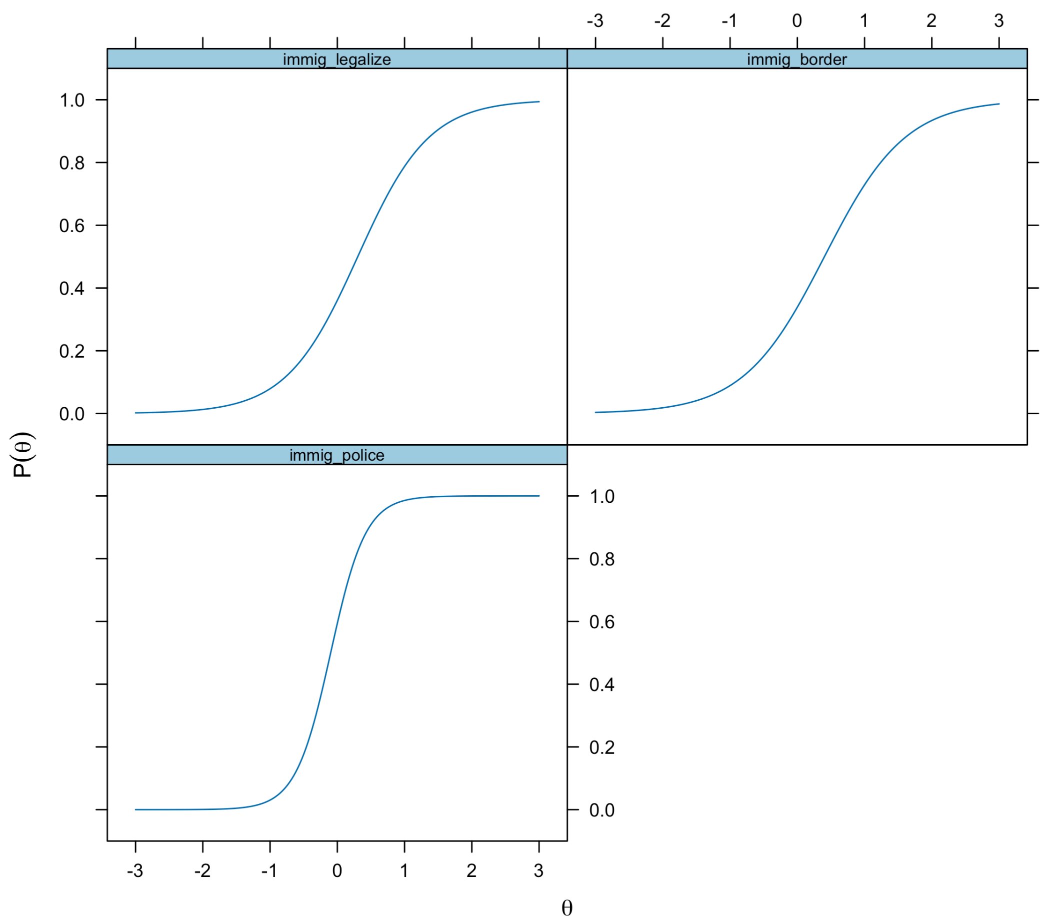


Figure D.3: ICC Plots for Questions of Attitudes Toward Immigrants (2010)

```
> q3 <- residuals(irt_model, type = "Q3") # check local independence problem
Q3 summary statistics:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -0.556  -0.504  -0.452  -0.414  -0.342  -0.233

               immig_legalize immig_border immig_police
immig_legalize          1.000       -0.233       -0.556
immig_border           -0.233        1.000       -0.452
immig_police           -0.556       -0.452        1.000
> summary(q3[lower.tri(q3)])
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-0.5562 -0.5041 -0.4520 -0.4136 -0.3423 -0.2327
```

Figure D.4: Fit Test (2010)

D.4 2012

All of the six questions about immigrants asked in 2012 are kept in the IRT model. 43,153 cases remain.

D.4.1 Item Coefficients

```
> coef(irt_model, IRTpars = TRUE, simplify = TRUE)
$items
                   a      b g u
immig_border   2.094  0.190 0 1
immig_employer 1.800  0.474 0 1
immig_legalize 2.154  0.068 0 1
immig_police   2.548 -0.334 0 1
immig_services 2.257 -0.611 0 1
immig_citizen  2.715 -0.422 0 1
```

Figure D.5: Item Coefficients (2012)

D.4.2 Goodness of Fit

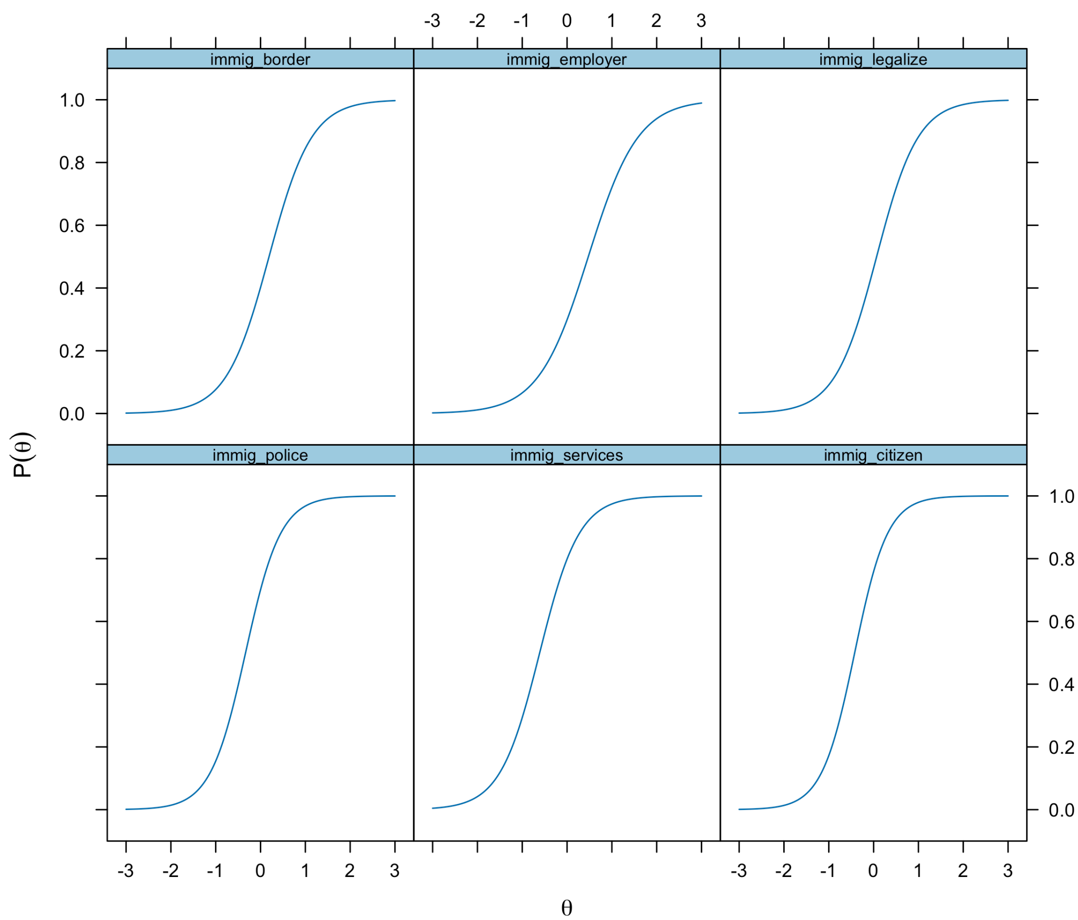


Figure D.6: ICC Plots for Questions of Attitudes Toward Immigrants (2012)

```
> M2(irt_model)
            M2 df p      RMSEA    RMSEA_5   RMSEA_95      SRMSR      TLI      CFI
stats 832.5079  9 0 0.04604815 0.04342949 0.04872105 0.02352982 0.987165 0.992299
> itemfit(irt_model)
            item    S_X2 df.S_X2 RMSEA.S_X2 p.S_X2
1   immig_border  28.151       3      0.014      0
2 immig_employer 480.007       3      0.061      0
3 immig_legalize 819.440       3      0.079      0
4   immig_police  31.063       3      0.015      0
5 immig_services  37.068       3      0.016      0
6  immig_citizen  19.659       3      0.011      0
> q3 <- residuals(irt_model, type = "Q3") # check local independence problem
Q3 summary statistics:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -0.329  -0.211  -0.184  -0.182  -0.139  -0.096

               immig_border immig_employer immig_legalize immig_police immig_services immig_citizen
immig_border          1.000         -0.099         -0.207       -0.105         -0.205        -0.255
immig_employer       -0.099          1.000         -0.215       -0.169         -0.096        -0.149
immig_legalize       -0.207         -0.215          1.000       -0.185         -0.184        -0.130
immig_police         -0.105         -0.169         -0.185        1.000         -0.229        -0.329
immig_services       -0.205         -0.096         -0.184       -0.229          1.000        -0.171
immig_citizen        -0.255         -0.149         -0.130       -0.329         -0.171         1.000
> summary(q3[lower.tri(q3)])
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-0.32896 -0.21107 -0.18402 -0.18186 -0.13931 -0.09554
```

Figure D.7: Fit Test (2012)

D.5 2016

Four questions about immigrants are kept in 2016. There are four other questions that were asked only to 13,269 respondents and thus dropped. 62,288 cases remain. However, the IRT model has poor global fit (RMSEA=0.172) and dropping one of the items does not improve the model.

D.5.1 Item coefficients

```
> coef(irt_model, IRTpars = TRUE, simplify = TRUE)
$items
                   a      b g u
immig_border   1.253 -0.013 0 1
immig_dreamer  1.470  0.124 0 1
immig_deport   3.139 -0.261 0 1
immig_legalize 2.254 -0.187 0 1
```

Figure D.8: Item Coefficients (2016)

D.5.2 Goodness of Fit

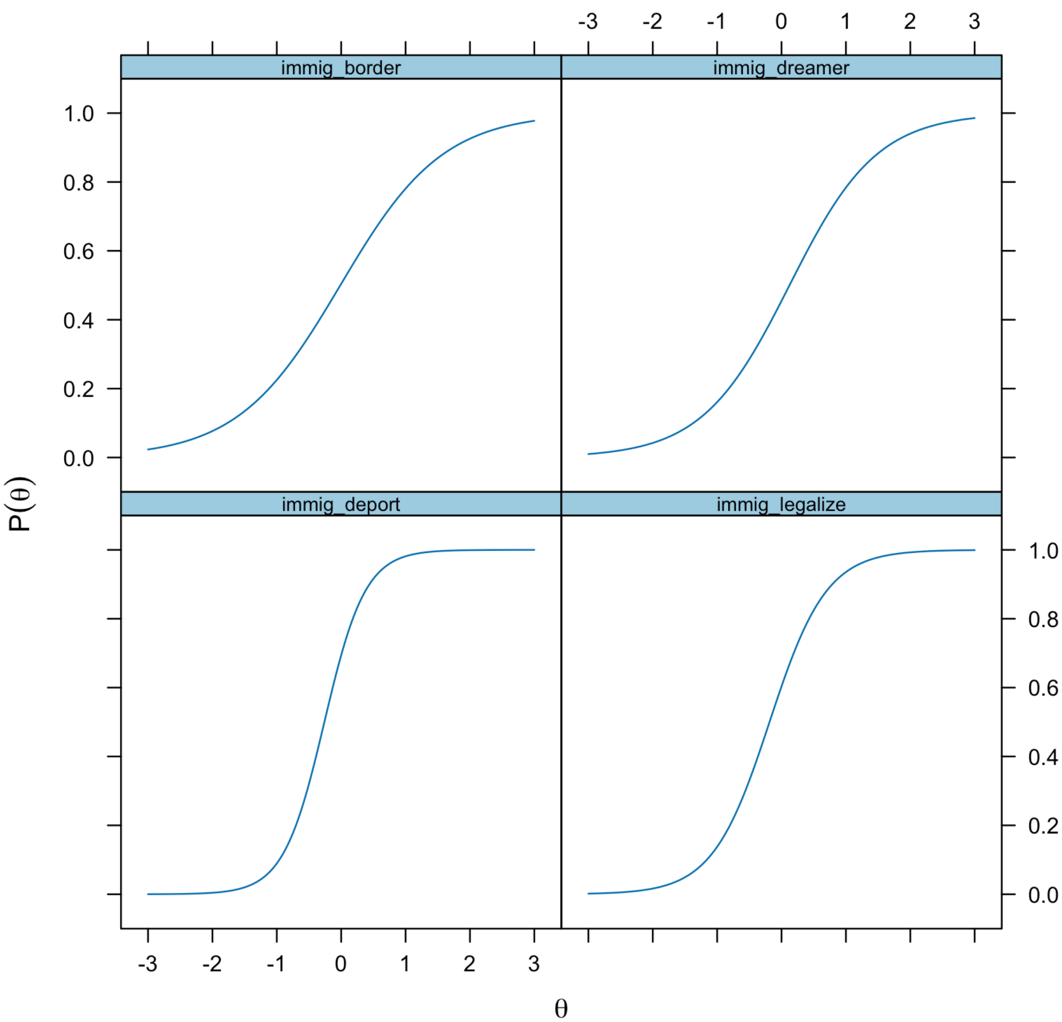


Figure D.9: ICC Plots for Questions of Attitudes Toward Immigrants (2016)

```
> M2(irt_model)
            M2 df p     RMSEA   RMSEA_5  RMSEA_95     SRMSR       TLI       CFI
stats 3694.297  2 0 0.1721609 0.1675223 0.1768434 0.0692987 0.7846676 0.9282225
> itemfit(irt_model)
            item    S_X2 df.S_X2 RMSEA.S_X2 p.S_X2
1   immig_border 148.473       1      0.049      0
2  immig_dreamer 281.849       1      0.067      0
3   immig_deport  99.155       1      0.040      0
4 immig_legalize  57.791       1      0.030      0
> q3 <- residuals(irt_model, type = "Q3") # check local independence problem
Q3 summary statistics:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -0.599  -0.363  -0.283  -0.273  -0.109  -0.033

               immig_border immig_dreamer immig_deport immig_legalize
immig_border          1.000        -0.276       -0.054         -0.291
immig_dreamer        -0.276         1.000       -0.387         -0.033
immig_deport         -0.054        -0.387        1.000         -0.599
immig_legalize       -0.291        -0.033       -0.599          1.000
> summary(q3[lower.tri(q3)])
    Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
-0.59901 -0.36258 -0.28315 -0.27315 -0.10942 -0.03304
```

Figure D.10: Fit Test (2016)

D.6 2020

Attitudes toward immigrants are modeled with a unidimensional 2-parameter logistic (2PL) item response theory (IRT) model with the mirt package in R, following the guidance from Paek and Cole (2020). All questions are recoded so that 1 means pro-immigration and 0 means anti-immigration. The question about Dreamers is not included because it causes poor global model-data fit. The other five questions are kept. 41,118 cases remain.

D.6.1 Item coefficients

```
> coef(irt_model, IRTpars = TRUE, simplify = TRUE)
$items
                   a      b g u
immig_legalize 1.738 -0.795 0 1
immig_border   3.308  0.242 0 1
immig_report   2.719 -0.229 0 1
immig_reduce   2.418 -0.394 0 1
immig_wall     6.398 -0.273 0 1
```

Figure D.11: Item Coefficients (2020)

a and b are the discrimination and difficulty parameter estimates respectively. The ability θ population is assumed to be normally distributed with fixed parameters of 0 for the mean and 1 for the variance. Discrimination values indicate that immig_wall is the most informative ($a = 6.398$), while immig_legalize is the least discriminating. So supporting/opposing a "wall" sharply separates respondents in terms of being high or low on the latent factor. Difficulty values suggest that supporting immig_legalize is relatively easy for pro-immigration respondents ($b = -0.80$), whereas immig_border is likely to be selected only by respondents with around-average attitude toward immigrants ($b = 0.24$). The other items require slightly below average, i.e., more anti-immigration attitudes.

D.6.2 Goodness of Fit

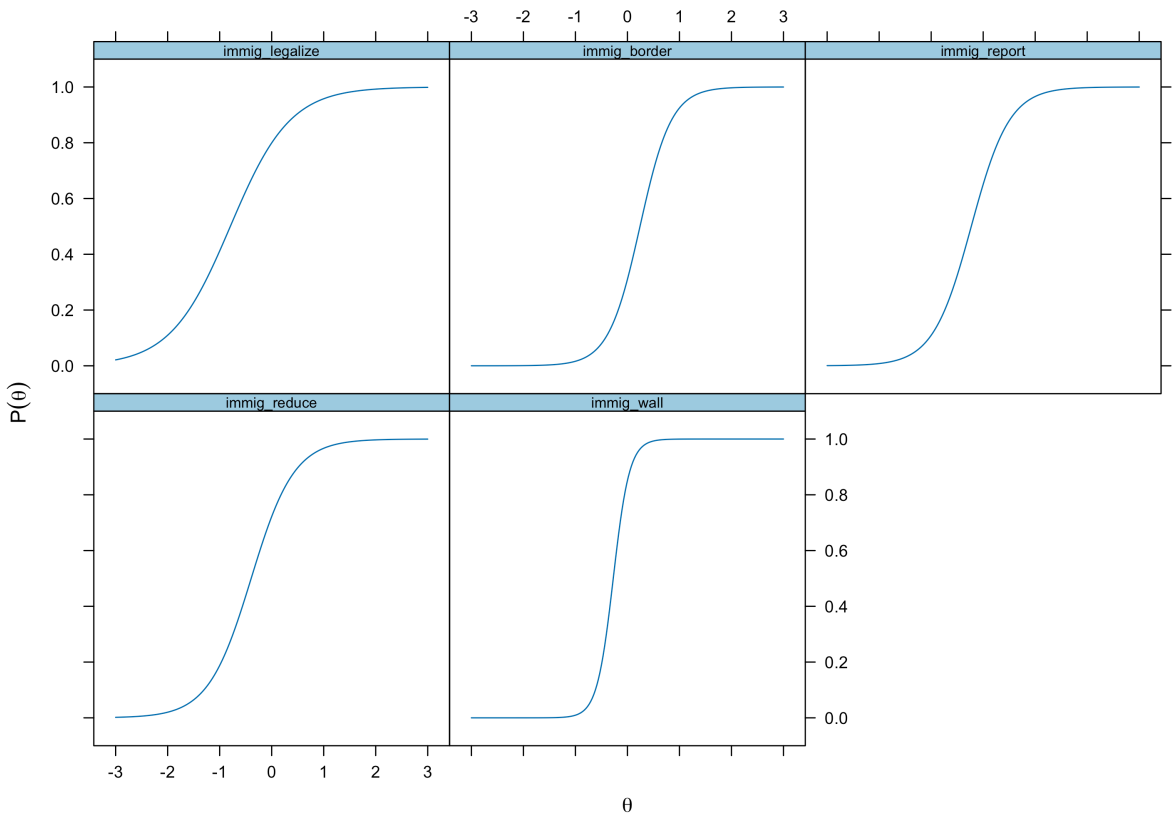


Figure D.12: ICC Plots for Questions of Attitudes Toward Immigrants (2020)

```
> M2(irt_model)
            M2 df p      RMSEA    RMSEA_5   RMSEA_95      SRMSR       TLI       CFI
stats 129.6361  5 0 0.02462217 0.02106016 0.02837388 0.01049952 0.997487 0.9987435
> itemfit(irt_model)
            item    S_X2 df.S_X2 RMSEA.S_X2 p.S_X2
1 immig_legalize 112.343       2      0.037      0
2   immig_border 148.892       2      0.042      0
3   immig_report  19.166       2      0.014      0
4   immig_reduce 110.123       2      0.036      0
5     immig_wall 151.586       2      0.043      0
> q3 <- residuals(irt_model, type = "Q3") # check local independence problem
Q3 summary statistics:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -0.391  -0.294  -0.208  -0.224  -0.120  -0.115

               immig_legalize immig_border immig_report immig_reduce immig_wall
immig_legalize          1.000       -0.120       -0.115       -0.120     -0.222
immig_border           -0.120        1.000       -0.281       -0.194     -0.298
immig_report           -0.115       -0.281        1.000       -0.118     -0.391
immig_reduce           -0.120       -0.194       -0.118        1.000     -0.377
immig_wall             -0.222       -0.298       -0.391       -0.377      1.000
> summary(q3[lower.tri(q3)])  # See average magnitude
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-0.3908 -0.2938 -0.2081 -0.2235 -0.1198 -0.1146
```

Figure D.13: Fit Test (2020)

Although the p-value of M2 (0) rejects the fitted 2PLM, it is because of the large sample size. RMSEA (0.025) is very small, which indicates excellent approximate fit. SRMSR is only 0.010, which indicates minimal residual correlations. TLI & CFI are bigger than 0.99, which suggest excellent comparative fit. In short, the model fits the data very well.

A similar situation happens to item-level fit. the p-value for S_X2 for all items are 0, which rejects the item-level fit due to the large sample size. But RMSEA values are very small, which indicate that approximate fit is acceptable. Items immig_border and immig_wall have slighly worse fit than immig_report, as their S_X2 values show.

Although the Q3 value of the pair immig_report & immig_wall (-0.391) shows modest negative local dependence, most other correlations have acceptable Q3 values. The mean Q3 (-0.224) indicates slightly negative overall local dependence, but nothing extreme is found.

D.7 2024

The question about Dreamers is not included because it causes poor global model-data fit. The other four questions are kept. 49,112 cases remain.

D.7.1 Item Coefficients

```
> coef(irt_model, IRTpars = TRUE, simplify = TRUE)
$items
                    a      b g u
immig_legalize 1.921 -0.411 0 1
immig_wall     4.492 -0.001 0 1
immig_border   2.131  1.118 0 1
immig_asylum   2.894  0.342 0 1
```

Figure D.14: Item Coefficients (2024)

D.7.2 Goodness of Fit

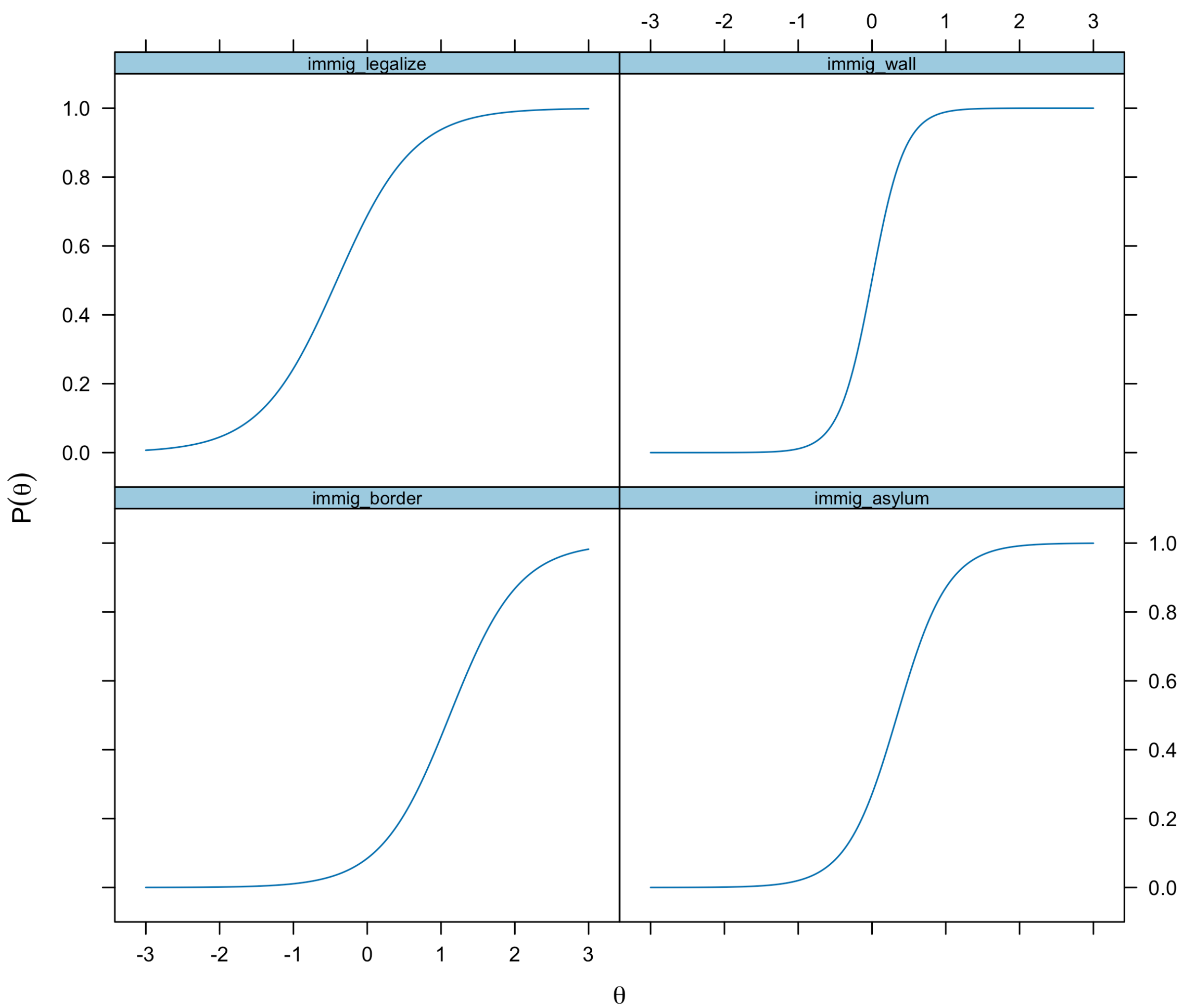


Figure D.15: ICC Plots for Questions of Attitudes Toward Immigrants (2024)

```
> M2(irt_model)
            M2 df p      RMSEA    RMSEA_5   RMSEA_95      SRMSR       TLI       CFI
stats 421.4181  2 0 0.06534603 0.06017158 0.07067445 0.02089516 0.9768961 0.9922987
> itemfit(irt_model)
            item   S_X2 df.S_X2 RMSEA.S_X2 p.S_X2
1 immig_legalize 150.888       1      0.055  0.000
2     immig_wall   4.550       1      0.009  0.033
3   immig_border   8.131       1      0.012  0.004
4   immig_asylum  46.549       1      0.030  0.000
> q3 <- residuals(irt_model, type = "Q3") # check local independence problem
Q3 summary statistics:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -0.622  -0.304  -0.196  -0.281  -0.177  -0.160

               immig_legalize immig_wall immig_border immig_asylum
immig_legalize          1.000     -0.335       -0.182       -0.160
immig_wall             -0.335      1.000       -0.175       -0.622
immig_border           -0.182     -0.175        1.000       -0.210
immig_asylum           -0.160     -0.622       -0.210        1.000
> summary(q3[lower.tri(q3)])
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-0.6221 -0.3039 -0.1958 -0.2807 -0.1767 -0.1604
```

Figure D.16: Fit Test (2024)

D.8 Supplementary Tables

D.8.1 DV is From IRT models

Table D.1: Complete Results of 2010 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	1.715	0.058	1.603	1.828	✓	1.584	0.042	1.501	1.663	✓
ideology	-0.415	0.014	-0.444	-0.387	✓	-0.368	0.009	-0.386	-0.350	✓
segregation	-0.429	0.129	-0.682	-0.178	✓	-0.109	0.104	-0.308	0.100	
proportion	0.004	0.004	-0.003	0.011		-0.002	0.001	-0.005	0.001	
seg.×ideo.	0.142	0.033	0.079	0.208	✓	0.042	0.027	-0.011	0.093	
prop.×ideo	0.001	0.001	0.000	0.002		0.000	0.000	-0.000	0.000	
prop×seg.	-0.013	0.010	-0.032	0.006		0.006	0.003	-0.000	0.012	
male	-0.091	0.006	-0.104	-0.079	✓	-0.092	0.006	-0.104	-0.079	✓
white	-0.223	0.008	-0.238	-0.207	✓	-0.224	0.008	-0.239	-0.209	✓
income	0.000	0.001	-0.002	0.002		0.001	0.001	-0.002	0.003	
education	0.090	0.008	0.074	0.105	✓	0.091	0.008	0.075	0.106	✓
unemployed	-0.033	0.013	-0.058	-0.008	✓	-0.033	0.012	-0.057	-0.009	✓
age	-0.003	0.000	-0.004	-0.003	✓	-0.003	0.000	-0.004	-0.003	✓
evangelical	-0.038	0.008	-0.053	-0.023	✓	-0.038	0.008	-0.053	-0.022	✓
relig. importance	-0.011	0.003	-0.018	-0.004	✓	-0.012	0.003	-0.018	-0.005	✓
unemploy. rate	-0.005	0.002	-0.008	-0.002	✓	-0.005	0.002	-0.008	-0.001	✓
urban 1	0.008	0.009	-0.010	0.025		0.001	0.009	-0.017	0.018	
urban 2	0.001	0.019	-0.038	0.038		-0.006	0.019	-0.043	0.034	
urban 3	0.004	0.016	-0.027	0.035		-0.005	0.015	-0.036	0.025	
urban 4	-0.004	0.017	-0.038	0.030		-0.009	0.017	-0.043	0.025	

Note: The DV is the estimate of the latent trait from IRT models, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

Table D.2: Complete Results of 2012 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	1.841	0.067	1.708	1.972	✓	1.858	0.070	1.722	1.993	✓
ideology	-0.411	0.017	-0.445	-0.377	✓	-0.431	0.018	-0.467	-0.396	✓
segregation	-0.591	0.152	-0.884	-0.287	✓	-0.511	0.133	-0.771	-0.256	✓
proportion	-0.001	0.005	-0.010	0.008		0.001	0.002	-0.003	0.005	
seg.×ideo.	0.152	0.041	0.072	0.231	✓	0.174	0.035	0.106	0.243	✓
prop.×ideo	0.002	0.001	0.001	0.003	✓	0.000	0.000	0.000	0.001	
prop×seg.	-0.007	0.012	-0.031	0.017		-0.004	0.004	-0.012	0.004	
male	-0.119	0.007	-0.133	-0.104	✓	-0.119	0.007	-0.133	-0.105	✓
white	-0.309	0.009	-0.327	-0.292	✓	-0.312	0.009	-0.330	-0.295	✓
income	-0.002	0.001	-0.004	0.001		-0.002	0.001	-0.004	0.001	
education	0.074	0.008	0.058	0.090	✓	0.075	0.008	0.059	0.091	✓
unemployed	-0.043	0.013	-0.069	-0.017	✓	-0.042	0.013	-0.069	-0.015	✓
age	-0.004	0.000	-0.004	-0.004	✓	-0.004	0.000	-0.004	-0.004	✓
evangelical	-0.040	0.009	-0.058	-0.023	✓	-0.042	0.009	-0.060	-0.025	✓
relig. importance	-0.004	0.004	-0.012	0.003		-0.005	0.004	-0.012	0.003	
unemploy. rate	-0.005	0.002	-0.009	-0.001	✓	-0.004	0.002	-0.008	0.000	
urban 1	-0.009	0.010	-0.030	0.012		-0.022	0.010	-0.042	-0.002	✓
urban 2	-0.045	0.023	-0.089	0.001		-0.061	0.023	-0.107	-0.016	✓
urban 3	-0.032	0.018	-0.067	0.003		-0.054	0.018	-0.088	-0.020	✓
urban 4	-0.017	0.020	-0.057	0.023		-0.035	0.020	-0.073	0.004	

Note: The DV is the estimate of the latent trait from IRT models, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

Table D.3: Complete Results of 2020 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	1.988	0.060	1.870	2.103	✓	1.845	0.038	1.770	1.920	✓
ideology	-0.502	0.016	-0.534	-0.470	✓	-0.472	0.009	-0.489	-0.454	✓
segregation	-0.599	0.123	-0.840	-0.359	✓	-0.384	0.108	-0.594	-0.175	✓
proportion	-0.031	0.005	-0.040	-0.021	✓	-0.001	0.002	-0.004	0.002	
seg.×ideo.	0.155	0.034	0.088	0.222	✓	0.174	0.029	0.118	0.231	✓
prop.×ideo	0.006	0.001	0.005	0.008	✓	0.001	0.000	0.000	0.001	
prop×seg.	0.048	0.013	0.023	0.073	✓	-0.004	0.004	-0.011	0.004	
male	-0.158	0.007	-0.171	-0.145	✓	-0.157	0.007	-0.171	-0.144	✓
white	-0.069	0.008	-0.084	-0.053	✓	-0.074	0.008	-0.089	-0.058	✓
income	0.002	0.001	-0.001	0.004		0.002	0.001	-0.000	0.004	
education	0.128	0.008	0.114	0.143	✓	0.130	0.007	0.115	0.145	✓
unemployed	-0.025	0.012	-0.049	-0.002	✓	-0.024	0.012	-0.048	-0.001	✓
age	-0.004	0.000	-0.004	-0.004	✓	-0.004	0.000	-0.004	-0.004	✓
evangelical	-0.088	0.009	-0.105	-0.071	✓	-0.089	0.009	-0.106	-0.073	✓
relig. importance	-0.059	0.003	-0.066	-0.053	✓	-0.060	0.003	-0.066	-0.053	✓
unemploy. rate	-0.009	0.002	-0.013	-0.004	✓	-0.009	0.002	-0.013	-0.005	✓
urban 1	-0.004	0.009	-0.022	0.015		-0.014	0.009	-0.032	0.004	
urban 2	-0.060	0.019	-0.097	-0.023	✓	-0.079	0.018	-0.116	-0.043	✓
urban 3	-0.017	0.015	-0.047	0.013		-0.042	0.014	-0.070	-0.013	✓
urban 4	0.000	0.018	-0.036	0.035		-0.020	0.018	-0.055	0.014	

Note: The DV is the estimate of the latent trait from IRT models, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

Table D.4: Complete Results of 2024 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	2.128	0.056	2.020	2.238	✓	2.236	0.055	2.129	2.344	✓
ideology	-0.485	0.015	-0.515	-0.455	✓	-0.516	0.015	-0.545	-0.487	✓
segregation	-0.617	0.118	-0.847	-0.388	✓	-0.757	0.107	-0.966	-0.547	✓
proportion	-0.016	0.004	-0.024	-0.007	✓	-0.004	0.002	-0.007	-0.001	✓
seg.×ideo.	0.148	0.033	0.083	0.212	✓	0.205	0.029	0.147	0.262	✓
prop.×ideo	0.004	0.001	0.003	0.005	✓	0.001	0.000	0.001	0.001	✓
prop×seg.	0.021	0.012	-0.002	0.044		0.004	0.003	-0.002	0.010	
male	-0.096	0.006	-0.107	-0.084	✓	-0.095	0.006	-0.106	-0.084	✓
white	-0.106	0.007	-0.119	-0.092	✓	-0.108	0.007	-0.121	-0.095	✓
income	-0.002	0.001	-0.004	-0.000		-0.002	0.001	-0.004	-0.000	
education	0.094	0.007	0.081	0.107	✓	0.095	0.007	0.082	0.108	✓
unemployed	-0.006	0.012	-0.030	0.018		-0.006	0.012	-0.029	0.017	
age	-0.006	0.000	-0.006	-0.006	✓	-0.006	0.000	-0.006	-0.006	✓
evangelical	-0.033	0.008	-0.048	-0.018	✓	-0.035	0.007	-0.050	-0.021	✓
relig. importance	-0.075	0.003	-0.081	-0.069	✓	-0.074	0.003	-0.080	-0.068	✓
unemploy. rate	-0.012	0.003	-0.018	-0.005	✓	-0.013	0.004	-0.020	-0.005	✓
urban 1	0.014	0.008	-0.003	0.030		0.004	0.008	-0.012	0.020	
urban 2	-0.015	0.017	-0.050	0.019		-0.028	0.018	-0.063	0.006	
urban 3	0.001	0.014	-0.026	0.028		-0.013	0.014	-0.039	0.014	
urban 4	0.026	0.016	-0.006	0.058		0.011	0.016	-0.019	0.042	

Note: The DV is the estimate of the latent trait from IRT models, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

D.8.2 DV is an Index

Table D.5: Complete Results of 2010 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	3.753	0.083	3.591	3.917	✓	3.537	0.061	3.417	3.657	✓
ideology	-0.592	0.021	-0.633	-0.551	✓	-0.520	0.013	-0.546	-0.494	✓
segregation	-0.666	0.183	-1.026	-0.314	✓	-0.113	0.148	-0.401	0.179	
proportion	0.006	0.005	-0.004	0.017		-0.003	0.002	-0.007	0.001	
seg.×ideo.	0.211	0.048	0.117	0.306	✓	0.046	0.038	-0.028	0.121	
prop.×ideo	0.002	0.001	0.000	0.003		0.000	0.000	-0.000	0.001	
prop×seg.	-0.017	0.014	-0.045	0.012		0.008	0.005	-0.000	0.017	
male	-0.128	0.009	-0.146	-0.110	✓	-0.128	0.009	-0.146	-0.109	✓
white	-0.302	0.011	-0.324	-0.281	✓	-0.305	0.011	-0.327	-0.282	✓
income	0.001	0.002	-0.003	0.004		0.001	0.002	-0.002	0.004	
education	0.124	0.011	0.101	0.147	✓	0.125	0.012	0.103	0.148	✓
unemployed	-0.050	0.018	-0.086	-0.016	✓	-0.049	0.018	-0.085	-0.014	✓
age	-0.004	0.000	-0.005	-0.003	✓	-0.004	0.000	-0.005	-0.003	✓
evangelical	-0.058	0.011	-0.081	-0.036	✓	-0.058	0.011	-0.080	-0.036	✓
relig. importance	-0.019	0.005	-0.028	-0.009	✓	-0.020	0.005	-0.029	-0.010	✓
unemploy. rate	-0.008	0.002	-0.012	-0.003	✓	-0.007	0.002	-0.012	-0.003	✓
urban 1	0.015	0.013	-0.010	0.040		0.005	0.012	-0.020	0.029	
urban 2	0.014	0.028	-0.042	0.067		0.005	0.028	-0.048	0.060	
urban 3	0.013	0.022	-0.030	0.057		-0.000	0.022	-0.043	0.043	
urban 4	0.004	0.025	-0.044	0.052		-0.002	0.025	-0.051	0.046	

Note: The DV is an index of the questions about attitudes toward immigrants, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

Table D.6: Complete Results of 2012 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	7.566	0.156	7.258	7.866	✓	7.624	0.165	7.299	7.951	✓
ideology	-0.969	0.040	-1.048	-0.890	✓	-1.017	0.042	-1.099	-0.934	✓
segregation	-1.322	0.349	-1.988	-0.636	✓	-1.190	0.308	-1.793	-0.596	✓
proportion	-0.001	0.011	-0.022	0.020		0.002	0.005	-0.008	0.011	
seg.×ideo.	0.342	0.095	0.153	0.528	✓	0.402	0.082	0.241	0.559	✓
prop.×ideo	0.005	0.002	0.002	0.008	✓	0.001	0.000	0.000	0.002	
prop×seg.	-0.019	0.029	-0.075	0.037		-0.009	0.010	-0.028	0.011	
male	-0.275	0.017	-0.308	-0.242	✓	-0.274	0.017	-0.309	-0.241	✓
white	-0.743	0.021	-0.783	-0.702	✓	-0.750	0.021	-0.792	-0.708	✓
income	-0.005	0.003	-0.011	0.000		-0.005	0.003	-0.010	0.001	
education	0.167	0.020	0.128	0.205	✓	0.170	0.019	0.132	0.208	✓
unemployed	-0.094	0.031	-0.156	-0.034	✓	-0.092	0.031	-0.153	-0.031	✓
age	-0.010	0.001	-0.011	-0.009	✓	-0.010	0.001	-0.011	-0.009	✓
evangelical	-0.093	0.022	-0.135	-0.050	✓	-0.098	0.021	-0.140	-0.056	✓
relig. importance	-0.011	0.009	-0.030	0.007		-0.011	0.009	-0.030	0.006	
unemploy. rate	-0.011	0.005	-0.020	-0.001	✓	-0.009	0.005	-0.019	0.001	
urban 1	-0.020	0.025	-0.069	0.029		-0.051	0.025	-0.098	-0.001	✓
urban 2	-0.107	0.052	-0.208	-0.006	✓	-0.145	0.054	-0.252	-0.041	✓
urban 3	-0.078	0.043	-0.160	0.005		-0.130	0.042	-0.210	-0.047	✓
urban 4	-0.037	0.048	-0.130	0.057		-0.081	0.047	-0.171	0.012	

Note: The DV is an index of the questions about attitudes toward immigrants, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

Table D.7: Complete Results of 2016 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	4.667	0.101	4.470	4.869	✓	5.098	0.103	4.901	5.302	✓
ideology	-0.611	0.028	-0.666	-0.557	✓	-0.721	0.028	-0.776	-0.666	✓
segregation	-0.047	0.234	-0.504	0.405		-0.979	0.205	-1.383	-0.580	✓
proportion	-0.019	0.007	-0.033	-0.005	✓	-0.007	0.003	-0.013	-0.001	✓
seg.×ideo.	-0.022	0.065	-0.147	0.105		0.254	0.057	0.143	0.367	✓
prop.×ideo	0.008	0.001	0.006	0.010	✓	0.002	0.000	0.002	0.003	✓
prop×seg.	0.010	0.019	-0.027	0.048		0.005	0.006	-0.007	0.017	
male	-0.187	0.011	-0.208	-0.166	✓	-0.185	0.011	-0.206	-0.164	✓
white	-0.263	0.013	-0.289	-0.239	✓	-0.267	0.013	-0.293	-0.242	✓
income	0.006	0.002	0.002	0.010	✓	0.006	0.002	0.003	0.010	✓
education	0.175	0.013	0.150	0.200	✓	0.176	0.013	0.150	0.201	✓
unemployed	-0.113	0.025	-0.162	-0.065	✓	-0.112	0.026	-0.164	-0.060	✓
age	-0.006	0.000	-0.007	-0.005	✓	-0.006	0.000	-0.007	-0.005	✓
evangelical	-0.081	0.014	-0.108	-0.053	✓	-0.084	0.014	-0.113	-0.057	✓
relig. importance	-0.067	0.006	-0.078	-0.056	✓	-0.066	0.006	-0.077	-0.055	✓
unemploy. rate	-0.018	0.005	-0.028	-0.008	✓	-0.019	0.005	-0.029	-0.009	✓
urban 1	0.014	0.016	-0.018	0.045		-0.006	0.015	-0.036	0.024	
urban 2	-0.033	0.034	-0.100	0.034		-0.057	0.034	-0.124	0.010	
urban 3	-0.026	0.027	-0.080	0.027		-0.054	0.026	-0.106	-0.002	✓
urban 4	-0.060	0.032	-0.121	0.004		-0.086	0.032	-0.147	-0.024	✓

Note: The DV is an index of the questions about attitudes toward immigrants, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

Table D.8: Complete Results of 2020 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant)					Model 2 (Hispanic)				
	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	8.412	0.144	8.133	8.698	✓	8.132	0.096	7.944	8.325	✓
ideology	-1.216	0.040	-1.294	-1.140	✓	-1.158	0.022	-1.202	-1.115	✓
segregation	-1.341	0.299	-1.926	-0.754	✓	-1.112	0.266	-1.627	-0.591	✓
proportion	-0.068	0.012	-0.090	-0.045	✓	-0.003	0.004	-0.010	0.005	
seg.×ideo.	0.346	0.083	0.186	0.509	✓	0.459	0.072	0.317	0.601	✓
prop.×ideo	0.016	0.002	0.013	0.020	✓	0.001	0.001	0.000	0.003	
prop×seg.	0.091	0.031	0.030	0.152	✓	-0.006	0.009	-0.023	0.012	
male	-0.406	0.016	-0.439	-0.375	✓	-0.405	0.016	-0.436	-0.374	✓
white	-0.197	0.019	-0.235	-0.158	✓	-0.208	0.020	-0.247	-0.168	✓
income	0.004	0.003	-0.002	0.009		0.004	0.003	-0.001	0.009	
education	0.274	0.019	0.238	0.311	✓	0.278	0.019	0.241	0.314	✓
unemployed	-0.060	0.030	-0.117	-0.002	✓	-0.057	0.029	-0.115	0.001	
age	-0.009	0.000	-0.010	-0.008	✓	-0.009	0.000	-0.010	-0.008	✓
evangelical	-0.198	0.021	-0.238	-0.158	✓	-0.203	0.021	-0.244	-0.163	✓
relig. importance	-0.109	0.008	-0.125	-0.093	✓	-0.109	0.008	-0.125	-0.093	✓
unemploy. rate	-0.020	0.005	-0.030	-0.011	✓	-0.021	0.005	-0.031	-0.011	✓
urban 1	-0.012	0.023	-0.057	0.034		-0.042	0.022	-0.085	0.001	
urban 2	-0.158	0.046	-0.246	-0.068	✓	-0.206	0.044	-0.292	-0.120	✓
urban 3	-0.039	0.037	-0.113	0.035		-0.100	0.036	-0.171	-0.031	✓
urban 4	0.000	0.044	-0.085	0.086		-0.051	0.042	-0.133	0.031	

Note: The DV is an index of the questions about attitudes toward immigrants, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

Table D.9: Complete Results of 2024 (DV: Attitudes Toward Immigration)

Variable	Model 1 (Immigrant) Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?	Model 2 (Hispanic) Mean	SE	2.5%	97.5%	95% *CrI* excl. 0?
Intercept	3.753	0.083	3.591	3.917	✓	3.537	0.061	3.417	3.657	✓
ideology	-0.592	0.021	-0.633	-0.551	✓	-0.520	0.013	-0.546	-0.494	✓
segregation	-0.666	0.183	-1.026	-0.314	✓	-0.113	0.148	-0.401	0.179	
proportion	0.006	0.005	-0.004	0.017		-0.003	0.002	-0.007	0.001	
seg.×ideo.	0.211	0.048	0.117	0.306	✓	0.046	0.038	-0.028	0.121	
prop.×ideo	0.002	0.001	0.000	0.003		0.000	0.000	-0.000	0.001	
prop×seg.	-0.017	0.014	-0.045	0.012		0.008	0.005	-0.000	0.017	
male	-0.128	0.009	-0.146	-0.110	✓	-0.128	0.009	-0.146	-0.109	✓
white	-0.302	0.011	-0.324	-0.281	✓	-0.305	0.011	-0.327	-0.282	✓
income	0.001	0.002	-0.003	0.004		0.001	0.002	-0.002	0.004	
education	0.124	0.011	0.101	0.147	✓	0.125	0.012	0.103	0.148	✓
unemployed	-0.050	0.018	-0.086	-0.016	✓	-0.049	0.018	-0.085	-0.014	✓
age	-0.004	0.000	-0.005	-0.003	✓	-0.004	0.000	-0.005	-0.003	✓
evangelical	-0.058	0.011	-0.081	-0.036	✓	-0.058	0.011	-0.080	-0.036	✓
relig. importance	-0.019	0.005	-0.028	-0.009	✓	-0.020	0.005	-0.029	-0.010	✓
unemploy. rate	-0.008	0.002	-0.012	-0.003	✓	-0.007	0.002	-0.012	-0.003	✓
urban 1	0.015	0.013	-0.010	0.040		0.005	0.012	-0.020	0.029	
urban 2	0.014	0.028	-0.042	0.067		0.005	0.028	-0.048	0.060	
urban 3	0.013	0.022	-0.030	0.057		-0.000	0.022	-0.043	0.043	
urban 4	0.004	0.025	-0.044	0.052		-0.002	0.025	-0.051	0.046	

Note: The DV is an index of the questions about attitudes toward immigrants, with a higher value indicating more pro-immigration. PID is not controlled for. The base category of urban is large metro. Urban 1 is small metro, urban 2 is nonmetro adjacent to large metro, urban 3 is nonmetro adjacent to small metro, and urban 4 is rural.

D.9 Supplementary Figures

D.9.1 No PID

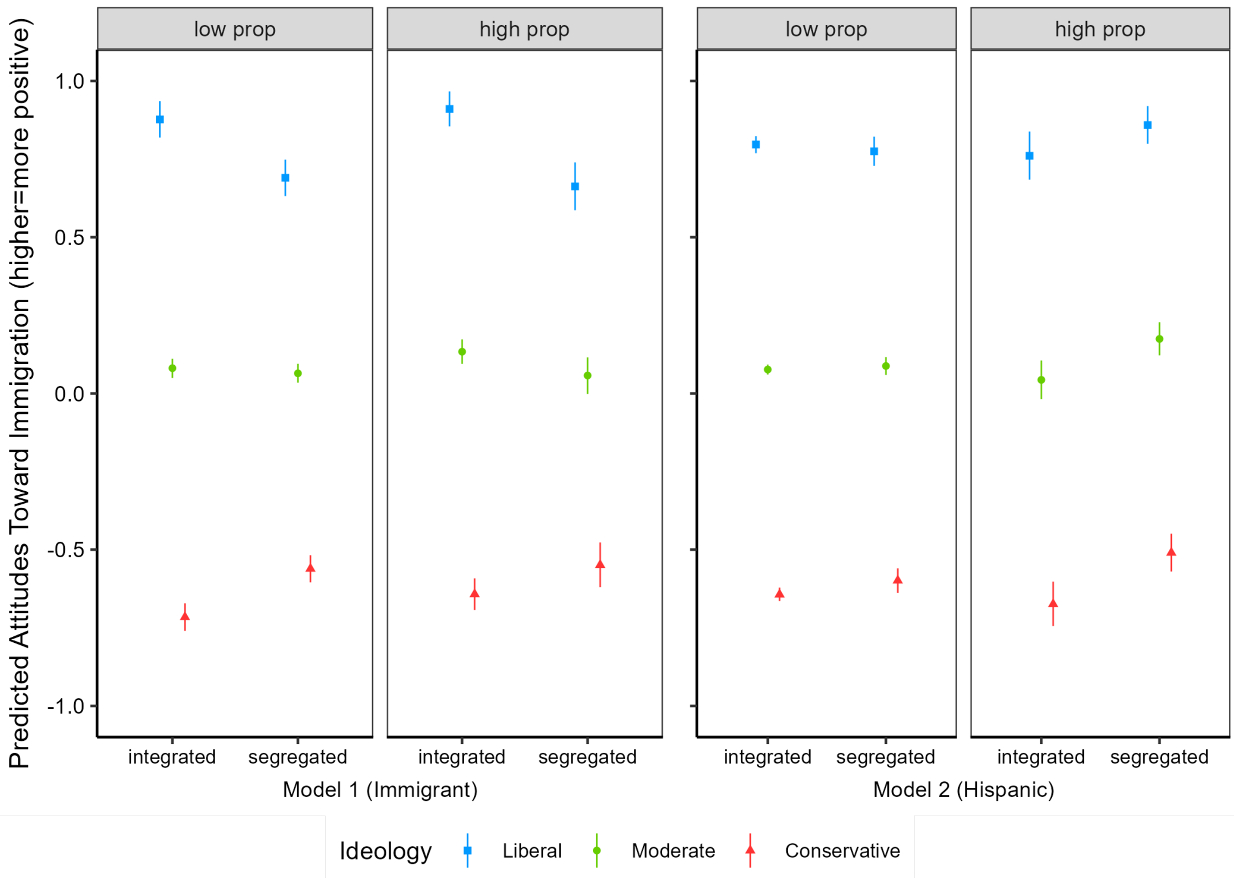


Figure D.17: Predicted Immigration Attitudes (2010)

Note: The DV is the result from IRT models. PID is not controlled for.

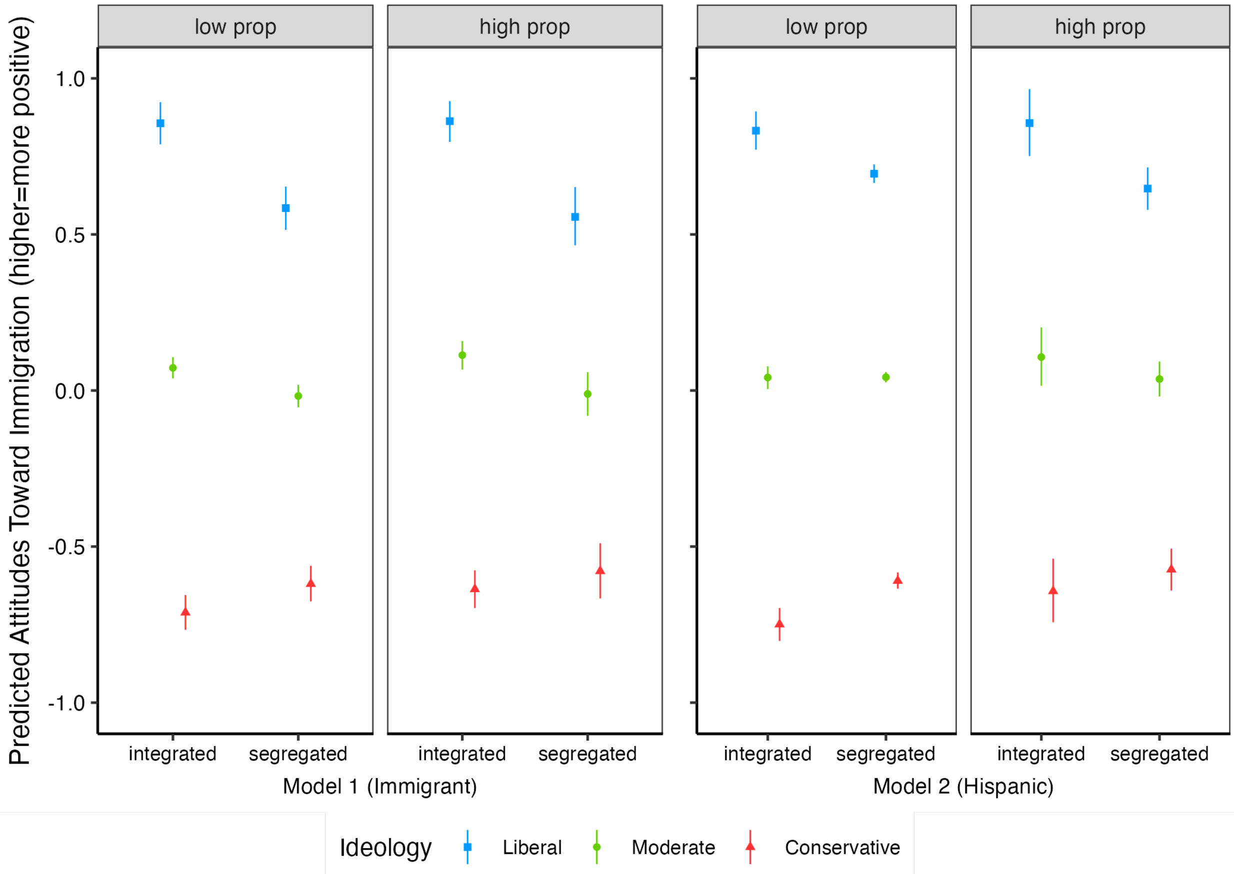


Figure D.18: Predicted Immigration Attitudes (2012)

Note: The DV is the result from IRT models. PID is not controlled for.

2016 is not included because the IRT model has poor global fitness.

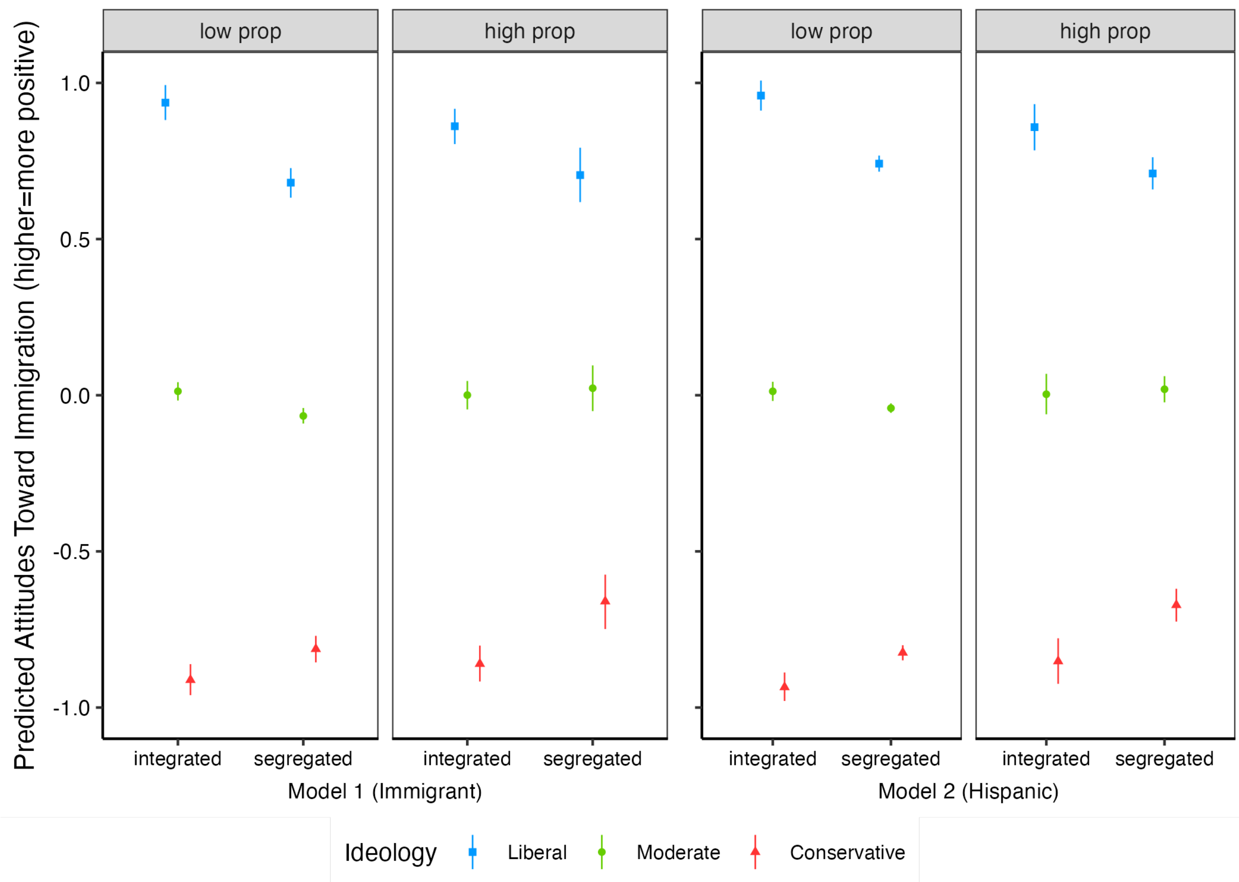


Figure D.19: Predicted Immigration Attitudes (2024)

Note: The DV is the result from IRT models. PID is not controlled for.

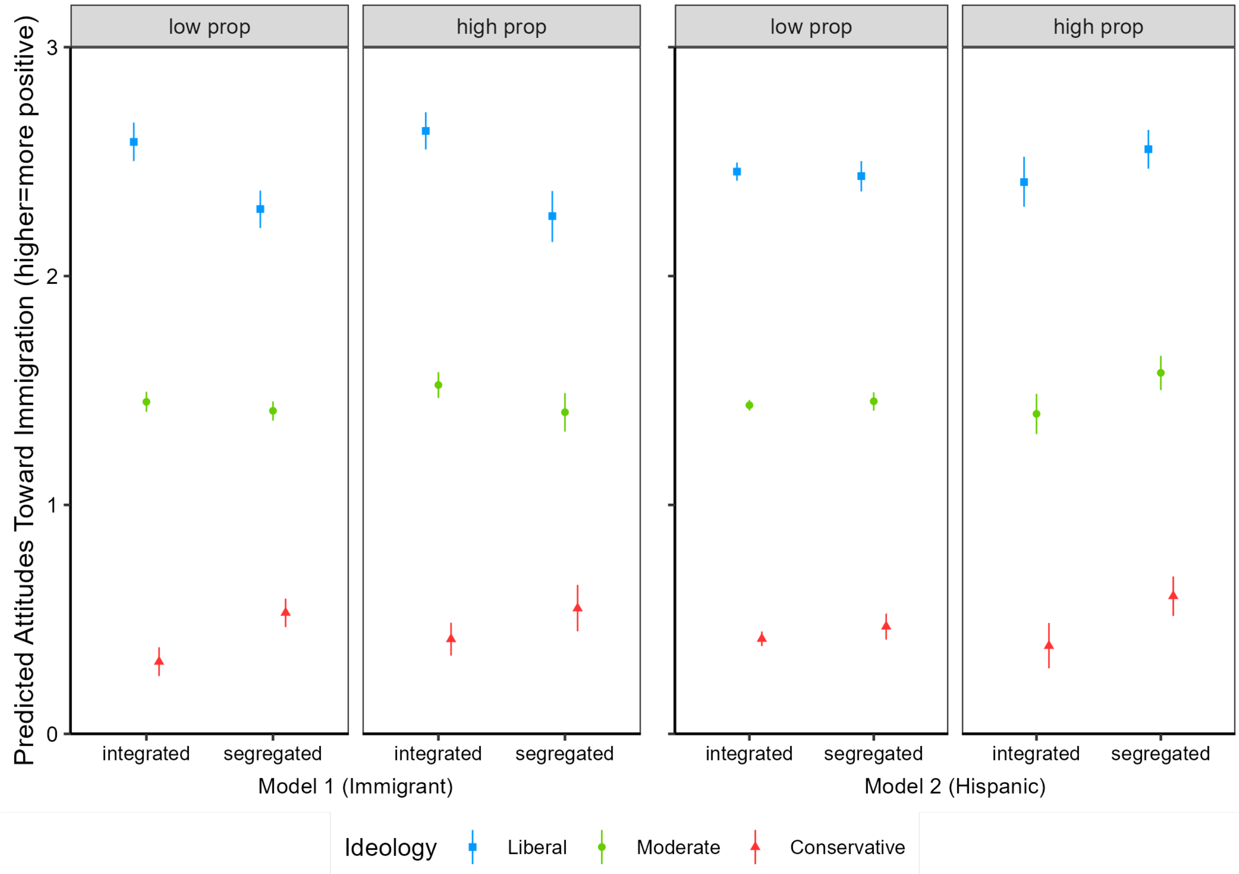


Figure D.20: Predicted Immigration Attitudes (2010)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is not controlled for.

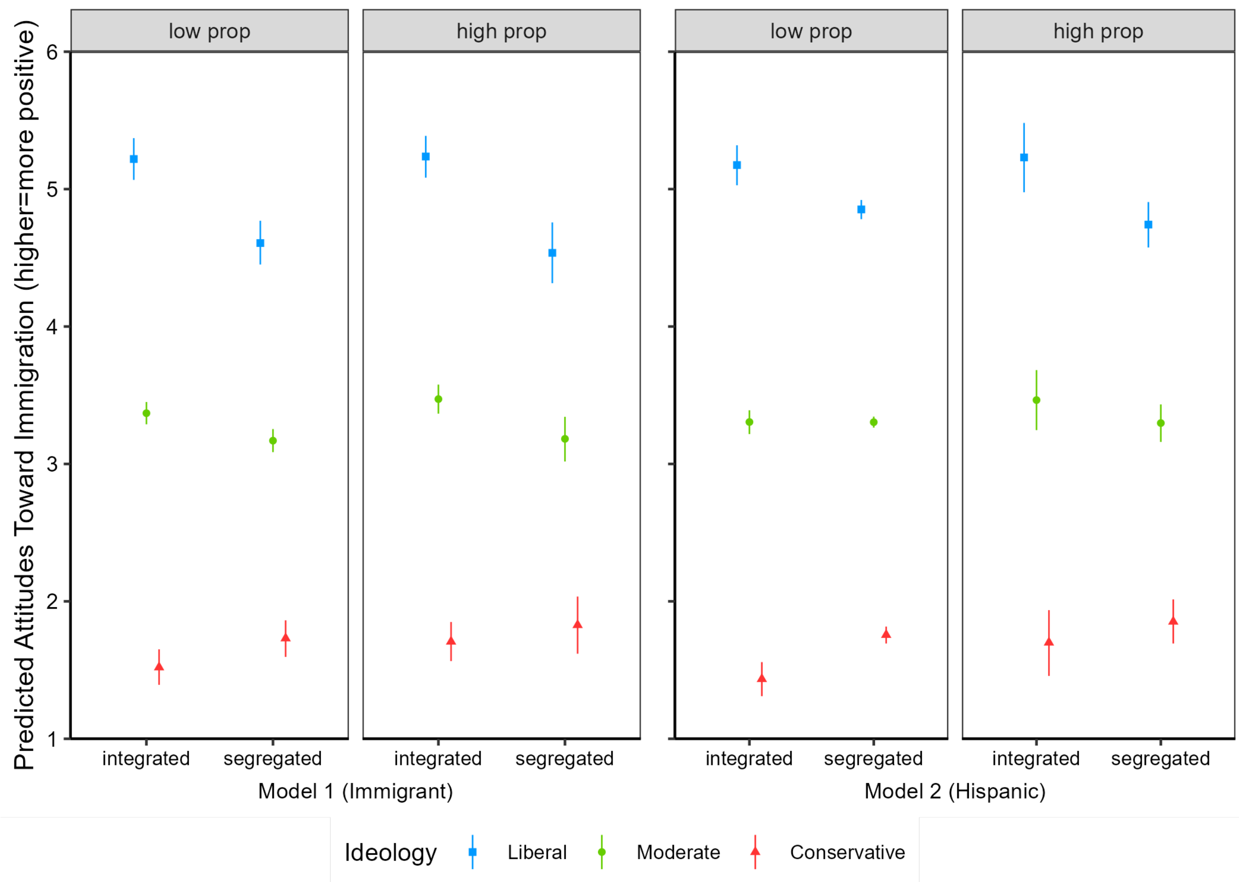


Figure D.21: Predicted Immigration Attitudes (2012)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is not controlled for.

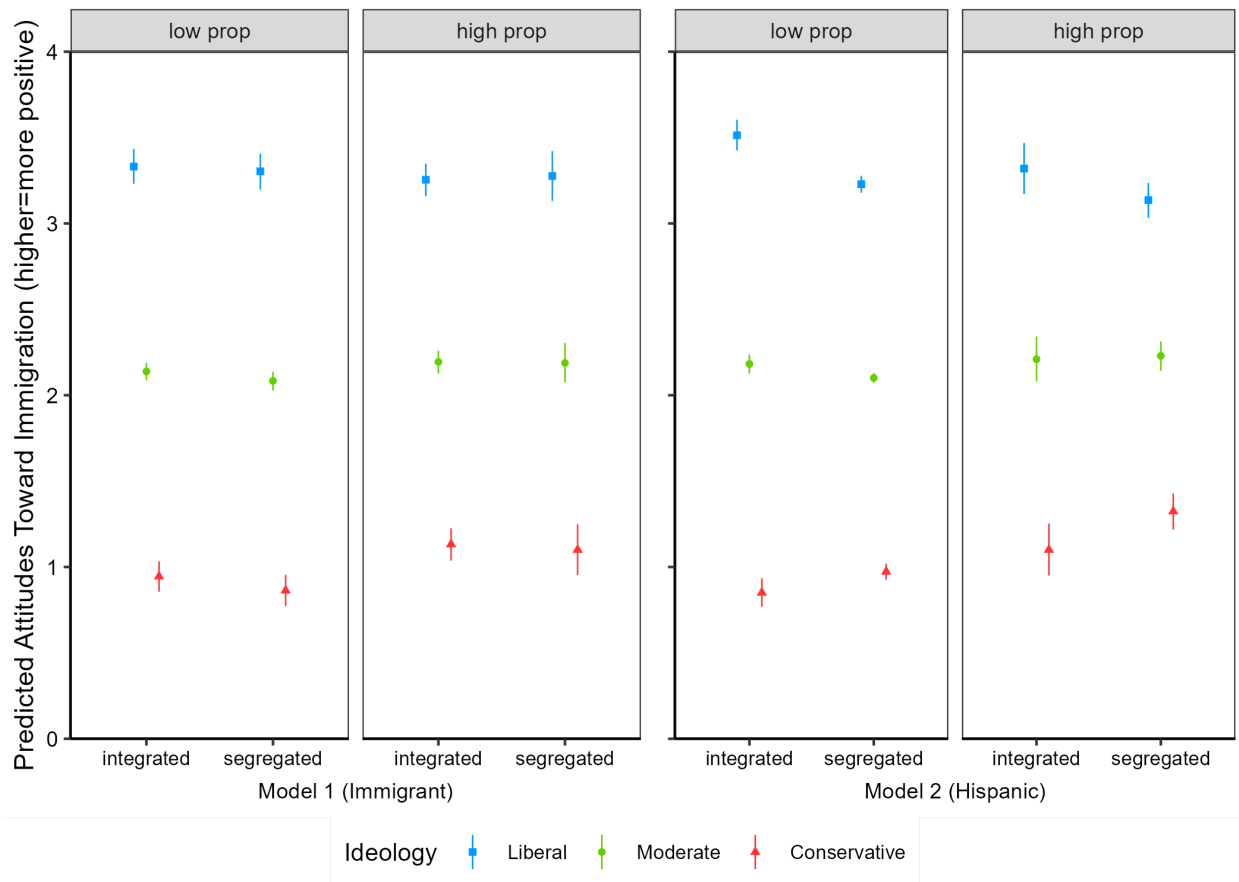


Figure D.22: Predicted Immigration Attitudes (2016)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is not controlled for.

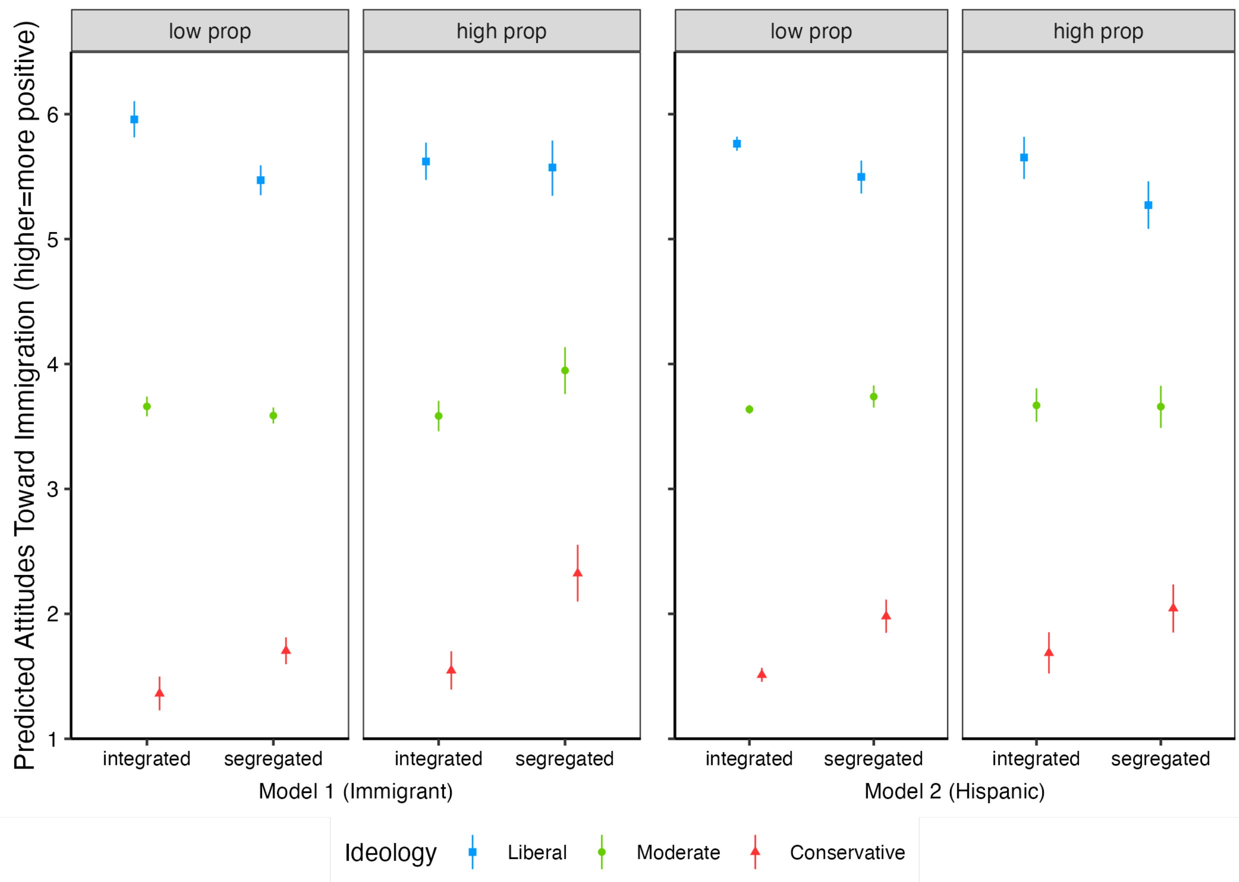


Figure D.23: Predicted Immigration Attitudes (2020)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is not controlled for.

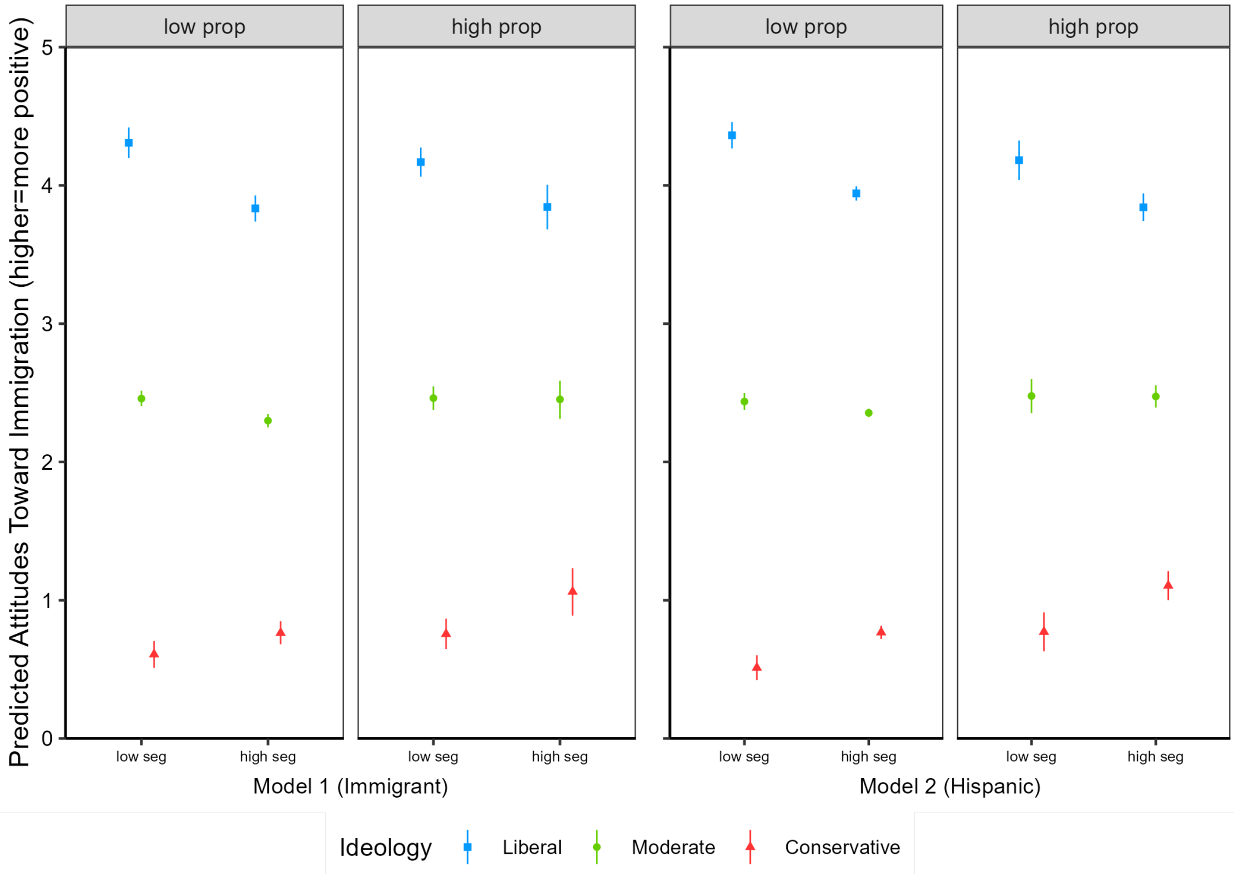


Figure D.24: Predicted Immigration Attitudes (2024)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is not controlled for.

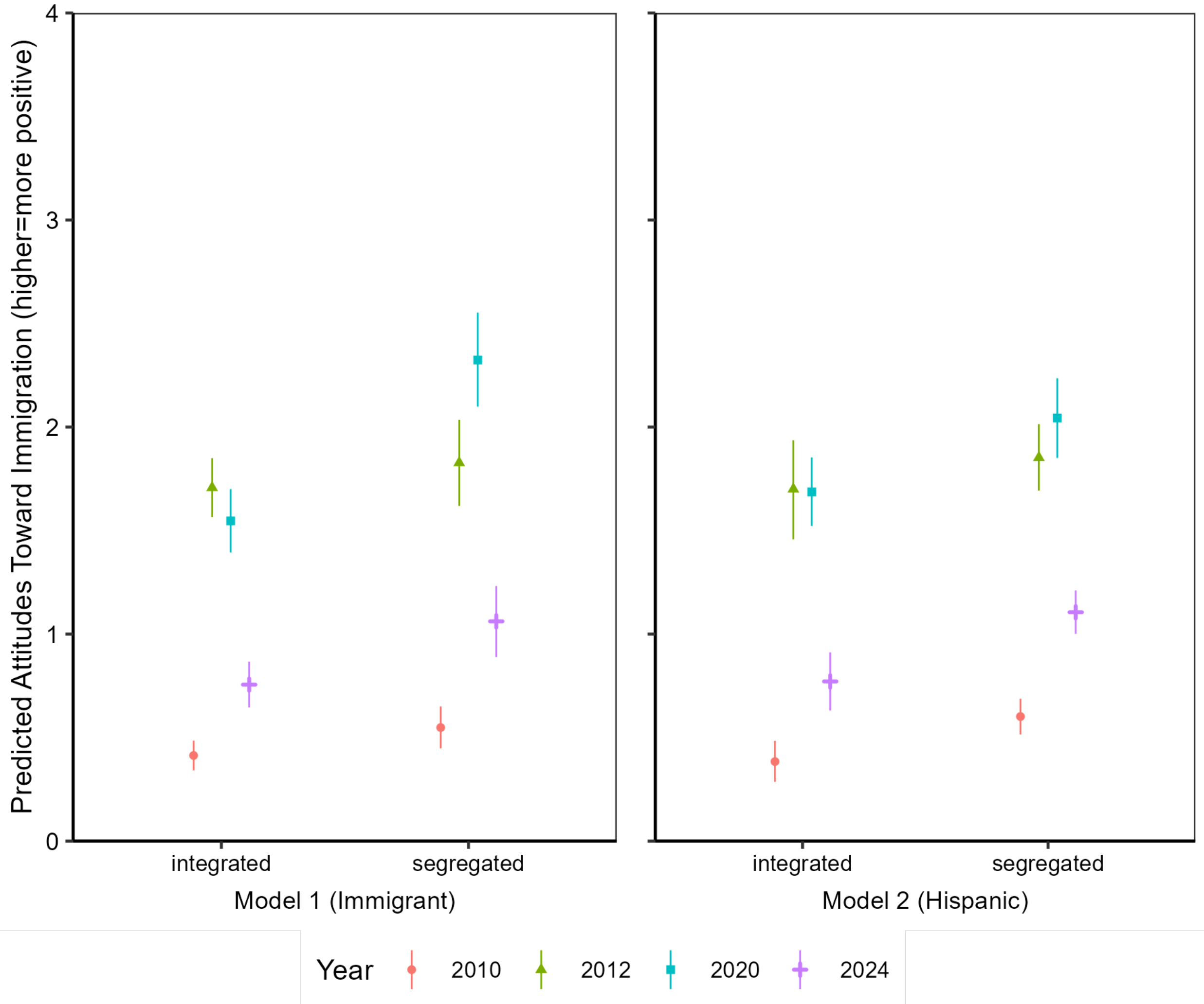


Figure D.25: Predicted Immigration Attitudes (Conservatives in High-Proportion Counties Only)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is not controlled for.

D.9.2 PID is Included

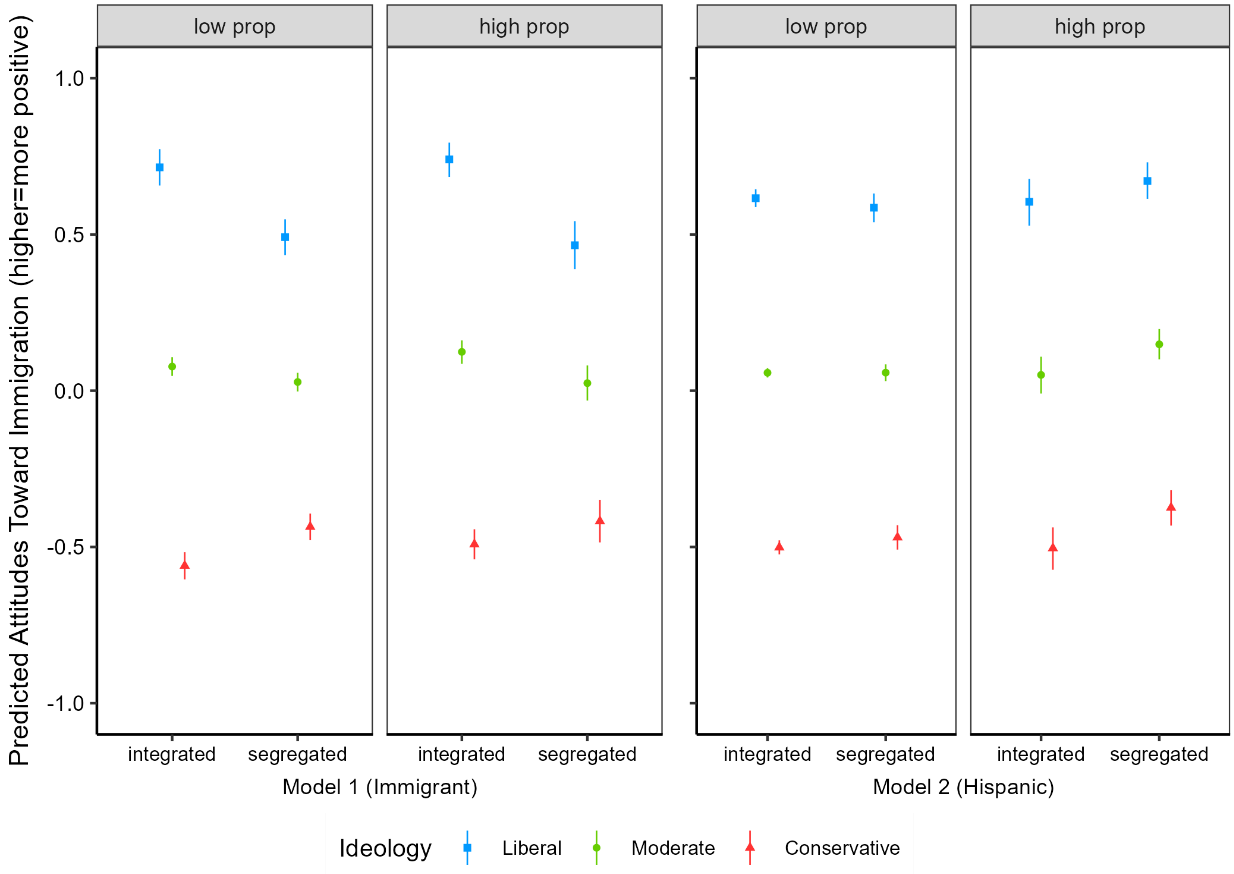


Figure D.26: Predicted Immigration Attitudes (2010)

Note: The DV is the estimate of the latent trait from IRT models. PID is included in the models.

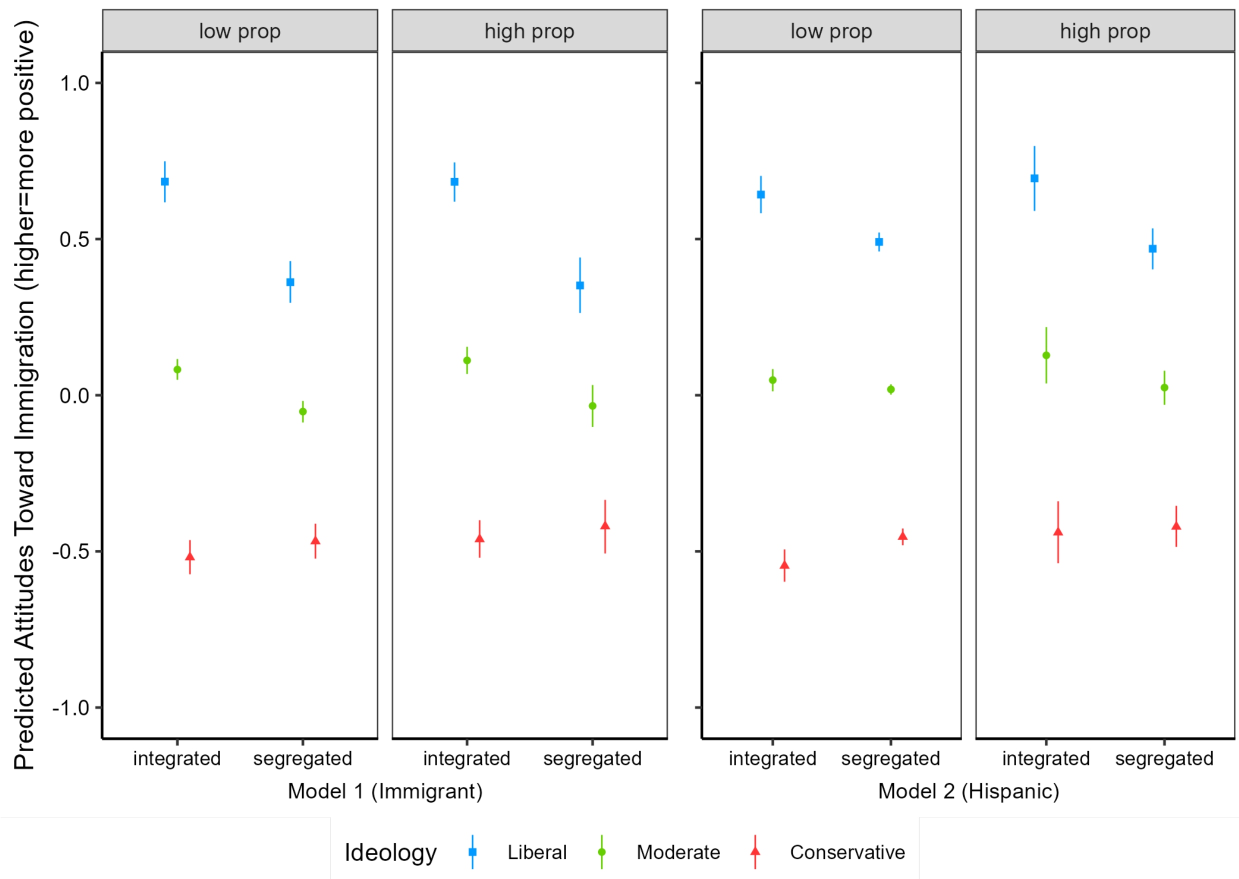


Figure D.27: Predicted Immigration Attitudes (2012)

Note: The DV is the estimate of the latent trait from IRT models. PID is included in the models.

2016 is not included because the IRT model has poor global fitness.

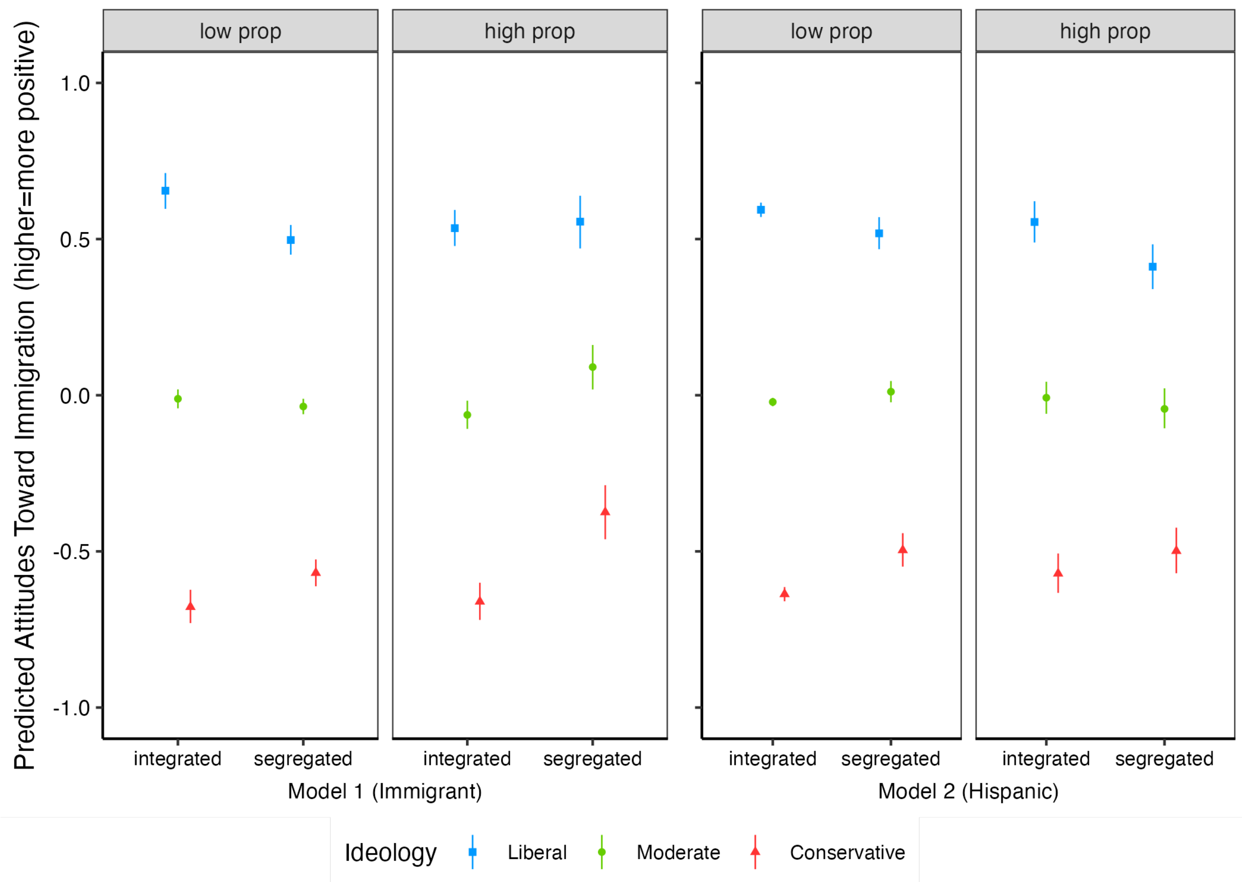


Figure D.28: Predicted Immigration Attitudes (2020)

Note: The DV is the estimate of the latent trait from IRT models. PID is included in the models.

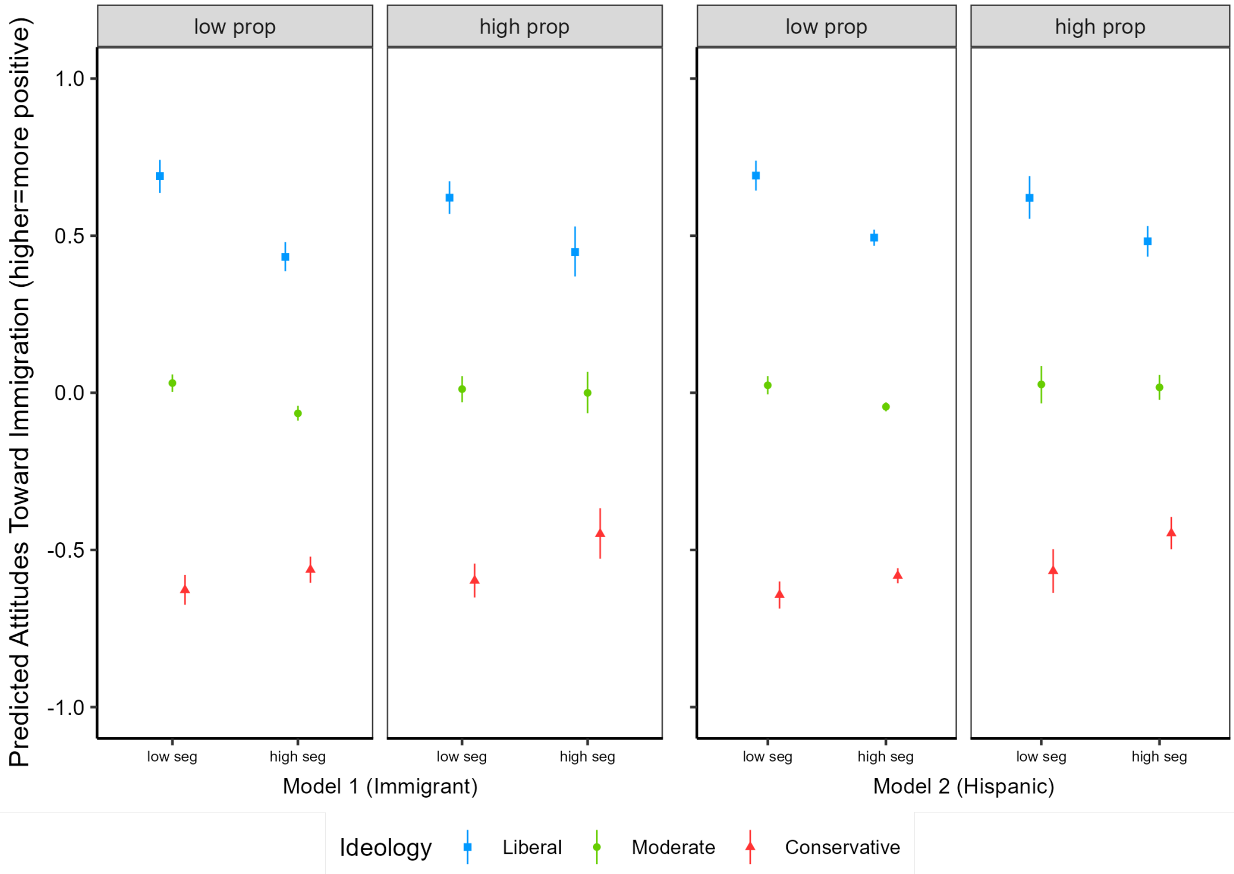


Figure D.29: Predicted Immigration Attitudes (2024)

Note: The DV is the estimate of the latent trait from IRT models. PID is included in the models.

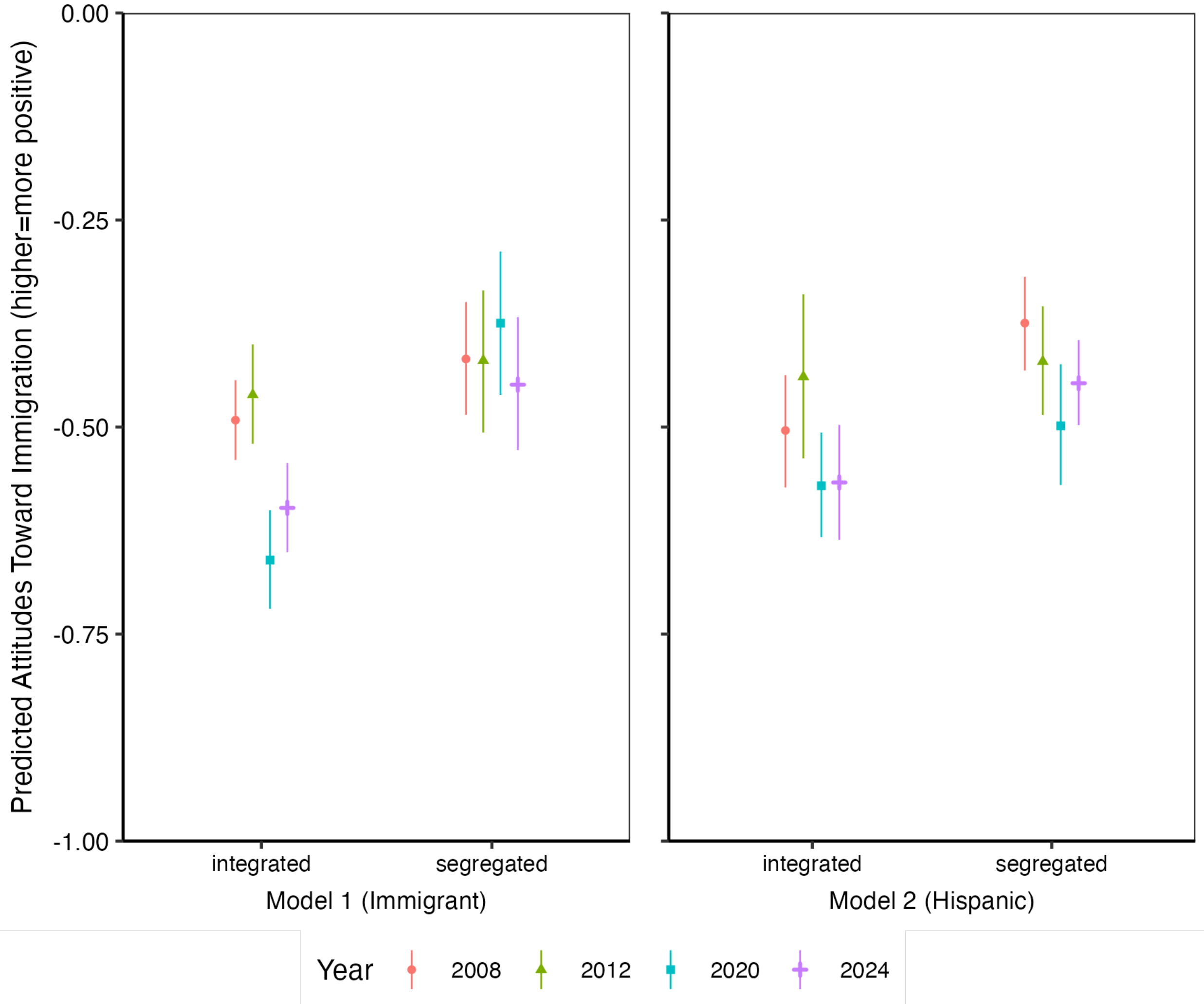


Figure D.30: Predicted Immigration Attitudes (Conservatives in High-Proportion Counties Only)

Note: 2016 is not included because the IRT model has poor global fitness. PID is included in the models.

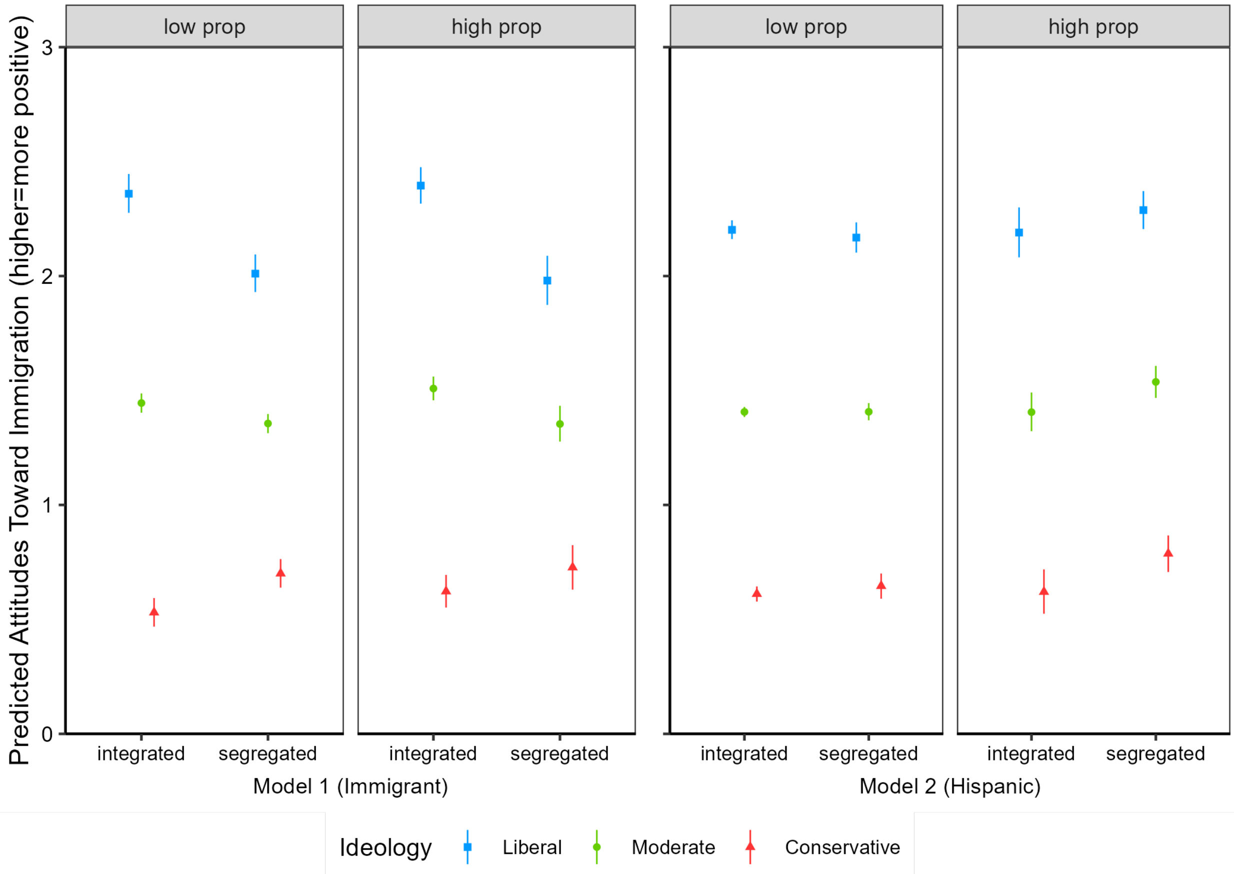


Figure D.31: Predicted Immigration Attitudes (2010)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is included in the models.

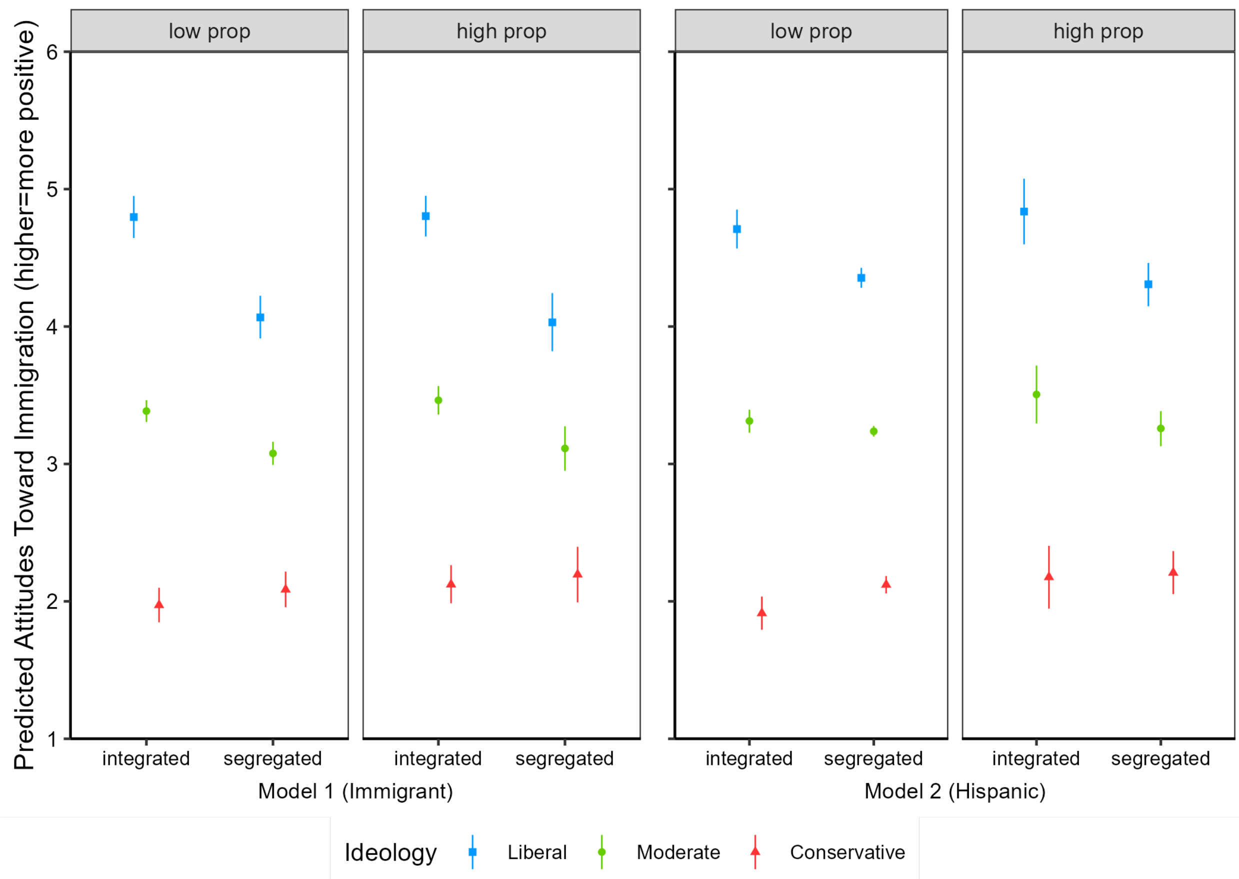


Figure D.32: Predicted Immigration Attitudes (2012)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is included in the models.

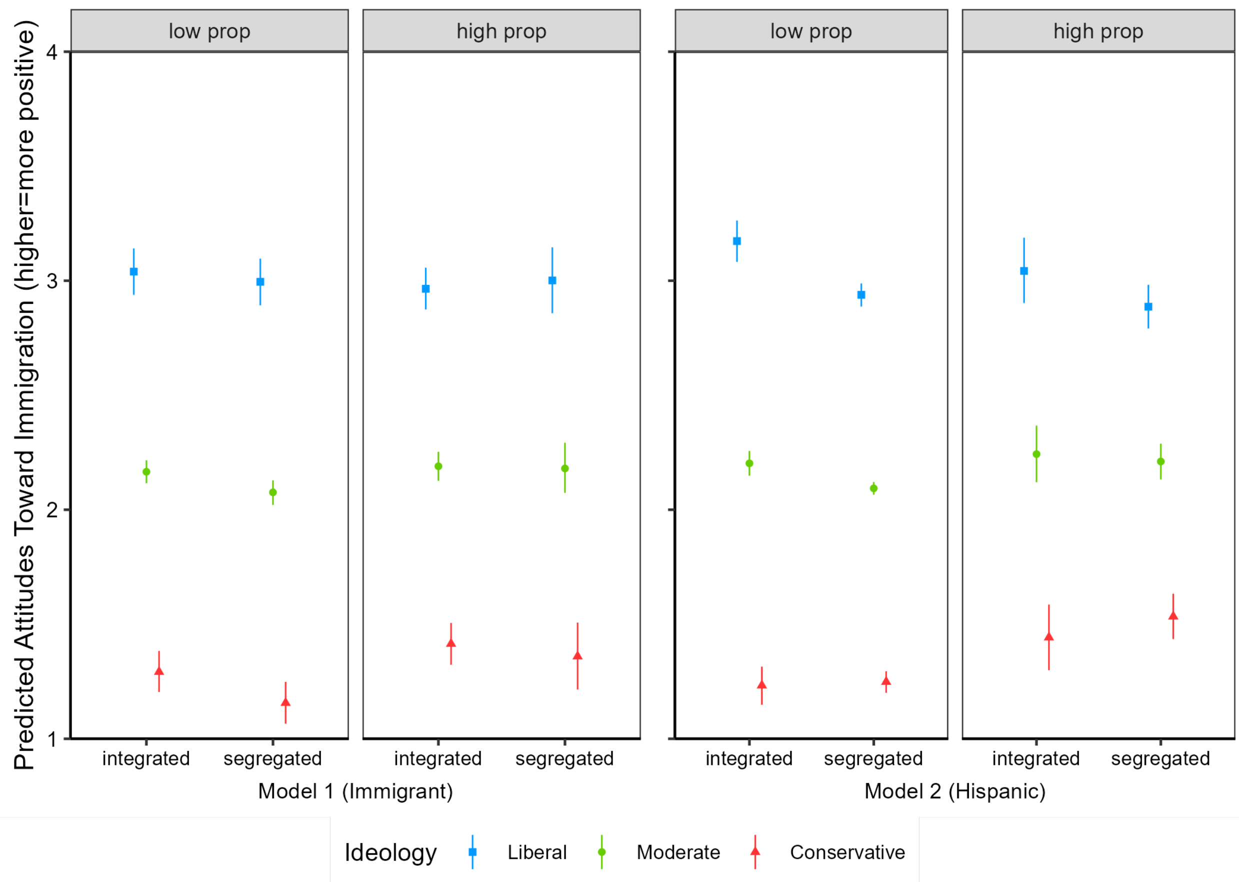


Figure D.33: Predicted Immigration Attitudes (2016)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is included in the models.

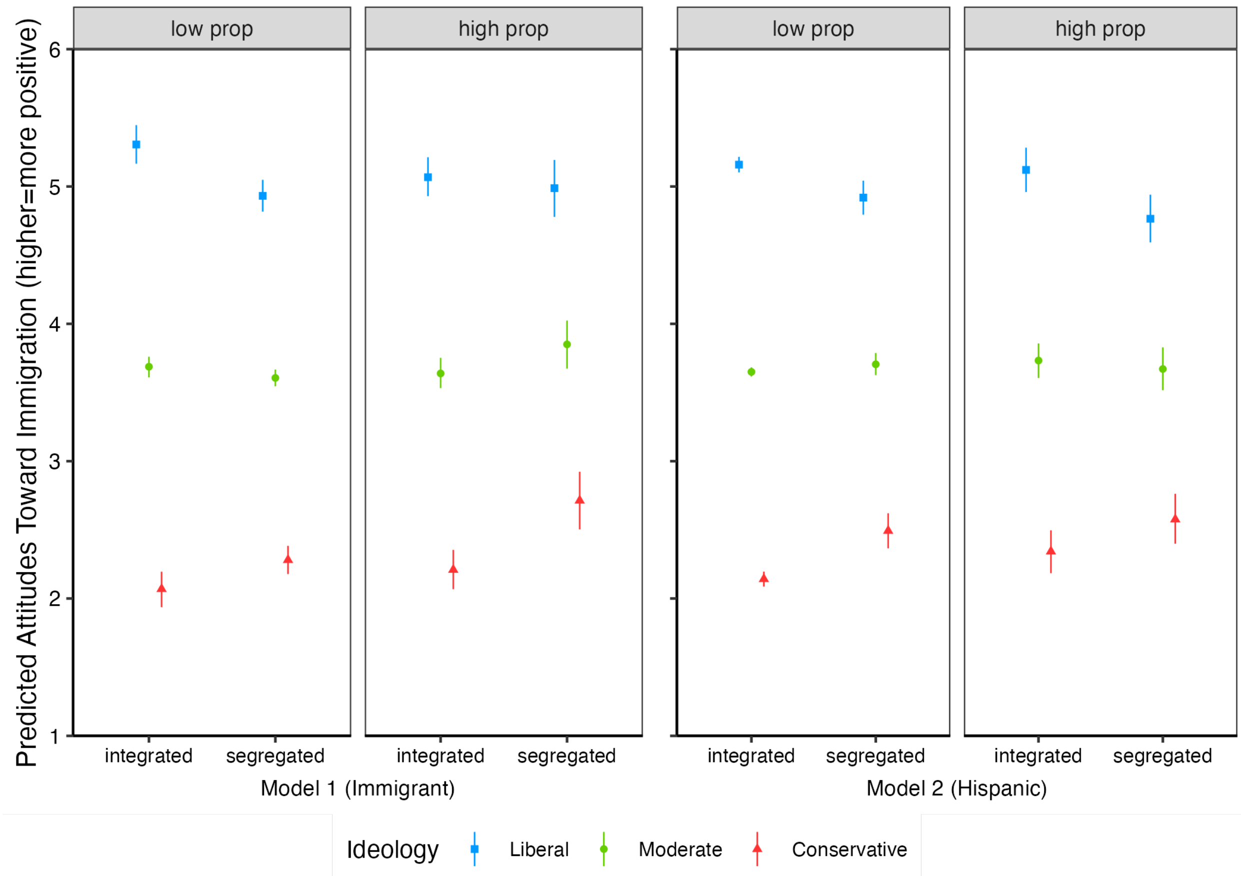


Figure D.34: Predicted Immigration Attitudes (2020)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is included in the models.

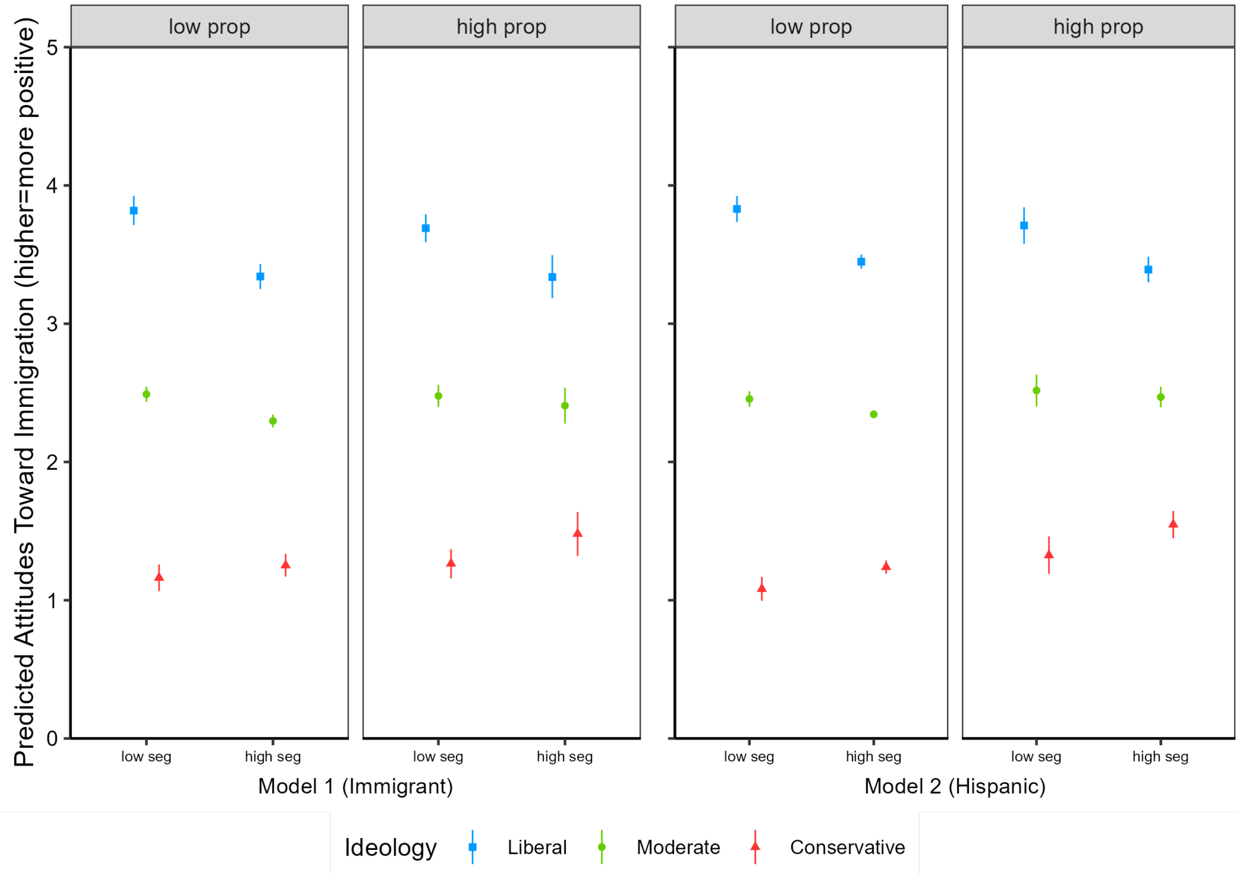


Figure D.35: Predicted Immigration Attitudes (2024)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is included in the models.

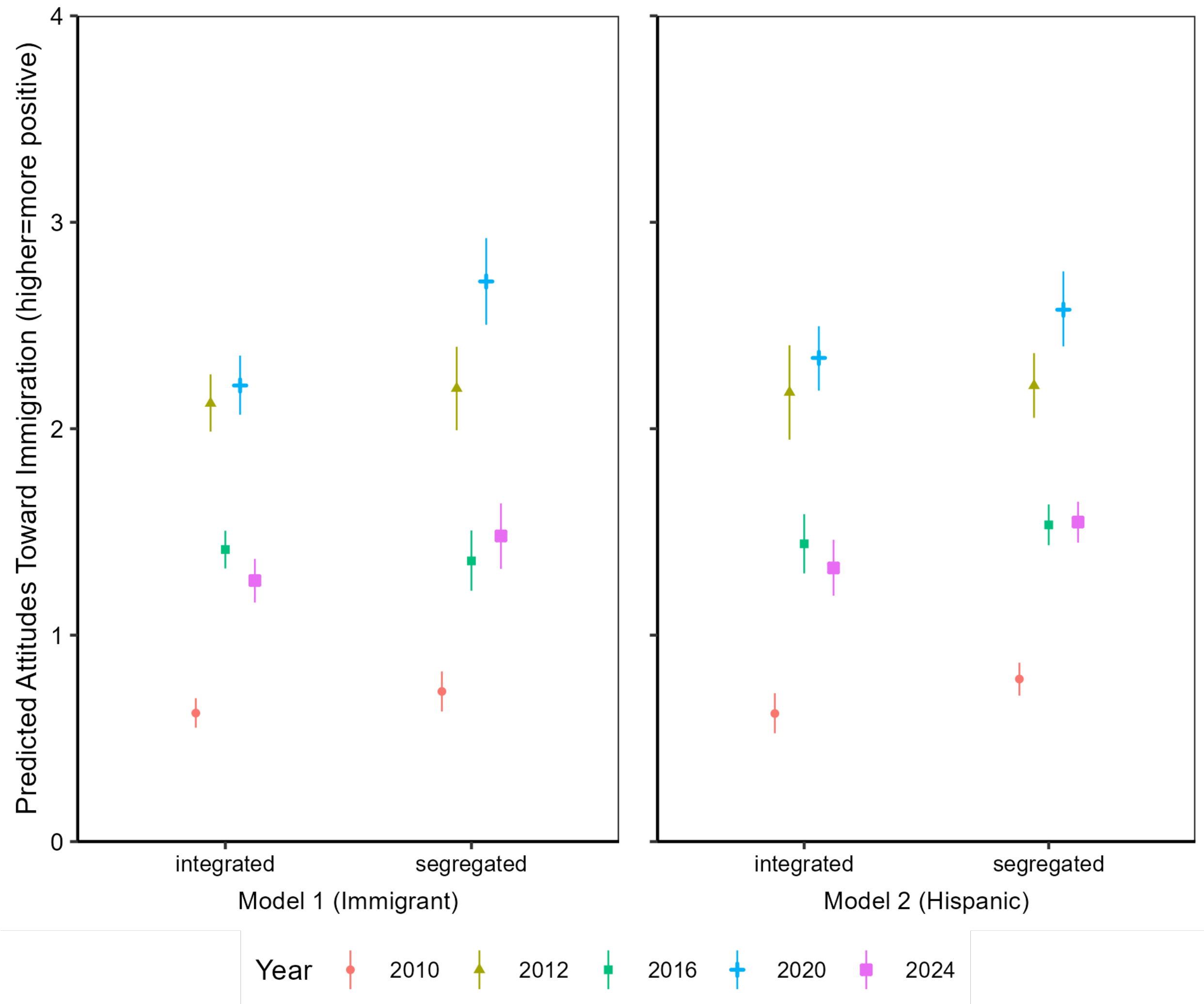


Figure D.36: Predicted Immigration Attitudes (Conservatives in High-Proportion Counties Only)

Note: The DV is an index of the questions about attitudes toward immigrants. PID is included in the models.

D.9.3 Segregation is Continuous

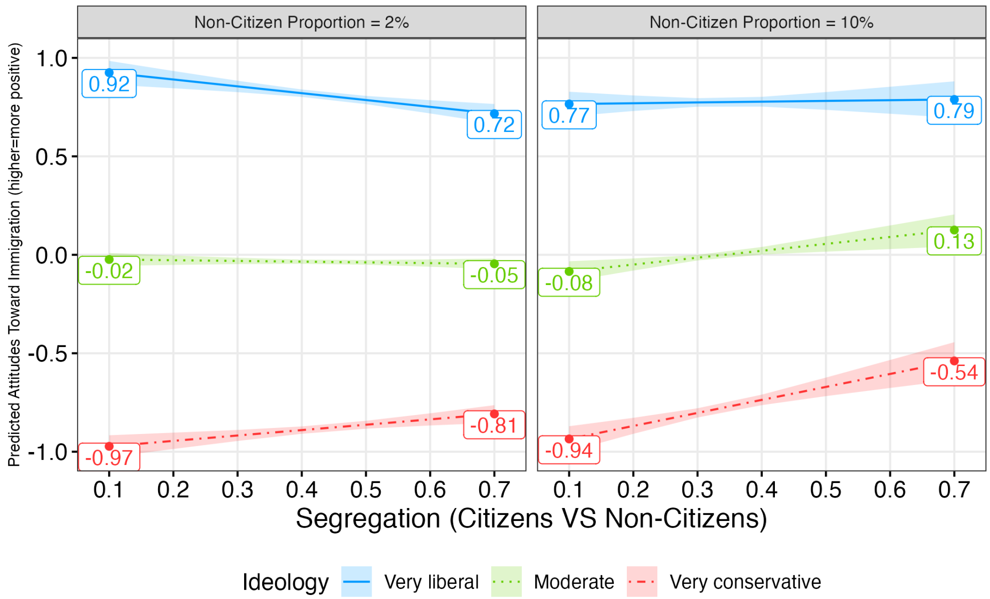


Figure D.37: Immigrant Segregation Interacting with Ideology (Model 1, 2020, no PID)

The DV is the estimate of the latent trait from the IRT model. The left one plots the situation where the immigrant proportion is only 2%, while it is 10% in the right one. The x axis is the county-level segregation value of citizens from non-citizens (from census tract to county in 2020, ranging from 0.1 to 0.7), and y is the posterior estimate of attitudes toward immigrants (a higher value indicates more pro-immigration).

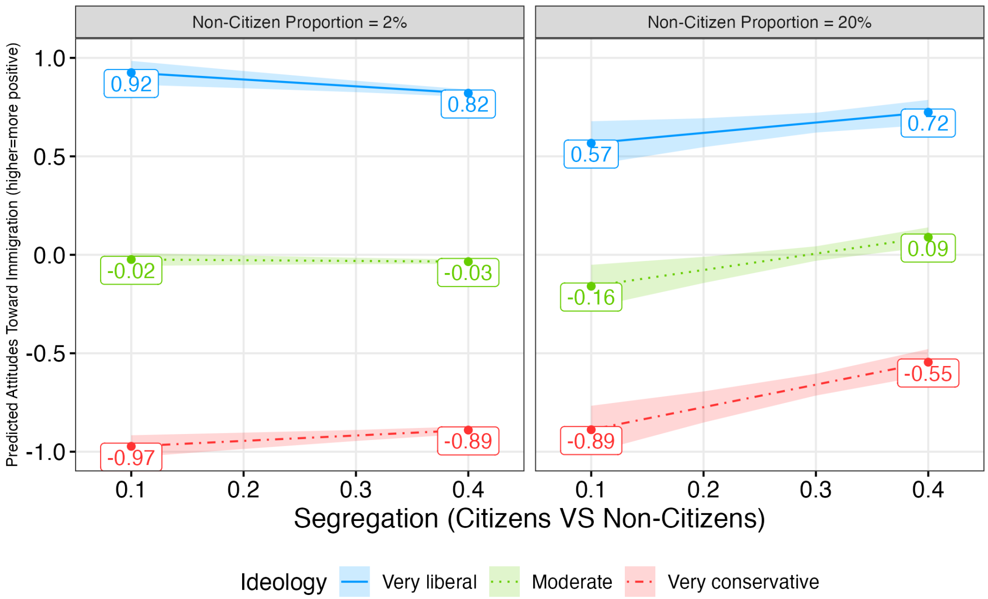


Figure D.38: Immigrant Segregation Interacting with Ideology (Model 1, 2020, no PID)

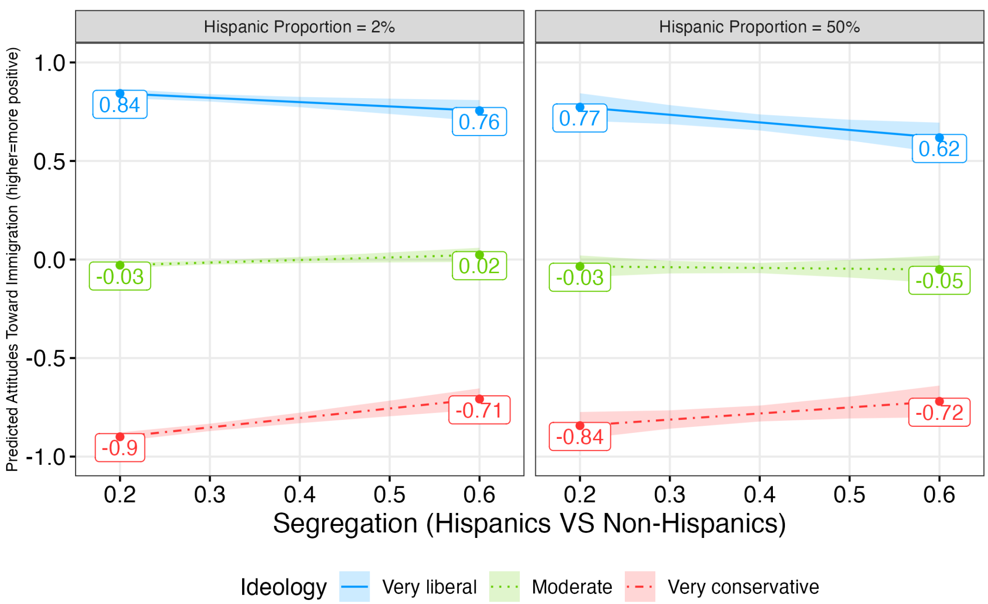


Figure D.39: Hispanic Segregation Interacting with Ideology (Model 2, 2020)

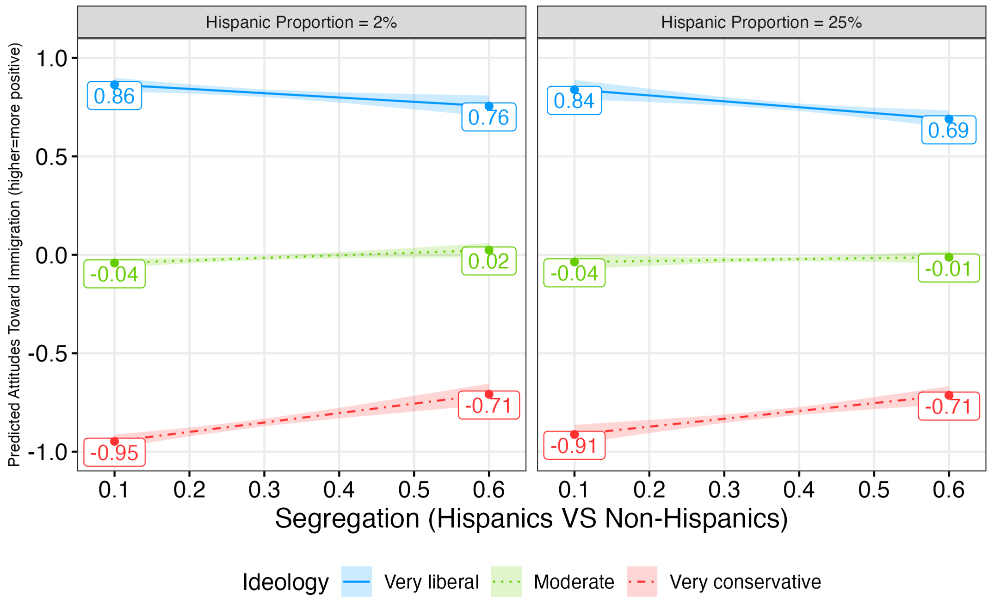


Figure D.40: Hispanic Segregation Interacting with Ideology (Model 2, 2020)

D.10 Whites VS Blacks

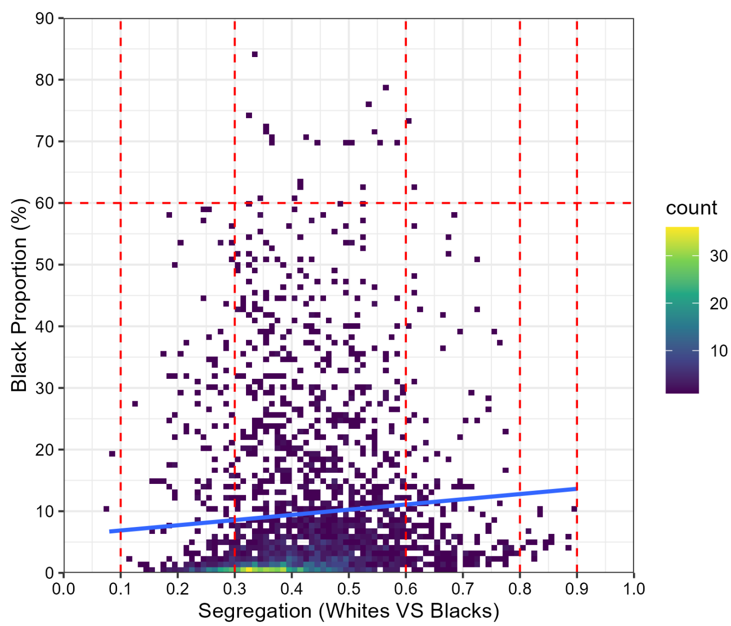


Figure D.41: Proportion and Segregation of Blacks (From Block Group to County) in 2020

Note: Only counties with a population bigger than 10,000 are kept. Counties with an NA value for segregation or exactly 0% for proportion are omitted.

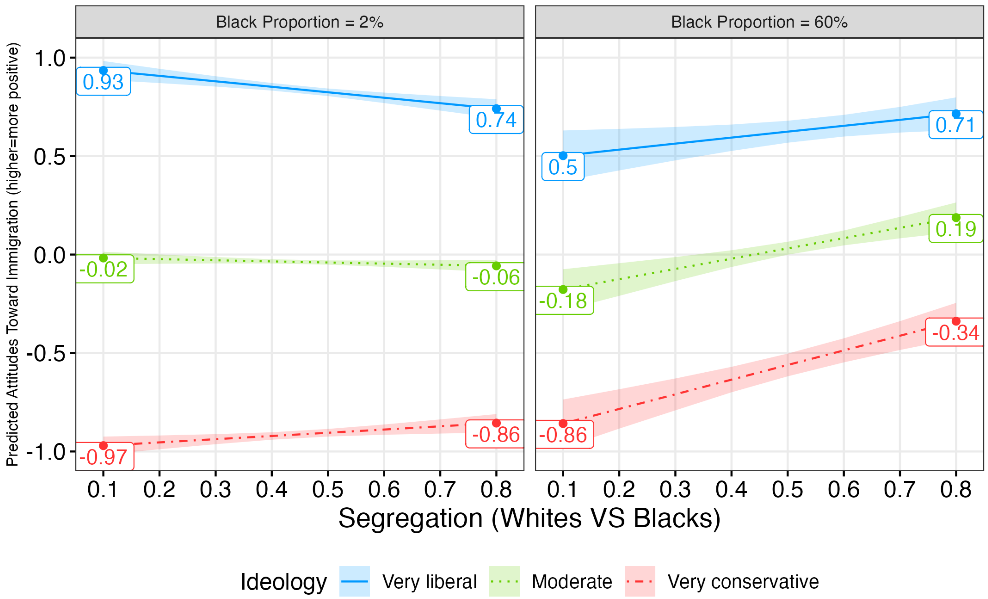
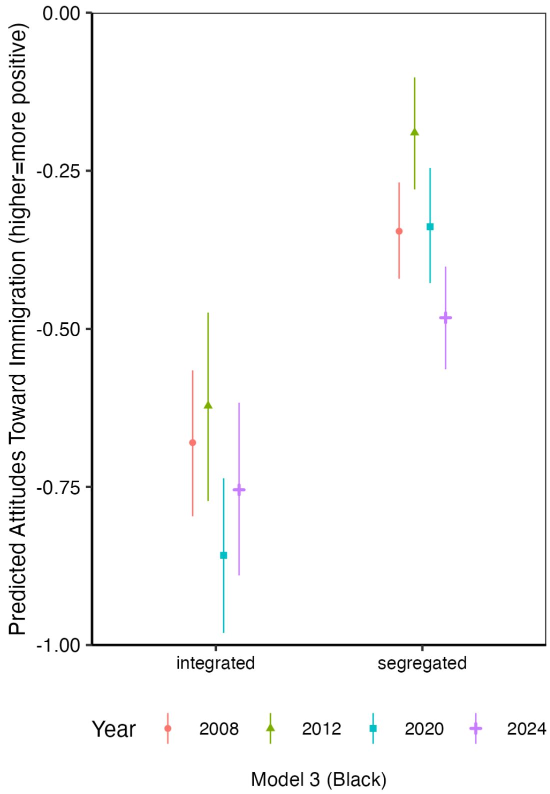
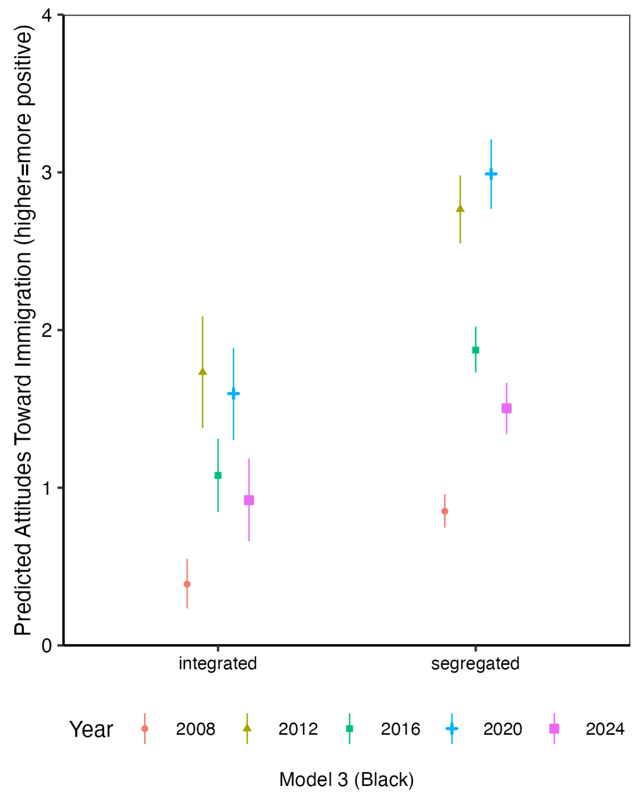


Figure D.42: Predicted Immigration Attitudes (2020)

Note: The DV is the results from the IRT models. PID is not included in the models.



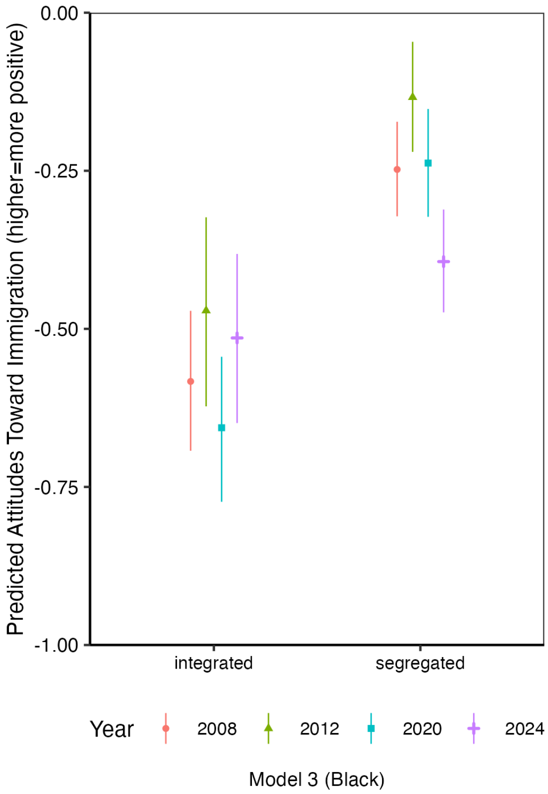
(a) DV is from IRT



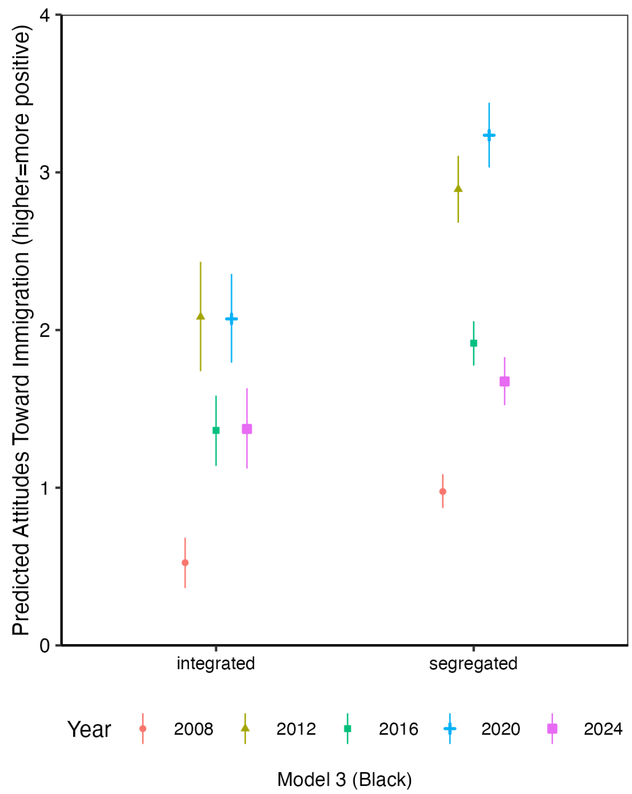
(b) DV is an index

Figure D.43: Predicted Immigration Attitudes (Conservatives in High-Proportion Counties Only, 2008-2024)

Note: On the left, the DV is the results from the IRT models. 2016 is not included because the IRT model has poor global fitness. On the right, the DV is an index of the questions about attitudes toward immigrants. PID is not included in both.



(a) DV is from IRT



(b) DV is an index

Figure D.44: Predicted Immigration Attitudes (Conservatives in High-Proportion Counties Only, 2008-2024)

Note: On the left, the DV is the results from the IRT models. 2016 is not included because the IRT model has poor global fitness. On the right, the DV is an index of the questions about attitudes toward immigrants. PID is included in both.

References

Paek, Insu, and Ki Cole. 2020. *Using R for Item Response Theory Model Applications.* Routledge.